Final Report
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During my time at UC Berkeley I have finalized a first draft of the first empirical chapter of my dissertation, which I have attached here as a final academic report of my stay.

A Simple Question of more with less? Labour-Productivity-Dynamics and their determinants in the Automotive and Generalized Manufacturing Sectors between 2011 and 2019

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Tables and Figures

1. Purpose and Structure of this Chapter

As a first starting point in understanding the relation between present levels of industrial employment and automation, a closer look at its most direct intermediary is unavoidable: *labour-productivity*. Labour-productivity is, after all, measured as the real value added (meaning how much "output" is produced[1]) per hour worked[2]. It thereby directly expresses, albeit in an abstracted and aggregated sense, the relationship between the *mass* of production, and its required amount of labour (-*time)*. This ratio is, for the most part, assumed to be constantly increasing[3], either because of the constant development of technological levers, such as automation, or due to organizational effects or simply by virtue of simply extending production (Verdoorn's law). More concretely, the question is thereby usually not *whether* labour-productivity increases, but rather by *how much*, with the stagnation of growth-rates figuring as problem. Since most economic theories suppose that "technological change", in particular in industrial production, is labor-*saving*, meaning methods of automation are developed

[1] Subtracting the intermediate products of different stages of production, and adjusted for inflation.
[2] Other denominators such as "number of workers" or "capital units" are also used.
[3] Starting with industrial production that is.

and implemented in order to reduce the need for labour-input, and thus its associated costs[4] ,for a given mass of production, automation's consequence should quite simply equal an increase in labour-productivity. With such an increase, if the mass of production is not increased alongside it, we would also quite simply assume employment to drop, as less labour is required for the same output. This very simple line of argument, where many contributions in economics stop in their theoretical analysis, shows, despite its simplicity, the intimate relationship, up to congruence, of questions of labour-productivity and employment, in particular in industrial production. The goal of this chapter is, however, not to end analysis here but begin it, and to understand the determinants of the dynamics of labour-productivity as precursor to the in-depth analysis of employment dynamics in the Austrian automotive sector, undertaken in the subsequent substantive chapters of this dissertation. The empirical horizon for this chapter not only includes the automotive sector, the focus of the overall dissertation, but also the generalized manufacturing sector, which will allow to put the results of the former into context, as well as increase empirical variation and heterogeneity. The sample is also not limited at this stage to Austria, but a panel of 22 countries between the years of 2011 and 2018. The method for establishing the relations in question is a fixed-effects panel regression

While the relation of employment and automation via the transmission-mechanism of productivity thus seems fairly clear cut in theory (as suggested above: automation increases labour-productivity and thus reduces employment in producing certain levels of output etc.), empirical data has recently complicated this assumption significantly at the first link of this chain. In the debate surrounding what has been labelled as the (new) "Productivity Paradox"[5] (Goldin et al. 2019 and 2020; OECD 2019; Brynjolfsson et al. 2019; Gordon 2015 and 2016), it has been pointed out that productivity growth rates, have in fact been stagnating over the past decade. The "paradox" consisting in the fact that this has been the case in parallel to supposed massive technological strides and claims of imminent, unheard-of productivity increases. Based on this problematization, the question becomes: what *is* the development of productivity? What determines its dynamics, and how does automation fit into all of this? The present chapter will attempt an answer to these questions, for the cases of the automotive sector, vis a vis general manufacturing of 22 countries, between the years 2011 and 2018.

The central additional explanatory factor- considered, next to of course productivity and automation, is the influence of different degrees of sectoral concentration. Depending on the theoretical position, concentration can be equally assumed to fetter, or spur productivity as well as technological development, rendering the role of concentration an open empirical question. In other words: the focus of this chapter is the question whether automation and industry concentration may explain labour-productivity dynamics. This chapter will thus bring together three large contemporary debates: 1. On automation and technological displacement (and its expressions in the new "Automation Debate"); 2. On the supposed stagnation of productivity growth in developed economies (as expressed in contributions on the "Productivity Paradox")[6] and 3., on oligopolistic and monopolistic tendencies of sectoral concentration, (as expressed in recent debates and empirical analysis of concentration, in particular of technology companies). All of these interlinked, yet distinct, debates are themselves of great import for questions of employment and technological displacement. The goal of this chapter is

[4] Notoriously the highest in any production.

[5] The "original" version had been formulated in the 1980s, by Robert Solow, of course, regarding proliferating computer technology.

[6] For an illustration of attempt in the UK of "reframing" said "productivity puzzle" see: https://productivityinsightsnetwork.co.uk/about/

thus to consider them in their possible interrelation in addressing one of the most contentious topics in economic research (Kapeller, 2022)[7].

The following section 2 will delineate, in greater detail, the theoretical considerations, relevant literatures as well as empirical results chosen for positing and answering the research questions of this chapter. Section 3 will illustrate the used data sources (Orbis, Conference Board, IFR) and method (Fixed Effects Panel Regression) used in the analysis, as well as their relevance and suitability. The subsequent section 4 will provide summary statistics and preliminary descriptive analyses. Section 5 will discuss considerations on the selection of model specifications for the multivariate analysis and section 6 will discuss and interpret the results of estimating a chosen fixed effects model variant of labour-productivity with lagged concentration and automation indicators. Finally, section 7 will discuss limitations and robustness of these findings, and section 8 will detail their relevance in moving on with the larger analysis of this dissertation.

2. The "Automation-Productivity-Concentration Nexus"

In approaching why there are still as many industrial workers as there are, a question deceptive in its seeming simplicity but in fact loaded with metaphysical subtleties and empirical problems, the goal of this chapter is to begin unravelling its complexities from the perspective of labour-productivity. This has two advantages: 1. labour-productivity relates to automation, qua production technology used for a certain output, as well as employment, qua labour used for a certain output. Yet, the metric and its literatures are distinct from its constitutive parts. 2. Focusing on explaining the dynamics of labour-productivity, allows to connect three recent debates: 1. The Automation-Debate, 2. The Productivity-Paradox debate, and 3. The "Concentration-Stagnation" debate. The theoretical interrelation of the three variables in question has elsewhere been summarized as the "Digitalisation-Concentration-Productivity-Nexus" (Ferschli et al., 2021). This term is also adopted here, as guiding theoretical category, with the exception of specifying the concrete process of "automation" rather than the general paradigm of "digitalization". *While there a no publications, to my present knowledge and at this point in time, excluding the one above, on the interrelation of all the variables in question, there exists much work on the development of single variables (see their corresponding debates) and less so, but still, on the interaction of variable pairs (automation and productivity; concentration and productivity etc.). The most relevant of these contributions will be mapped below according to their import for interpreting the results of the empirical analysis undertaken in this chapter.* This engagement with productivity thus serves as background, or rather prelude, to the analyses in the second and third substantive chapters of this dissertation, which more directly question the variable of employment itself vis a vis automation. An important part of the discussions below will thus be to stress their meaning for employment.

2.1. Productivity and its topical Paradox

As established in the introduction, the chosen approach of this dissertation is to focus on the logic of technological displacement in explaining manufacturing employment, or rather interrogating the precise dynamics between the two. In other words: what is the reason that automation leads to the displacement of workers, or why and where is this not the case? The assumption in almost all economic

[7] Kapeller refers here to a recent survey among economists of the American Economic Association pointing out that "Out of 46 policy propositions, there is only one where "no consensus" was achieved. This 'most divisive issue' related to the question of hysteresis or, more generally, Kaldor-Verdoorn effects." Meaning, that productivity grows proportionally to the square root of output. The controversy consisting, of course, in whether supply or demand determine the rate of accumulation.

schools of thought is that (industrial) technology is *labor-saving*. Automation should thus increase *labour-productivity, and thus, given a constant level of output, decrease employment (see neoclassical growth models: Solow, 1956; Romer, 1986; Rebelo, 1991; Schumpeterian evolutionary thought: Kemp et al., 2001; and Marxian schools: Shaikh, 2016)*[8]. Empirically, however, a complication of the first link in this chain has recently (re)-emerged *(the complication of the second link will follow in subsequent chapters).* A slowdown in productivity (-growth rates) in OECD countries over the past decade, has recently been noted, despite proclamations of great parallel technological strides (Gordon, 2015; 2016; Schmalensee, 2018; OECD, 2019). This "modern" "productivity paradox"[9] is well documented (Brynjolfsson et al. 2019; Goldin et al., 2019/2020, OECD 2019), opening the question that, if productivity has not increased, or has stagnated in its growth, despite supposed technological advancement, what does this mean for manufacturing employment? Or rather, could stagnating productivity explain continuing manufacturing employment in Austria? If so, how does its high industrial robot-density figure in this? Those questions are answered below. At this stage, the central contention in the literature appears to be whether the empirically observed productivity slowdown is a temporary phenomenon (Crafts, 2017), or structural and thus permanent (Gordon, 2015). Theoretically, several explanations are imaginable for this paradox. Brynjolfsson et al., (year?) for example suggest the following: 1. "False Hopes" meaning that technological is largely hype, 2. "Mismeasurement", meaning that technological developments are significant and productivity increasing, however the way productivity is measured or data collected wrong or incomplete, 3. "Distribution", productivity is increasing, but these increases are kept and contained by single companies in monopolistic positions, and 4. "Implementation and Restructuring Lags," productivity is on its way, it just takes time. Brynjolfsson et al. ultimately argue for a mixture between measuring failures and time lags to explain the present paradox. It is also important to point out that this discussion concerns the reduction of productivity-growth rates, meaning that the "surprise" concerns the relative speed with which productivity is growing, but it is growing and thus the concern is not about a "decrease" of overall productivity. In addition, industrial robots, at least in Germany, appear to be clearer in their positive productive effects (Dauth et al., 2017), relativizing the existence of a paradox for German manufacturing. As also mentioned earlier, such questions of productivity are nonetheless paramount for other economic developments. Kaldor, for example, specifically extended his thoughs on productivity to growth regimes, such as his "export-led growth". It is not per se technology or sience which drives productivity increases there but rather specialization and connected skills, lowering prices, increasing competitiveness, increasing exports and output etc.

2.2. Concentration and its Relevance for Understanding Productivity Dynamics

An engagement with the productivity of labour appears imperative for thinking about the tension between automation and industrial employment. The proclamation of a productivity paradox, in turn, forces questions on what the empirical dynamics of *labour's productivity* in manufacturing in fact are, and which factors determine those dynamics. First and foremost in determining those factors, must be the point that productivity is certainly not a goal upon itself, in particular not from the perspective of firms. Hence, there must be other factors determining it. The entire purpose of saving labour input can reasonably have three dimensions, and it is also these four dimensions that historical and present contributions can be sorted by: 1. reducing costs (of labour) and thus increasing the profit margin of the products sold, 2. Increasing production to meet unmet demand, 3. reducing the costs (of labour),

[8] While negative effects of technology on productivity are imaginable, they are maximally considered temporary artefacts of processes of transformation.

[9] A term originally coined by Robert Solow in the 1980s regarding the "missing" productivity effects of ICT technologies.

subsequently reducing the prices of products, thus selling more (sic) and thus gaining market share and increasing overall profits, and 3. Increasing control over the production process and reducing that of labour plus, increasing control over the concrete expenditure of labour power, as well as improving the conditions or negotiating the buying of labour-power, reducing the overall cost of its use, and thereby increasing profits. Hence, reducing costs, control and competition, all ultimately serving profits, must be the central reasons for attempts of increasing the productivity of labour in a given firm. In a lot of ways, we can already see that the consequences for employment must depend on which reason for the reduction of labour-input/ increase of labour-productivity is chosen. Equally, where the costs of labour are very low to being with, we can also already see why an inherent impediment to automation might exist. Since the point of contention here is not the productivity of single firms, however, but their sectoral aggregate and dynamics, we must also consider that the sum may be greater than its parts, or rather that firm behavior may result in opposing or different effects in the aggregate, than originally intended, or even realized in the cases of single firms. For example, productivity may be reduced, or rather the overall productivity growth rate may be stagnating in a sector, despite the successful attempts of single firms of greatly increasing productivity, if these productivity gains are highly concentrated, unifying both the appearance of great movement next to actual stagnation (see also Bjornfolson's (2019) number three on hist list of potential explanations for the productivity-paradox). For example, maybe a new type of robot is greatly productive in comparison to older models, but is has been developed by a firm in-house and thus not diffused to competitors, because monopoly rents.

Thus, emerges the importance for levels of concentration in understanding productivity dynamics. For example: the tension of high automation parallel to high employment could be explained by, say Austrian, manufacturers seeking favorable terms in global competition, succeeding in this endeavor, establishing (quasi-)monopolies and expanding their production and productivity at the expense of other national manufacturing sectors. However, that being said, the relationship between concentration and labor productivity is not as clear as it may seem, neither theoretically nor empirically. There are three corresponding points of interest here on which the state of the literature must be questioned: 1. What have been the recent empirical developments of concentration? 2. How is concentration theoretically and empirically related to productivity? 3. What other relevant economic consequences may such concentration have?

Ad 1.) While the empirical literature documents rising market concentration in the United States in recent decades relatively uniformly (Autor et al., 2020), results for Europe are more inconclusive (Döttling et al. (2017), DeLoecker and Eckhout (2017), and Valetti (2017); Barkai (2016), Bourguignon (2017), Weche and Wambach (2018), and Stiebale et al. (2020). Bighelli et al. (2020) for one find rising market concentration in Europe and also trace this increase it to the most productive firms, arguing a link between productivity and concentration.The rise of digital monopolies, or technological "Super-Star firms" (Acemoglu and Restrepo 2017), and their creation of artificial scarcity, has in addition complicated the perspective on the role of competition in economic development, notably so in the work of otherwise very orthodox economists such as Summers and Delong. They appear to be locked in a simple (and not new for heterodox economists) conundrum of on the one hand viewing monopoly rents as a necessary prerequisite of private enterprise, but recognizing its overall detriment to efficiency and the use of resources, with the conclusion: "*it is clear that the competitive paradigm cannot be fully appropriative we do not yet know what the right replacement paradigm might be."*

Ad 2.) Standard microeconomic theory suggests that monopolistic markets, and many manufacturing sub-sectors certainly fall into this category and indubitably so the automotive sector, should grow less in productivity (Varian, 2017), since production factors are inefficiently allocated, and the development of innovation stagnant. However*,* market concentration might also be positively associated with productivity. For instance, monopolies may be able to drive technological progress by being the only ones able to bankroll large investments, or implement new technology in a meaningful scale, due to accrued monopoly rents, or through simple economies of scale (see Verdoorn's law above). Also, the high and increasing productivity of new technological "superstar firms", (Autor et al., 2019; Stiebale et al., 2020; Ponattu et al., 2018) may be due to their ability to attract *highly skilled and productive workers in global labor markets* with over-proportional wages. Finally, however, "real competition" might force firms to invest into innovation independently of the level of market concentration, since they are always under *the threat of market capture by competitors (Shaikh, 2016). Hence, there is no clear uniform theoretical understanding of these dynamics in varying empirical instances.*

Ad 3.) Next to the question whether concentration has been increasing or not and the reasons behind it and how this interacts with labour-productivity, it is important to also highlight other, seenigly unrelated, consequences high concentration may entail. The main agreement here, in particular in contributions surrounding the automation debate (Benanav, 2020; Smith, 2021) is that high market concentration, or monopolistic and oligopolistic sectoral structures would result in stagnation. This has been a varyingly prominent position, at least since the work of Steindl (1952), certainly after Baran and Sweezy (1970) and perhaps as far back as HIlferding (1919). While ,surprisingly, this has been a marginal position in orthodox economic commentary, it has recently, equally surprising, entered the repertoire of orthodox pundits (Summers, 2013; Stiglitz, 2014; Stiglitz, 2016, see also Disslbacher 2018 for a comprehensive overview). The corresponding argument is that firms which have achieved a monopolistic position would hardly need to increase their labour-productivity or automation, meaning that productivity increases would decrease, in relation to the control that large firms have in a sector. Large firms, or rather monopolies, thus primarily engage in "rent-seeking", most notably digital monopolies, dampening productivity growth. Equally, processes of "financialization", a phenomenon closely related to concentration processes and meaning the short-term realization of financial goals, may simply make long-term and large investments in productivity increases unattractive for boards and owners (Ferschli et al. 2019a,b; Spencer 2017; Spencer and Slater 2020). This stagnation of investment *despite* parallel profitability has also been worked out elsewhere (Orhangazi 2008; Stockhammer 2006).

2.3. *Automation and its relation to Productivity and Concentration*

This, of course begs, the question how technological change, or more specifically automation, or even more specifically the use of industrial robots fits into the complex interrelations described above. Most contributions at this point deal with the effects of automation on absolute employment and its relative changes in wage and skill, which will be engaged in the following substantive chapter, and are thus not listed here. Dedicated works on the effects of robot-use on questions besides employment, are rare and most often contained within other analyses. The specific points are, however, interesting and relevant here, namely, 1. the relation between robots and productivity, and 2. The relation between robots and concentration (where it can be separated from the effects of productivity).

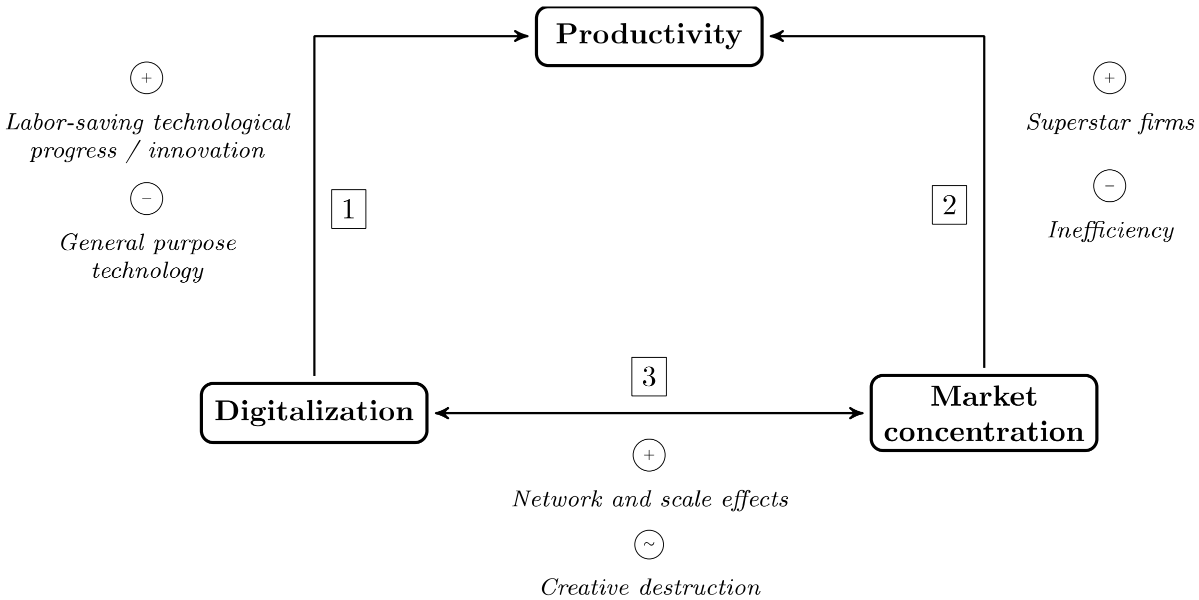
Ad.1.) One of the central publications in the vein of productivity, robots and employment is Graetz and Michaels (2018) who, as a partial result, find that robots do increase productivity (and they do reduce the employment share, however primarily of low-skilled labour). A capable methodological contestation of this is found in Bekhtiar et al. (2021), which will be engaged in greater depth in the following chapter. Dauth et al. (2017) find the same for the case of Germany, that industrial robots do increase productivity, as would be expected.

Ad.2.) Both theoretically as well as empirically, it is unclear whether the link between automation (or technological change more generally) and concentration is positive or negative (Moen et al., 2018). Theoretically it can be imagined that it is the most productive (and thus most automated) firms which are able to establish and defend monopolies, or rather win in competition, which would mean increasing market-concentration. For this argument we would empirically need to see a parallel increase in productivity, however. Standard Micro-economic theory would suggest, however, that more competitive markets would show higher productivity increases, due to overall and general efficiency, and concentrated markets would thus see labour-productivity decreases parallel to a process of concentration. Notably, Aghion et al. (2005) have argued that neither is the case, or rather both: firms both, at the very bottom and very top, of competition-levels are low in innovation and productivity increases. Only the middle-field thus drives the overall technological development of a sector, upward. Note that this is an in-sector argument, presupposing that different levels of competition exist within one sector. While this may be true, it is perhaps simplest to extend this argument to differently concentrated sectors (low/mid/high) etc. Thus, sectors with a "mid" level of competition and concentration should see the highest increases in productivity. Empirically, most assessment find a positive relation between technological change and concentration, in iterations of works of technological "Superstar firms" already outlined above (CEA, 2016, Autor et al., 2020, Stiebale et al. 2020). Finally, Ferschli et al., (2021) find that, in the case of Germany, digitalization (albeit not automation or industrial robots) is not related to concentration. There are highly concentrated sectors in the German economy, as well as highly digitized ones, and they do not necessarily overlap. However, they do find that both digitalization and concentration both affect labour-productivity positively independently form another.

2.4. Summary of Hypotheses, Gaps in the Literature and Corresponding Research Questions

Thus, I have argued why a focus on the role of technology, in particular industrial robots, takes precedence over other channels in this project for explaining manufacturing employment. In turn, laying out what we know of technological displacement in manufacturing, in particular the automotive sector, I have argued that the dynamics of productivity are a significant variable in explaining technological displacement, connecting to a topical literature on a new "productivity paradox". In understanding productivity, I have argued for the relevance of market structures as potential explanatory variable. Thus, the relation between industrial technology, productivity and market concentration becomes pivotal in an upstream understanding of manufacturing displacement. Hence, based on most economic theory, we would 1. expect automation, and its approximation of industrial robot-density, to be constantly increasing in any given time period, and given the faith in recent proclamations, expect a particularly great leap forward presently unfolding. This assumption in turn drives explanations of technological displacement in past and ongoing de-industrialization and the problem of the productivity-paradox. We would 2. expect labour-productivity to be increasing as complement to automation, due to the labour-saving character of productive technology. In turn, we would 3. expect sectoral concentration to be a central determinant in labour-productivity (and thus employment). The direction of this influence remains unclear, however. It may, affect productivity positively, because large companies are able to afford machinery, or enter and upwards concentration-productivity cycle of superstar firms; or stagnation may lead to intense battle over market shares through technology. Or it may affect productivity negatively through an inefficient allocation of resources, rent-seeking making large investment unnecessary and financialization hindering automation and thus productivity. Both points might yet be integrated in the form of "U-shape" where both very high and very low concentration affect automation and productivity negatively. These interrelations have also been gathered visually by Ferschli et al. (2021), see figure 1 below, with the stand-in of "digitalization" for automation. Where it is important to realise and emphasise the differences: "*Although the current discussion about the future of work often confuses the terms digitalization and automation, it must be clearly emphasized that both denote different processes, even if they overlap in part*." (Krw M., 2021).

Figure 1: Digitalization-Concentration-Productivity Interrelation Schematic



While there are many contributions on selected pairs of the variables in question, to my knowledge there is not one beside Ferschli et al. (2021) to connect all three. I would argue that we need theoretical and empirical evidence on the detailed interrelation between automation, productivity and market structure. In particular before questions of employment are asked, which are mostly mashed in with other analyses. Only if this nexus is better understood and clearly stated can inferences about effects on the displacement of manufacturing employment be made. Dominant contributions in the recent debates are insufficient since they lack a comprehensive theoretical description of the dynamics in question, as well as compelling empirical evidence. Overall, I would argue that works on the empirical effects on automation are lacking, and in particular where it updates and references debates of the 1980s and 90s (such as the Solow-Paradox and De-Industrialisation). The following guiding research questions have been selected to address these gaps and establish a sound basis for the analyses of employment in the Austrian automotive sector in the substantive chapters 2 and 3.

RQ 1: How can robot density and market concentration explain the variation of the productivity dynamics in the automotive and manufacturing sectors?

- *a.) How do their respective robot densities connect to their productivity dynamics?*
- *b.) How do their respective degrees of sectoral concentration influence these results?*
- *c.) What are the specific difference between the automotive and general manufacture sector, which drive its divergent results and which similarities drive the comparable results?*

I situate my engagement with these questions within the approach and tradition of institutional Political Economy (Chang, 2002), methodologically described in greater detail in section 3. The method employed is a standard fixed-effects panel regression.

3. Data and Method

In order to find answers to the research questions delineated above, I will draw on data from the *International Federation of Robotics (IFR)* (for data on industrial robots), *Orbis Bureau van Dyk* (for data on company-level revenues, used for the calculation of concentration measures) and *The Conference Board* (for labour-productivity estimates). The largest available common-denominator time-series between these sources runs from 2011 to 2018. The final balanced panel contains 22 countries (12 of the 20 largest automotive producing countries globally (the remaining countries are not included because of lacking data); the 7 largest European economies; and a special area focus of the 7 most important central-eastern European countries for automotive production. Table 1 below summarizes the parameters of this sample selection.

Table 1: Summary of Data Sources

Data Source	Variable	Availability
IFR	*Robot-Density* :Number of robots per 10.000 workers	More countries than final sample 2004-2019 (China from 2006)
ORBIS	*HHI,c3-30*: Sectoral concentration measures	All countries 2010-2020 (at time of data access)
CONFB	*Labour-Productivity*: Real value added per hour worked	Limited Country Selection 1995-2018
Smallest common denominator		**2010-2018**
Country selection		**12 out of the 20** largest auto producing countries[10] (US;JPN;GER;MEX;SP;BRAZ;CAN;FRA;SLOV;CZ;UK;IT); **7 largest** European economies[11] (GER;UK;FR;SP;IT;NL;SWI); **7 central-eastern European** countries as special area focus (AUT;HU;POL;ROM and especially SLO; SLOV; CZ (topping the list of number of automobiles produced per 1000 people[12])

On of the central constraints in establishing this final panel was the 10-year limit of Orbis-data, meaning, that there are only ever 10 years of data available in the regular Orbis database, from the present into the past. At the time of finalization of the data this meant a series from 2011 to 2020.

[10] See https://www.statista.com/statistics/584968/leading-car-manufacturing-countries-worldwide/
[11] https://www.statista.com/statistics/685925/gdp-of-european-countries/
[12] https://statisticsanddata.org/data/top-countries-by-motor-vehicle-production-1950-2020/

Another central time-constraints was that the time-series on sectoral labour-productivities by The Conference Board, ends in 2018. Thus, unfortunate cut-offs in these databases have reduced the length of the time series. The number of represented countries in the panel was also lower than expected, constraints primarily deriving from those of the The Conference Board-database, which has resulted in relevant losses such as the cases of South-Korea, China, Russia and India. Despite these concessions, the total number of observations in the final panel are however still comparable to those of similar publications, and the final panel nonetheless represents a coherent selection. The following two sections will describe the processes and considerations in "wrangling" these different data sources in greater detail, as well as the rationale and procedure of a fixed-effects panel regression.

3.1. Data availability in Detail

The variables used in operationalizing RQ1 for econometric estimation are thus:

- *Robot-Density as operationalization of "Automation":* means the number of industrial robots per ten-thousand workers. The data on stock and installations of industrial robots provided by the IFR either has to be used for calculating this metric with employment data sourced from national bureaus, or pre-calculated robot-densities can be gathered from the IFR's annual reports.
- *Labour-Productivity*: calculated as real value added per hour worked, taken from The Conference Board, although manual calculation are feasible. There are also other denominators sometimes used in the calculation of labour-productivity. such as "number of workers" or "capital units". In "particular number of workers" is a distorting metric, however. We could for example imagine the number of workers to be increased by a factor of 2, while their labour-time is reduced by the same factor. This would mean that the relation of input and output is not changed, as double the workers work half the time for same output. But taking number of workers as denominator, now double the workers produce the same output, de facto decreasing labour-productivity by half, when really nothing in relation of how much work is required for a certain production has changed.
- *Sectoral Concentration*: operationalized through the Herfindahl-Hirschman Index which is defined as the sum of the squared market shares α of the N firms in a sector. The higher the corresponding value, the higher the share of n firms in the overall production. Formally this means: $H := \sum_{i=1}^{N} \alpha_i^2$. Normalizing the HHI would mean it ranges from 0 to 1: $HHI\_n := {(H - 1/N)}\big/{1 - 1/N}$ for $N > 1$ and $HHI\_n := 1$ for $N = 1$. In addition, concentration shares are calculated (c-measures), representing the relative share of, in this case revenue, in a sector by a number n of the largest companies within that sector. Effectively this provides a metric for the percentage of overall revenue in a sector is captured by a number (n) of firms. The measures chosen for computations are: c3 (i.e. the revenue of the three largest firms by the revenue of the entire sector), c10 and c30.

The International Federation of Robotics database (IFR)

The IFR database on industrial robot-use is based on the self-reported sales-data of companies, detailing yearly number of installations and current stock in different countries and sectors. Coverage starts, for the most part, in the early 1990s. While data is available on NACE-2 two-digit sectors, more disaggregated time-series only start around the 2000s, depending on country and sector. At the time when the data frame for this analysis was finalized, the latest available year in the database was for 2019. Perhaps conveniently so, as this will mean that the disruption resulting from the COVID-19 pandemic will not have to be considered in the analysis of the data. While the IFR has added a special report on the use of robots in the service industry, the main data, and the data used in this estimation, is for industrial use of robots.

There are two central interrelated reasons for why IFR data is used in the approximation of "automation" here: 1. Automation is difficult to quantify and operationalize, correspondingly, the available data sources which could potentially be drawn upon are sparse where they concern specific technologies, and abundant where they concern very general indicators of "technology use". The IFR database is by far the most comprehensive and accessible of the databases concerning a specific type of technology. And even more so, this type of technology, industrial robots, appears as one of the most directly relevant, historically and presently, in discussions on the automation of production processes. The second reason, is that 2. this data is used in most of the well-known publications on the subject of industrial robot use and its effects on employment (see Graetz and Michaels, 2018; Acemoglu and Restrepo, 2017; Dauth et al., 2018 etc. and table xx in the appendix). However, that being said, it is very important to be aware of the constraints, for example as formulated by Martin K., (2021). While both of the above reasons make the IFR data a good choice, it is certainly not perfect. One very central caveat is the use of this data for the operationalization of "automation" which cannot sufficiently be captured with a one-dimensional metric (Krzywdzinski, 2021). Strictly speaking, industrial robots and processes of automation are thus not necessarily the same thing, albeit certainly related. It is also important to remember that the use of "robots" is an abstraction when considered for entire countries or sectors, with more in-depth analysis being required to understand the role and extent of such robots in production and its (partial) automation. In particular, where inferences about employment are attempted. Also Bekhtiar et al., 2021 further elaborate on the econometric pitfalls in using IFR data, in particular for estimations of the effects on employment. Another caveat lies in the fact that this data is collected and published by a private for-profit organization, the international federation of robotics, and relies on the self-reported sales-data of companies which supply and develop industrial robots. This essentially means opacity regarding the data underlying the numbers presented in the database, which makes a bias towards the overestimation of robot-increases likely. This data set nonetheless represents the most reputable source of industrial robot use, at the present moment, and anyway, true alternatives are not available.

While the database itself contains data on stock and yearly installations of industrial robots, it does not contain the metric used in the estimation of sections 4 and 5, namely "robot density" meaning the number of robot stock per 10.000 workers. These metrics are contained, however, in the yearly reports published by the IFR. For the present purpose both possibilities were explored: calculating measures of robot density manually, or going through the work of collecting figures from yearly for all countries and sectors IFR reports. The pros and cons are intuitive: manual calculation would mean greater control and understanding how the metrics are constructed, while drawing on pre-calculated metrics gives the advantage of likely uniformity in calculation, plus getting likely correctly specified employment data with comparable statistical structure. For some countries of the sample the latter has proven more difficult than anticipated. In the end choice fell therefore on the use of official IFR calculations. Only in the case of Austria was it necessary to manually impute individual values to complete the time-series. As pointed out by the IFR itself, it is important to remember that both robotics data as well as the employment data used by them in the calculation of robot-densities somewhat differs between countries: "*The densities calculated should rather be interpreted in rough terms. On the other hand, the data lends itself to a more in-depth time-series analysis of the* *development of the densities in individual countries*." (IFR, 2019). While robot-densities have been collected as far back as 2008, a further extension is possible, although hardly reasonable given the constraints in time-series length from the other data sources. Table 2 in the appendix shows a selection of countries and the availability of time-series on them in the IFR database. The figures 1 through 3, also in the appendix, show the plotted data for 1: Robot Density in Manufacturing between 2010 and 2019 for a wider country panel than used in the estimation, the same for the automotive sector and for the manufacturing sector, without the automotive sector.

Orbis Bureau van Dijk (Orbis)

Orbis is the most widely used database on individual firm financials, containing observations disaggregated to the four-digit NACE 2 level, for every country and sector. The biggest constraints in using Orbis are, 1. its limited historical availability, meaning 10 years into the past from the year of access. While there is a separate database of historical data by Orbis, having gained exploratory access to this data, it became clear that its quality is too poor to warrant the effort of its cumbersome extraction. The second constraint lies in 2. the fact that while *formally* Orbis is a very complete database, in terms of sectors and countries, only the largest companies usually have complete time-series with other entries suffering from massive "n.a."s. At points this problem has been so severe that not even c30 measures could be computed for single countries, meaning that for specific years not even 30 observations with numerical values could be found with otherwise hundreds or even thousands of theoretical observations. Nonetheless, as also illustrated in table 18 in the appendix, despite its shortcomings Orbis still functions as the go-to database for firm-level financials and thus manually computed concentration measures. For the purposes of this analysis I have extracted revenues, employee numbers and accounting indices for all relevant countries, for both the automotive sector and the manufacturing sector, (excluding the automotive sector (D-29)). While the goal was to thus extract every single available observation for each country and sector, Orbis has implemented varying limitations on the sample-size which can be exported from the online-interface in one step. Thus, the number of observations per country does not only depend on the number of companies registered in a sector, but also by the export-limit imposed by Orbis. This limit is however in the thousands, and does therefore not represent a problem for calculations of concentration, for which only the largest observations are of significance in most cases (due to the pareto-distribution of revenues). It is nonetheless important to stretch that "larger" datasets extracted from Orbis are thus not necessarily "better" as, again a very large part of the contained observations may be "empty" without numerical values. The extent of this problem can be gauged by looking at the selection of some countries in table 2 below. For the case of Germany for example, out of the 5067 observations in the automotive sector in the year 2019 only 586 do not equal 0, meaning they have actual numerical values, which can be used in calculations.

Table 2: NA's in Orbis Automotive Sector 2019 Selected Countries

Automotive Sector, Country in 2019	**NA's / Total observations (valid observations)**
Austria	1051 / 1140 (89 =/ 0)
Germany	4511 / 5067 (586 =/0)
United Kingdom	11197 / 11581 97 (384=/0)
United States	12992 / 30000 (17008=/0)
Japan	249 / 4464 (4215=/0)
China	22484 / 30000 (7516=/0)

A third constraint in using Orbis data, and this was the central issue in priming this data for calculation, lies in 3. the possibility of double-counting. In Orbis, it is sometimes the case that subsidiary companies are listed in the same dataset as domestic parent companies. This is not a problem in and of itself. However, the accounting of the revenue of both parent as well as subsidiary can be recorded in four different ways, corresponding to different accounting-consolidation codes: C-codes (1 or 2), meaning "consolidated", having integrated other statements into one. And U-codes (1 and 2) meaning "unconsolidated", *not* having integrated statements. The precise phrasing can be gathered from Orbis (2011:390)[13]. Now, depending on the type of account of the observation in question, this could either include all revenues of subsidiaries, in the case of a parent, or not. If a consolidated parent company is listed in a dataset as well as its unconsolidated subsidiaries, this would mean that revenues are counted double, once for the consolidated parent and once for an unconsolidated subsidiary. If concentration indices were calculated without accounting for this, concentration levels would arguably be reduced by adding seemingly independent companies in the sample, which are not in fact independent. So say company A is the national parent company of company B, both collected in the same dataset and located in the same sector. If A shows a consolidation code of a "C" (1 or 2), this would mean that all its subsidiaries are already integrated into its statement. This means, that if there is, in addition, company B with a consolidation code of "U" (1 or 2) in the dataset, which also is a subsidiary of company A, the revenue of company B is counted twice: once integrated into the parent company's revenue, and once by itself. The solution adopted here is the same one as set out in Ferschli et al., (2019 and 2021 and suggested by Grabner, 2016). The programming steps for Mathematica are attached in the appendix. They generally follow this logic: first it must be determined whether the data set contains a national parent company which is consolidated as well as its subsidiaries which are unconsolidated, which could trigger double counting. Generally, if only U-codes can be found, meaning that all observations are unconsolidated, there is no problem. The observations would still need to be added up to represent the parent company's entire revenue. In the cases where double-counting could occur, either the parent company could be dropped while adding up all subsidiaries, or all unconsolidated subsidiaries could be dropped from the data set, leaving only the consolidated parent. This has to be done for each year, sector and country, of course. Which option is chosen has different repercussions: Option one estimates the resulting concentration conservatively while option two might ignore the revenue of subsidiaries in other sectors. While the safest approach would be to calculate both alternatives and compare their merits in-depth, in the calculation of the indices below, variant two was simply chosen. There are of course no right or wrong answers in which approach is chosen, it is important to be aware of how the corresponding choice may determine the result.

Theoretically there are also complications to consider which cannot be engaged on an aggregated statistical level: what if the parent company has an independent economic activity in addition to the sum of that of its subsidiaries? What if relevant subsidiaries are classified within a different sector, but organizationally still belong to the revenues of a parent? This could mean that the added U's do not equal the C. Such complications would unfortunately have to be assessed case by case, however. There

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C1: designating the statement of a mother company which integrates the statements of its controlled subsidiaries or branches with no unconsolidated companion
C2: designating a statement of a parent company integrating the statements of its controlled subsidiaries or branches with an unconsolidated companion
U1: designating that a statement is not integrated with the statements of possibly controlled subsidiaries or branches of the concerned company with no consolidated companion
U2: designating that a statement is not integrated with the statements of the possible controlled subsidiaries or branches of the concerned company with an consolidated companion

are also potential issues resulting from the fact that economic sectoral coding is a very crude grid to capture actually economic activity in the first place. For example, a parent company may easily be located in a different NACE sector than its subsidiaries event though their revenues belong together and are technically in the same sector, but legal fiction has placed one or several parts of the company in a different economic sector. These problems are additionally exacerbated when considering international borders and economic activity between countries. Adding the revenues of a global parent company would require very extensive research and analysis and knowledge of international tax-strategies. All this is especially true for the automotive sector of course, which is dominated by large global firms in constant flux of mergers and acquisition with each other. Under these constraints, however, and adapting the data in the ways described above, as well as being aware of partially massive “n.a.’s”, the revenue data of Orbis can be used to calculate sectoral concentration measures. It is also important to note here that industry, or sectoral, concentration derived by estimating the concentration of revenues serves as a proxy for market concentration. As Heidorn and Weche (2020) argue, available industry data can be used to approximate market concentration, but they do not fully meet the economic definition of markets, making this distinction necessary.

Lastly, in the process of constructing the concentration measures, which is however of minor importance, but nonetheless an operation which must be documented, is the linear interpolation of values in rare instances in order to complete timelines. Where observations did not suffice to calculate certain indices for certain years, linear interpolation was used. This concerns only very few numbers and almost exclusively for c30 measures in the automotive sector. The Orbis data itself cannot be reliably be interpolated to address the problem of large “n.a.”’s, due to the great extent of missing values. Linear interpolation determines a missing value through convex-combination of two other data points. In the formula below y denotes revenue and x, year.

$$y(x) = y_0 \frac{y_1 - y_0}{x_1 - x_0}(x - x_0) = y_0 \frac{(x_1 - x)}{x_1 - x_0} + y_1 \frac{(x - x_0)}{x_1 - x_0}$$

Figure 4 and 5 in the appendix shows the resulting c10 measures for an extended country sample between 2011-2019, for the automotive sector as well as the manufacturing sector. Equally plots for c3, c30 and HHI can be found in the appendix as well. Finally, Table 3 and 4 show examples of the “valid observation degradation” in Orbis data, once for the case of Automotive manufacturing in 2019 (for all 22 countries in the estimation) as well as the Manufacturing sector in 2019 (for all 22 countries in the estimation).

The Conference Board (CONFB)

The Conference Board is a non-profit organization collecting open-access data on global economic developments. It has also turned out to be one of the only sources through which labour-productivity at a reasonable sectoral disaggregation (NACE two digit) could be gathered. Unfortunately, the database does not contain information on China and India, or South-Korea, countries of central importance to the global automotive production tendencies globally, and which for this reason had to be dropped from the sample unfortunately. As is often the case, time-series which only concerns the entirety of manufacturing are longer than those of specific sectors. Unfortunately, the “*The Conference Board - International Comparisons of Manufacturing Productivity and & Unit Labor Cost*” database, from which labour-productivity estimates are taken for this analysis, has been discontinued in 2018, further limiting the time series. The figures 2 and 3 in the appendix show the developments of labour-productivity for an extended country sample from 1995 to 2018, for both the automotive as well as manufacturing sectors.

Conclusion Data Suitability

The IFR database, despite its weaknesses, is the most widely used and most comprehensive database for question of industrial robot use and its relations to employment. The use of the Conference Board for the measure of labour-productivity is uncontroversial. While Orbis is one of the most widely used firm databases, in particular for concentration estimations, it has several relevant flaws. However, as also shown in Table 18 in the appendix, contributions with similar ambitions to the present paper also rely on Orbis. Orbis thus, despite its shortcomings, still represents the most reasonable database for the calculation of concentration measures based on firm level financials. This table also shows that none of the papers listed there has a time series of over 10 years, meaning despite unfortunate curtailments of observations, the time-series of this analysis still falls within acceptable, publishable parameters.

3.2. Multivariate Country Time Series Analysis: Fixed Effects Panel Regression

Multivariate regression analysis is the most obvious starting point for the analysis of the panel data detailed above. It represents the econometric standard for country/industry time-series analysis, reflected in the fact that contributions with similar questions, have through the board also opted for its use (see for example Kollmeyer 2013;2019 and allt he econometric contirbutions- Bkethiar et al., 2021 etc.). The goal of the analysis is thereby to better understand the multivariate relationship between labour-productivity, concentration and automation, comparing the automotive- to a "general" manufacturing sector, between the years 2011 and 2018, for a panel of 22 countries.

Country and time fixed effects are used to account for invariant trends affecting labour-productivity which remain constant over time, but vary with each country (institutional features etc.). The reason for this is that the central methodological problem of panel analysis is the structural interrelation of observations (meaning that data of one year is structurally related to that of the next). This causes biased estimates and inaccurate standard errors if a simple, standard OLS estimation was run, or rather: OLS does not account for heterogeneity over group and time. Since the observations are *not* independent from one another, i.e. we must assume invariant "fixed" effects, OLS transfers the effects of unmeasured, unit-specific factors into the error term leading to heterogeneity bias. A fixed effects model thus allows for different invariant intercepts of observation-groups (country and time) to account for unmeasured but invariant differences across countries. There are several ways to construct such a model (Frees, 2004; Halaby, 2004). One way, as (followed for example by Kollmeyer, 2009 and 2013) is to introduce a dummy variable for each country and each year in the sample, to account for unmeasured cross-sectional and temporal heterogeneity, and estimating a least square dummy variable model. Another way to eliminate invariant effects is a "within transformation" by subtracting the group - level average over time hence taking a first difference (the merit of each being discussed in Wooldridge 2001). In our case, the fixed effects estimators are obtained by demeaning all variables.

As a first step in the analysis, a descriptive analysis of the stylised facts of the development of the variables in question will be produced in the following section four. Different versions of a fixed effects estimation will then be discussed in section five, with both time fixed effects ($\mathrm{v_t}$) and country fixed effects ($\mathrm{u_i}$) to account for aggregate time trends affecting all variables and unobservable country-specific characteristics that are constant across time but vary between countries. The general model is specified in the following way (where the HHI is used as stand-in for other concertation measures, which will also be estimated in the course of model selection):

$$LP_{it} = \alpha_i + \beta_1 HHI_{it} + \beta_2 RD_{it} + v_t + u_i + \epsilon_{it}, \qquad (1)$$

where the dependent variable is labor productivity (LP_{it}) for each time period t and country i, calculated as value added per hours worked. As explanatory variables, using different concentration measures such as c(3,10,30) and the normalized Herfindahl-Hirschmann Index (HHI_{it}), and robot intensity (RD_{it}) are used. Demeaning the above specification leads to a reduced form:

$$\widetilde{LP}_{it} = \beta_1 \widetilde{HHI}_{it} + \beta_2 \widetilde{RD}_{it} + \theta_{it}, \qquad (2)$$

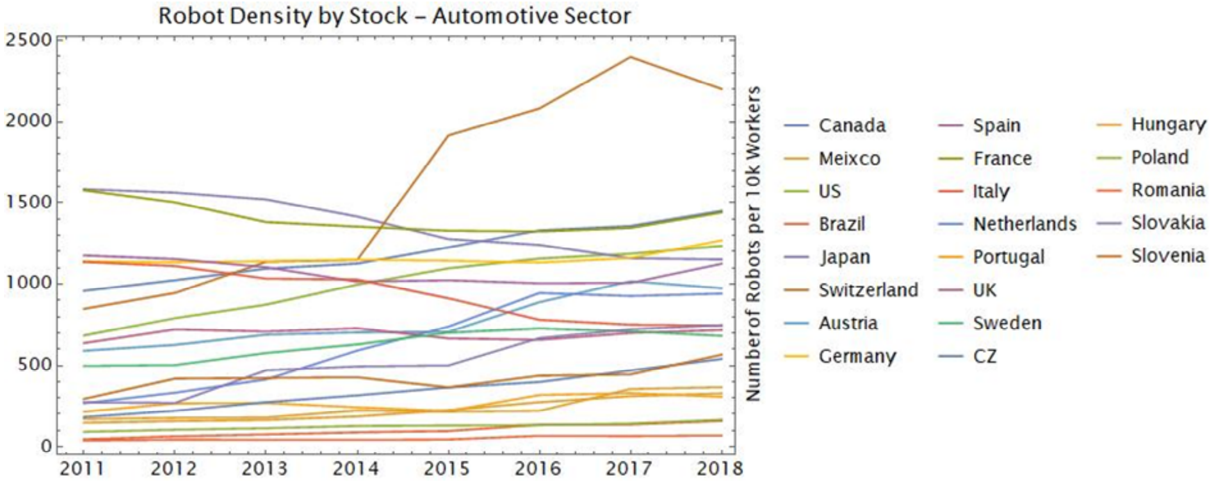
By demeaning, meaning subtracting the group average from each observation so that they are mean zero, unobserved and constant effects are removed. The estimator is now called the fixed effects estimator or within estimator. The estimated model now only contains the transformed stochastic error term θ_{it}, which is assumed to be exogenous with zero expected mean. Now that unobserved effects are removed, standard OLS can be used without bias to its estimates. Or rather in econometric language: inference procedures are asymptotically valid under homoskedasticity and exact inference is available under normality (see Wooldrige 2001 chapter appendix for detailed listing of the relevant statistical assumptions). As it is with differencing, any constant variable over time is thus lost, also the first time period. To deal with heteroskedasticity, autocorrelation, and serial correlation, which could all present in this empirical setting, Driscoll-Kraay standard error correction will be used. Furthermore labour-productivity is lagged by one period in order to counter endogeneity. In the course of the estimation, several additional factors will have to be considered such as the importance of using interaction terms (due to possible collinearity of explanatory variables). Further consideration on omitted variable bias should also be put forth, (i.e. the control of capital intensity introduced). A fixed effects model is chosen here, as opposed a random effects model as it is unreasonable to consider the observations to be random. While FE and RE estimates could be compared to test whether there is a correlation of errors and explanatory variables across all time periods (meaning the Hausman-test), this does not seem necessary here. It is also important to point out that FE models have natural drawbacks in that they exclude country and period specific effects one precisely might *want* to measure. Once models are established, robustness tests across various model specifications and estimation strategies can be performed. What follows is a first step in understanding the interrelation of the variables in question in the form of a descriptive analysis.

4. Descriptive Evidence

As a first step in analysis, a look at the descriptive developments of the variables in question is useful. These first results then remain to be assessed in greater statistical detail in the course of the multivariate analyses of the following sections.

4.1. Developments of Automation as operationalised by Robot-Density

Figure 2: Robot-Density Density Automotive Sector (Industrial Robots per 10.000 Workers)



Plotting the available data of the development of robot-density in the automotive sector gives us the following picture (figure 4). Due to the number of countries and the seemingly comparable, yet individually distinct, trajectories not much can be discerned from this collected perspective. What seems evident, however, is a segmentation of different levels of automation with the unsuspected outlier of Switzerland. Whether this segmentation is stale or moving cannot be discerned visually given the strength of the overlay. The view becomes less opaque when sorting all countries into three "classes of automation" according to their robot-densities (Low (RD<500); Mid (RD>500 and<1000), High (RD>1000), for each year of available data. These categories are, of course, randomly established and should not be used as definitive classification of the state of automation in a country or sector. It does show, however, the movement of countries in relation to their own past values and in particular relative to that of other countries.

Table 3: Classes of Automation Automotive

	2011	2012	2013	2014	2015	2016	2017	2018
Low (RD<500)	{Mexico, Brazil, Netherlands, Portugal, Sweden, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Netherlands, Portugal, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Netherlands, Portugal, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Portugal, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Portugal, CZ, Hungary, Poland, Romania, Slovenia}	{Mexico, Brazil, Portugal, CZ, Hungary, Poland, Romania, Slovenia}	{Mexico, Brazil, Portugal, CZ, Hungary, Poland, Romania, Slovenia}	{Mexico, Brazil, Portugal, Hungary, Poland, Romania}
Mid (RD>500<1000)	{Canada, US, Switzerland, Austria, United Kingdom}	{US, Switzerland, Austria, United Kingdom, Sweden}	{US, Austria, United Kingdom, Sweden}	{US, Austria, Netherlands, United Kingdom, Sweden}	{Austria, Italy, Netherlands, United Kingdom, Sweden}	{Austria, Italy, Netherlands, United Kingdom, Sweden, Slovakia}	{Italy, Netherlands, United Kingdom, Sweden, Slovakia}	{Austria, Italy, Netherlands, United Kingdom, Sweden, CZ, Slovakia, Slovenia}
High (RD>1000)	{Japan, Germany, Spain, France, Italy}	{Canada, Japan, Germany, Spain, France, Italy}	{Canada, Japan, Switzerland, Germany, Spain, France, Italy}	{Canada, Japan, Switzerland, Germany, Spain, France, Italy}	{Canada, US, Japan, Switzerland, Germany, Spain, France}	{Canada, US, Japan, Switzerland, Germany, Spain, France}	{Canada, US, Japan, Switzerland, Austria, Germany, Spain, France}	{Canada, US, Japan, Switzerland, Germany, Spain, France}

What is immediately apparent from this perspective, is that the number of countries in the "low" category, has significantly decreased between 2011 and 2018 (from 11 countries to 6), while the "mid"(from 5 to 8) and "high" categories (5 to 7) have extended. On a side note, Austria only very marginally fell within the "mid" category with a robot-density in the 900s. Thus, what we can now discern is significantly progressing automation, based on increasing use of industrial robots in the automotive sector. It is also important to note that even in the "low" category, robot-densities still reach up to 500 robots per 10.000 workers, which is important to keep in mind for the comparison with the figures of general manufacturing. Despite individual idiosyncrasies such as the case of Italy, the automotive industry has thus become more automated between the years 2011 and 2018. While Canada, the US and Switzerland have slipped into the "High" category of automation, only Italy has left it. A perhaps surprising number is that for Spain, consistently ranking in the "high" category. While this view is telling, it still does not allow to see how already highly automated countries have developed, as there is no upper bound to the class of "High" automation.

Another way to look at this development therefore, is to use Compound Annual Growth Rates (CAGRs), or rather the yearly growth required for a value to progress to another, in a given number of years (n).

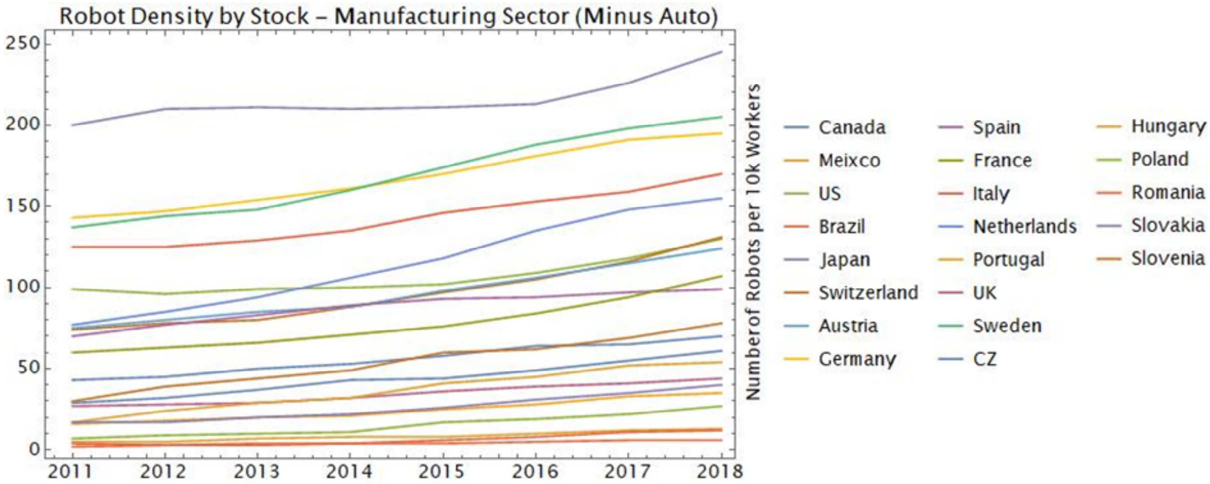
$$CAGR = \left(\frac{End\ Value}{Start\ Value}\right)^{1/n} - 1x100$$

This view reveals that even though almost all countries show positive growth rates, those which show negative ones (Japan, Spain, France and Italy) are all presently, or like Italy until 2014, in the "High" category of automation. Meaning, automation only shows negative growth-rates in already highly automated countries. This decrease, however, does not suffice to challenge their classification as "highly automated", except, again, in the case of Italy. A caveat which must be considered in using CAGRs is that they obviously depend entirely on the time-frame for which they are calculated. While the smooth developments, individual values of individual years, and thus their anomalies, fluctuations etc., are abstracted from. In this sense sharp inclines in one year, when countered by a sharp decline in the following one, are smoothed into a steady development or perhaps even stagnation. This downside may be of particular import regarding business cycles. Thus, if two countries in the sample would have the same start value in 2011 and same end value in 2018, they would show the same CAGR, even if their paths may have been fundamentally different, such as one country's automotive industry growing steadily in automation and one decreasing massively in automation, but then also increasing massively again.

Table 4: CAGRs Robot Density by Country

Country	**CAGR RD Auto**	**Country**	**CAGR RD Auto**
Italy	-5.83705	**United States**	8.79487
Japan	-4.45926	**Poland**	8.79707
France	-1.29971	**Slovenia**	9.80913
Spain	-0.631915	**Hungary**	11.4839
Germany	1.54452	**Mexico**	12.04
United Kingdom	1.70445	**Switzerland**	14.6093
Sweden	4.6243	**Slovakia**	15.4873
Portugal	5.22041	**CZ**	16.7171
Canada	6.08936	**Brazil**	19.3846
Austria	7.42392	**Netherlands**	19.6526
Romania	8.71526		

Figure 3: Robot-Density Density Manufacturing Sector (Industrial Robots per 10.000 Workers)



Repeating the above analysis for the manufacturing sector (excluding values for automotive manufacturing, see figure 9) we already see a quick glance, a smooth increase in the levels of robot density of all countries between 2011 and 2018. Again, there appear to be hardly any signs of convergence, but rather segmentation, meaning that while countries appear to be increasingly automating, they are doing so on different levels. The most immediate difference to the automotive sector to immediately note is the radically different levels of robot-density. Except for one outlier, the highest robot-densities in manufacturing are between 100 and 150 robots per 10.000 workers. This means a factor of 10 separates automation in the automotive and manufacturing sectors.

Table 5: Classes of Automation Manufacturing

	2011	2012	2013	2014	2015	2016	2017	2018
Low (RD<50)	{Canada, Mexico, Brazil, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Canada, Mexico, Brazil, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Mexico, Brazil, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia}	{Mexico, Brazil, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia}	{Mexico, Brazil, Portugal, United Kingdom, Poland, Romania, Slovakia}	{Mexico, Brazil, Portugal, United Kingdom, Poland, Romania, Slovakia}
Mid (RD>50<100)	{US, Switzerland, Austria, Spain, France, Netherlands}	{US, Switzerland, Austria, Spain, France, Netherlands}	{US, Switzerland, Austria, Spain, France, Netherlands}	{Canada, Switzerland, Austria, Spain, France}	{Canada, Switzerland, Austria, Spain, France, Slovenia}	{Canada, Spain, France, Slovenia}	{Canada, Spain, France, CZ, Hungary, Slovenia}	{Canada, Spain, CZ, Hungary, Slovenia}
High (RD>100)	{Japan, Germany, Italy, Sweden}	{Japan, Germany, Italy, Sweden}	{Japan, Germany, Italy, Sweden}	{Japan, Germany, Italy, Netherlands, Sweden}	{US, Japan, Germany, Italy, Netherlands, Sweden}	{US, Japan, Switzerland, Austria, Germany, Italy, Netherlands, Sweden}	{US, Japan, Switzerland, Austria, Germany, Italy, Netherlands, Sweden}	{US, Japan, Switzerland, Austria, Germany, France, Italy, Netherlands, Sweden}

Taking again a „group-perspective“, although with appropriately scaled down categories (Low (RD<50); Mid (RD>50 and<100), High (RD>100), also shows that the “low” category has greatly decreased its numbers, while the “high” category has strongly bolstered its numbers with the middle-field remaining largely steady. The composition of the countries „in the middle“ has however, entirely changed (except for Spain). There are no negative CAGRs to be found in manufacturing. The extent of different positive growth rates, however, varies greatly.

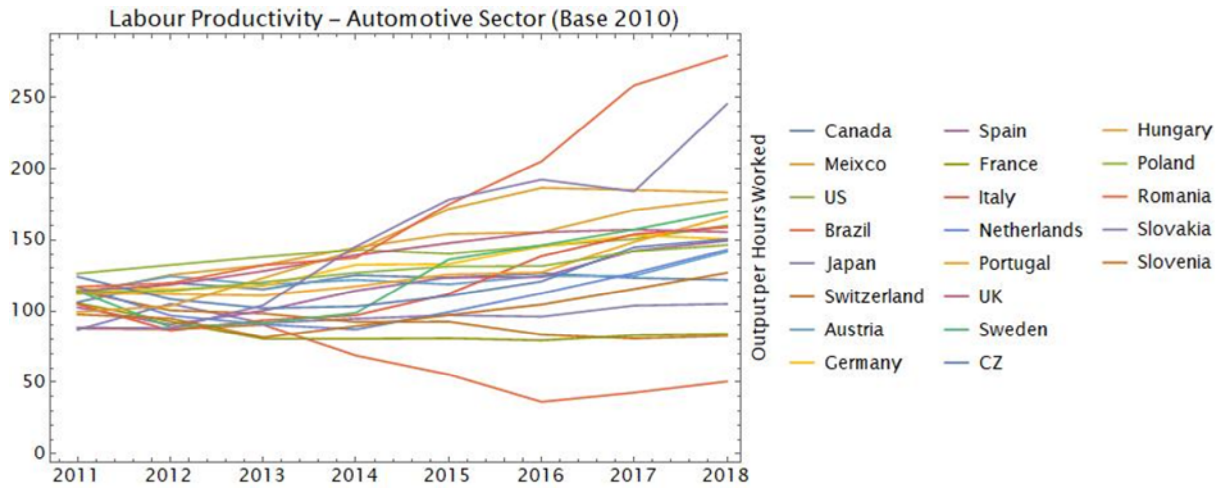
Table 6:CAGRs Robot Density by Country Manufacturing

Country	**CAGR RD Manu**	**Country**	**CAGR RD Manu**
Japan	2.94159	**France**	8.61514
US	3.96835	**Netherlands**	10.5111
Italy	4.49051	**CZ**	11.2073
Germany	4.53041	**Portugal**	11.8315
Spain	5.07643	**Slovakia**	13.0023
Sweden	5.92653	**Mexico**	14.6257
Brazil	5.9634	**Slovenia**	14.6257
Canada	7.20938	**Hungary**	17.9523
UK	7.22558	**Poland**	21.2697
Austria	7.44701	**Romania**	29.1706

Switzerland	8.50112		

4.2. Developments of Labour-Productivity measured as real-value added per hour worked

Figure 4: Real-value added per hour worked, Automotive Sector



Considering now the developments labour-productivity in the automotive sector (Figure 10), taking 2010 values as base, the divergence of changes in productivity are increasingly widening over the years. While there seems to be an overall increasing trend, individual cases do fall below their 2010 levels. The result is a widening gap between automotive sectors which are increasing their labour-productivity rapidly (some by around a factor of 2) and those whose productivity is decreasing, with a general trend of increase in the middle.

Table 7: Class perspective on Labour-Productivity developments Auto

	2011	2012	2013	2014	2015	2016	2017	2018
Low {<100}	{Brazil, Japan, Hungary, Slovakia, Slovenia}	{Brazil, Spain, France, Italy, Netherlands, Sweden, Slovakia, Slovenia}	{Brazil, Japan, Switzerland, France, Italy, Netherlands, Sweden, Slovenia}	{Brazil, Japan, Switzerland, France, Italy, Netherlands, Sweden, Slovenia}	{Brazil, Japan, Switzerland, France, Netherlands, Slovenia}	{Brazil, Japan, Switzerland, France}	{Brazil, Switzerland, France}	{Brazil, Switzerland, France}
Mid {100-150}	{Canada, Mexico, US, Switzerland, Austria, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom, Sweden, CZ, Poland, Romania}	{Canada, Mexico, US, Japan, Switzerland, Austria, Germany, Portugal, United Kingdom, CZ, Hungary, Poland, Romania}	{Canada, Mexico, US, Austria, Germany, Spain, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia}	{Canada, Mexico, US, Austria, Germany, Spain, Portugal, United Kingdom, CZ, Hungary, Poland, Romania, Slovakia}	{Canada, US, Austria, Germany, Spain, Italy, Portugal, United Kingdom, Sweden, CZ, Poland}	{Canada, US, Austria, Germany, Spain, Italy, Netherlands, Portugal, Sweden, CZ, Poland, Slovenia}	{Canada, Japan, Austria, Spain, Netherlands, Portugal, CZ, Poland, Slovenia}	{Canada, Japan, Austria, Spain, Netherlands, Poland, Slovenia}
High {>150}	{}	{}	{}	{}	{Mexico, Hungary, Romania, Slovakia}	{Mexico, United Kingdom, Hungary, Romania, Slovakia}	{Mexico, US, Germany, Italy, United Kingdom, Sweden, Hungary, Romania, Slovakia}	{Mexico, US, Germany, Italy, Portugal, United Kingdom, Sweden, CZ, Hungary, Romania, Slovakia}

Looking at the data from a categorized perspective again, („low“ denoting all countries which have dropped under their 2010 productivity values, „mid“ denoting countries which have increased their labour-productivity by up 50% from their 2010 value, and “high” countries which have exceeded this growth- see Table 6),

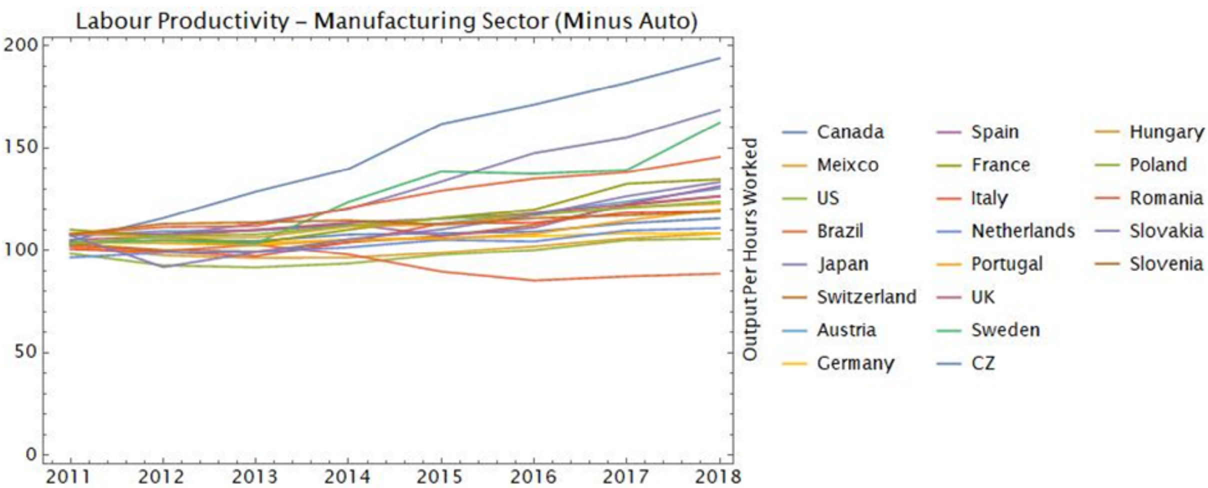
shows that with 2015 countries have starting entering a higher productivity threshold (in relation to their 2010 values of course). Since the values of 2010 are used as base, it should only be a matter of time for all countries to increase their productivity and end up in the “high” category. What appears more interesting thus, is at which point, or at which speed, countries reach those levels as that would express greater relative productivity growth. Correspondingly, the fastest gains are first realized not by those countries which we would expect to be at the forefront based on robot-densities: Mexico, Hungary, Romania, Slovakia. This suggests that productivity gains may have been realized due to catch-up investments reaping relatively larger productivity-returns for the robots that were installed. In 2018, only few countries remain in a "productivity contraction" relative to their 2010 values, with France and Switzerland as interesting and notable counterfactuals. In particular Switzerland, which was shown to be a leading figure in terms of robot-density in the automotive sector is here shown to be stagnating in productivity-growth, suggesting a plateau or stagnating effect of labour-productivity at a certain level of robot-density. From this perspective it doesn't seem like a "productivity paradox" is present for most countries of this sample and their automotive sectors, excluding he notable exceptions of Switzerland, France and possibly Brazil, for which such a diagnosis would fit.

While productivity may not have increased in "unimaginable" leaps, as suggested by technology commentary and pundits, increases where not low or stagnating in any way for most countries' automotive sector. Naturally, only the countries still within the "low" category in 2018 are the ones also showing negative CAGRs.

Table 8: Table 6:CAGRs Labour-Productivity by Country Automotive

Country	CAGR LP AUTO	Country	CAGR LP AUTO
Brazil	-7.60475	**Germany**	3.8822
Switzerland	-4.5062	**UK**	4.53314
France	-3.20768	**Spain**	5.537
Canada	1.99183	**Sweden**	5.84097
Japan	2.71184	**Italy**	6.12638
CZ	2.79539	**Mexico**	6.89137
Netherlands	2.8995	**Hungary**	9.1399
Austria	3.27539	**Romania**	13.1992
US	3.43859	**Slovakia**	15.655
Poland	3.76829		
Slovenia	3.80111		

Figure 5: Real-value added per hour worked, Manufacturing Sector



Repeating this analysis for the general manufacturing sector shows a comparable picture, although the general increase in productivity is more clearly visible, yet the spread between countries noticeably narrower. While tendencies seem comparable therefore, the effect also seems somewhat weaker.

Table 9: Class perspective on Labour-Productivity developments Manu

	2011	2012	2013	2014
Low (<100)	{US, Netherlands}	{Mexico, US, Brazil, Italy, Netherlands, Slovakia}	{Mexico, US, Switzerland, Italy, Netherlands, Slovakia}	{Mexico, US, Brazil}
Mid (100-150)	{Canada, Mexico, Brazil, Japan, Switzerland, Austria, Germany, Spain, France, Italy, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}	{Canada, Japan, Switzerland, Austria, Germany, Spain, France, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Romania, Slovenia}	{Canada, Brazil, Japan, Austria, Germany, Spain, France, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Romania, Slovenia}	{Canada, Japan, Switzerland, Austria, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Romania, Slovakia, Slovenia}
High (>150)	{}	{}	{}	{}

	2015	2016	2017	2018
Low (<100)	{Mexico, US, Brazil}	{Brazil}	{Brazil}	{Brazil}
Mid (100-150)	{Canada, Japan, Switzerland, Austria, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom, Sweden, Hungary, Poland, Romania, Slovakia, Slovenia}	{Canada, Mexico, US, Japan, Switzerland, Austria, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom, Sweden, Hungary, Poland, Romania, Slovakia, Slovenia}	{Canada, Mexico, US, Switzerland, Austria, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom, Sweden, Hungary, Poland, Romania, Slovakia, Slovenia}	{Canada, Mexico, US, Switzerland, Austria, Germany, Spain, France, Italy, Netherlands, Portugal, United Kingdom, Hungary, Poland, Romania, Slovakia, Slovenia}
High (>150)	{CZ}	{CZ}	{Japan, CZ}	{Japan, Sweden, CZ}

Repeating the „class"-view for manufacturing makes this picture even clearer. Almost all countries fare somewhat within the „mid" range of productivity increases. Only Brazil has seen a constant decrease between its 2010 levels, and only Japan, Sweden and CZ have increased it above the mid-range (it is also interesting to remember that Japan had a negative CAGR for robot-density and mid-field growth of labour-productivity in the automotive sector). This means that there are far fewer large increases and spread than in automotive manufacturing, but a very solid almost linear seeming development for all countries resulting in a comparable standing in 2018. Again, only Brazil shows a negative CAGR. All other countries' positive values are in comparable bounds, but can be ranked in the following way.

Table 10: Table 8: Table 6:CAGRs Labour-Productivity by Country Manufacturing

Country	CAGR LP MANU	Country	CAGR LP MANU
Brazil	-2.01304	**UK**	2.67173
Germany	0.585901	**Austria**	2.80982
Mexico	0.904051	**Spain**	2.85228
US	1.03747	**France**	2.91295
Slovenia	1.39754	**Switzerland**	2.92906
Canada	1.59256	**Slovakia**	3.15154
Hungary	1.8125	**Romania**	4.37007
Portugal	1.98695	**Sweden**	6.58647
Netherlands	2.00583	**Japan**	7.3284
Italy	2.46515	**CZ**	9.16206
Poland	2.65223		

4.3. Developments of Sectoral Concentration as measured by c-shares and the HHI

Figure 6: Concentration measures Automotive Sector (HHI)

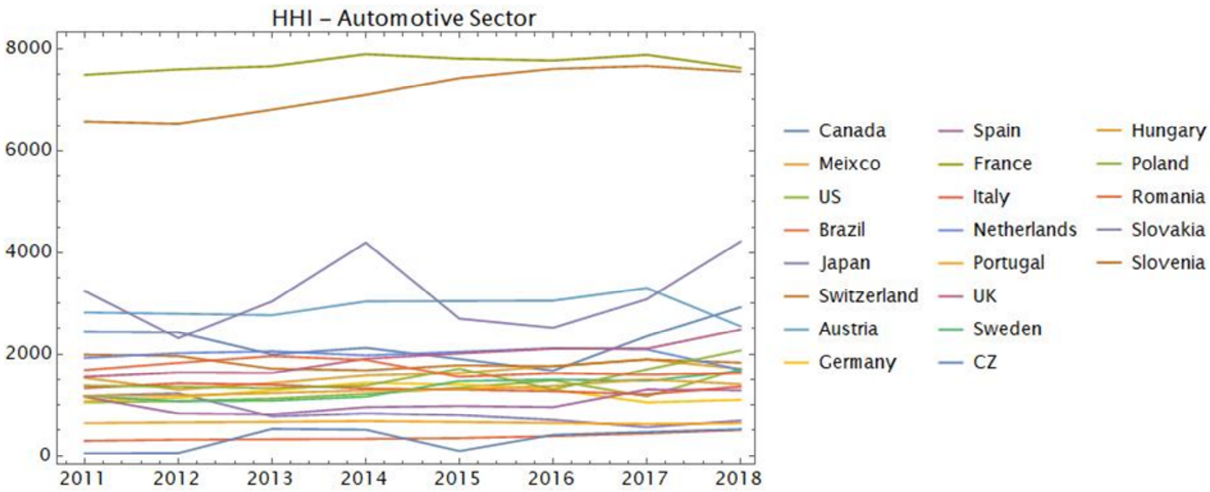


Figure 7 Concentration measures Automotive Sector (c3)

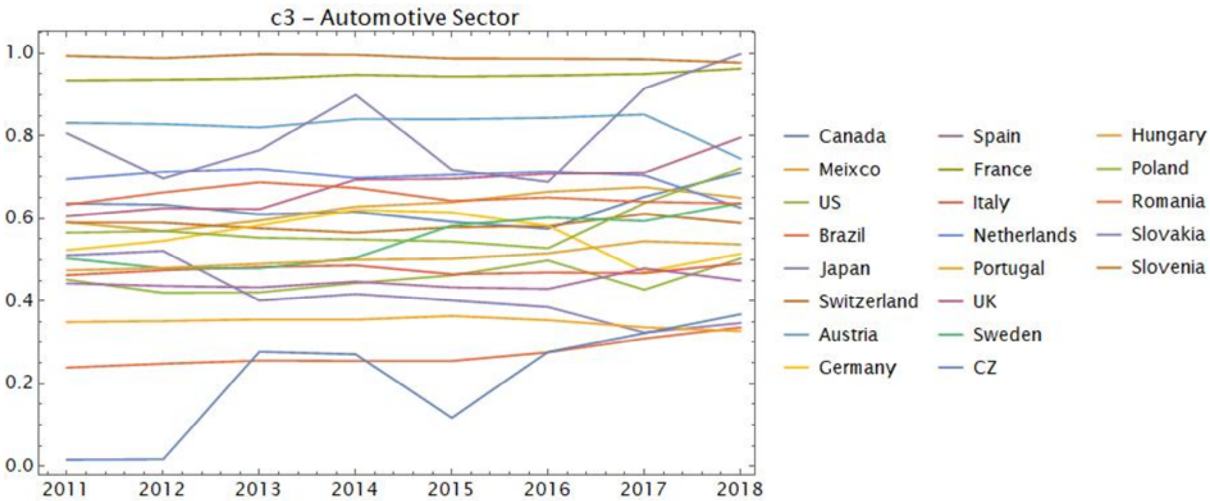


Figure 8 Concentration measures Automotive Sector (c10)

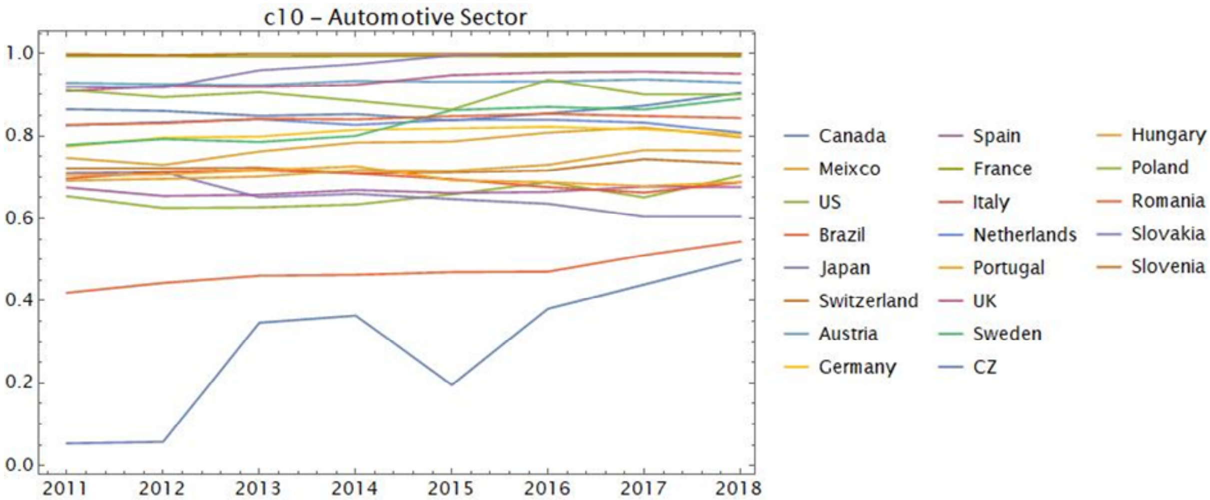
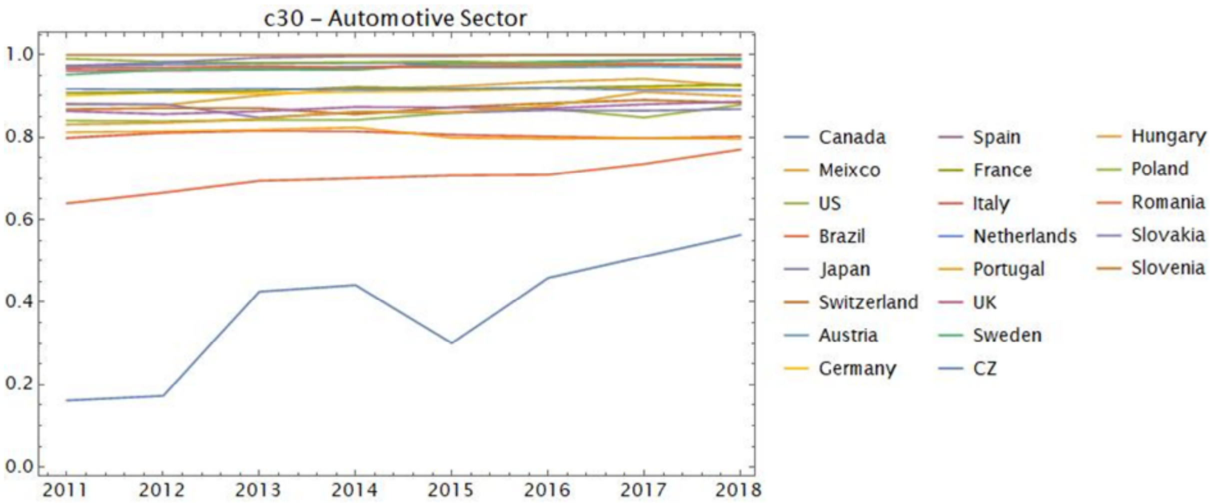


Figure 9: Concentration measures Automotive Sector (c30)



Turning now to various measures in estimating sectoral concentration, it is immediately apparent that the automotive sectors of almost all countries are very highly concentrated, to the point where the c30 measures show that in most cases at least 80% of a countries sector is dominated by the 30 largest firms. This assessment does not even include the epistemological uncertainties of the potentially "hidden" structure of ownership and control between and within countries in the automotive sector. On the other hand, these levels of concentration appear largely steady, which would speak to them being the result of oligopolistic structure of the automotive sector, inherently and through its historical process of concentration. Yet again, it is also difficult to discern movement from such a simple plot.

Table 11: Class view Concentration in the Automotive Sector

	2011	2012	2013	2014	2015	2016	2017	2018
Low {c10<0.5}	{Switzerland, Poland}	{Switzerland, Poland}	{Switzerland, Poland}	{Switzerland, Poland}	{Switzerland, Poland}	{Switzerland, Poland}	{Switzerland}	{Switzerland}
Mid {c10>0.5<0.8}	{Japan, Austria, Spain, Italy, Portugal, United Kingdom, CZ, Hungary, Romania, Slovakia}	{Japan, Austria, Spain, Italy, Portugal, United Kingdom, CZ, Hungary, Romania, Slovakia}	{Japan, Austria, Spain, Italy, Portugal, United Kingdom, CZ, Hungary, Romania, Slovakia}	{Japan, Spain, Italy, Portugal, CZ, Hungary, Romania, Slovakia}	{Japan, Spain, Italy, Portugal, CZ, Hungary, Romania, Slovakia}	{Japan, Spain, Italy, Portugal, CZ, Hungary, Romania}	{Japan, Spain, Italy, Portugal, CZ, Hungary, Poland, Romania}	{Japan, Spain, Italy, Portugal, CZ, Hungary, Poland, Romania, Slovakia}
High {c10>0.8}	{Canada, Mexico, US, Brazil, Germany, France, Netherlands, Sweden, Slovenia}	{Canada, Mexico, US, Brazil, Germany, France, Netherlands, Sweden, Slovenia}	{Canada, Mexico, US, Brazil, Germany, France, Netherlands, Sweden, Slovenia}	{Canada, Mexico, US, Brazil, Austria, Germany, France, Netherlands, United Kingdom, Sweden, Slovenia}	{Canada, Mexico, US, Brazil, Austria, Germany, France, Netherlands, United Kingdom, Sweden, Slovenia}	{Canada, Mexico, US, Brazil, Austria, Germany, France, Netherlands, United Kingdom, Sweden, Slovakia, Slovenia}	{Canada, Mexico, US, Brazil, Austria, Germany, France, Netherlands, United Kingdom, Sweden, Slovakia, Slovenia}	{Canada, Mexico, US, Brazil, Austria, Germany, France, Netherlands, United Kingdom, Sweden, Slovenia}

The Class-view shows very little movement here with most countries falling into the very high or mid-range of concentration measures („low" denoting a c10 smaller than 50%, „mid" a c10 between 50 and 80%, and "high" above 80%). Equally the CAGRs are not very telling in most cases. Most have negative sign with however very low values (except for Switzerland) which hardly allow these values to be considered a "trend", much less a significant one.

Table 12: Table 10: Table 8: Table 6:CAGRs c10 by Country Automotive

Country	**CAGR CONC AUTO**	**Country**	**CAGR CONC AUTO**
Switzerland	-27.2242	**CZ**	-0.228734
Poland	-3.62939	**Portugal**	-0.0194467
Austria	-1.9077	**Canada**	-0.0141324
Japan	-1.41752	**Sweden**	-0.00891805
Mexico	-1.18705	**Netherlands**	0.00630042
Romania	-1.03051	**Brazil**	0.167883
Slovakia	-0.921265	**Italy**	0.183179

Germany	-0.65006	**France**	0.325834
Slovenia	-0.630023	**Spain**	0.348658
UK	-0.550315	**Hungary**	2.31923
US	-0.283382		

While the same dynamics seem to be at play for the case of manufacturing, the levels of concentration are much lower and much more dispersed than for the automotive sector. This may also lie, as already mentioned above, in the statistical fiction of calculation a concentration measure of "general manufacturing", where companies are aggregated together, which might in fact not stand in direct competition

Figure 10: Concentration measures Manufacturing Sector (HHI)

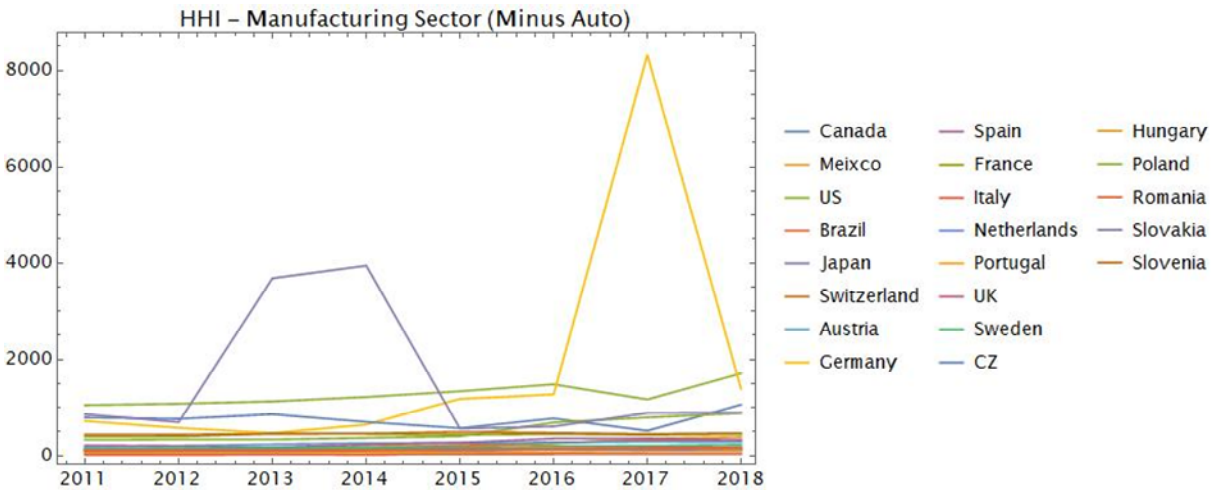


Figure 11: Concentration measures Manufacturing Sector (c3)

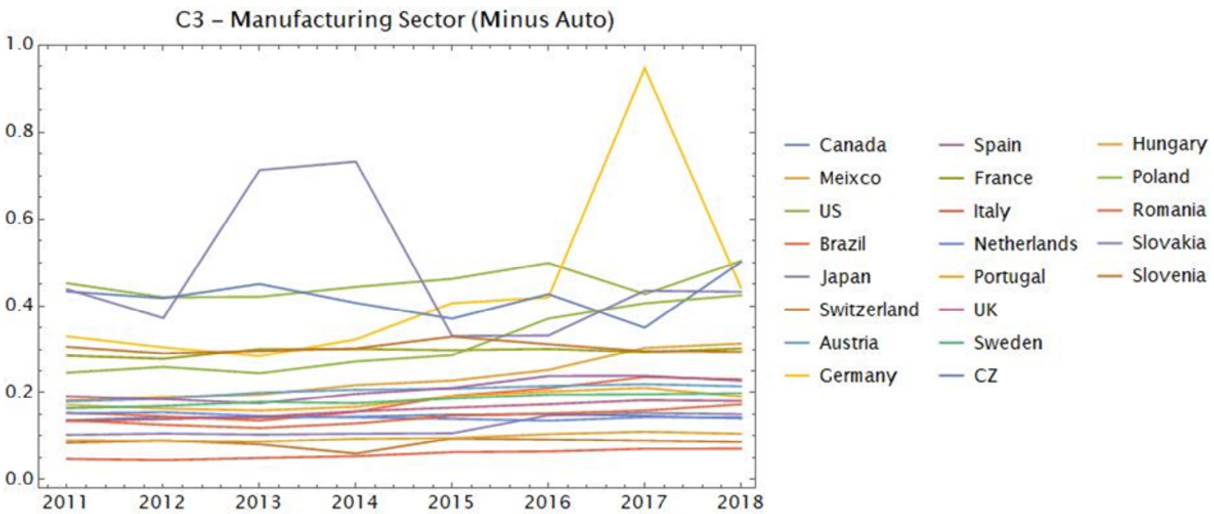


Figure 12: Concentration measures Manufacturing Sector (c10)

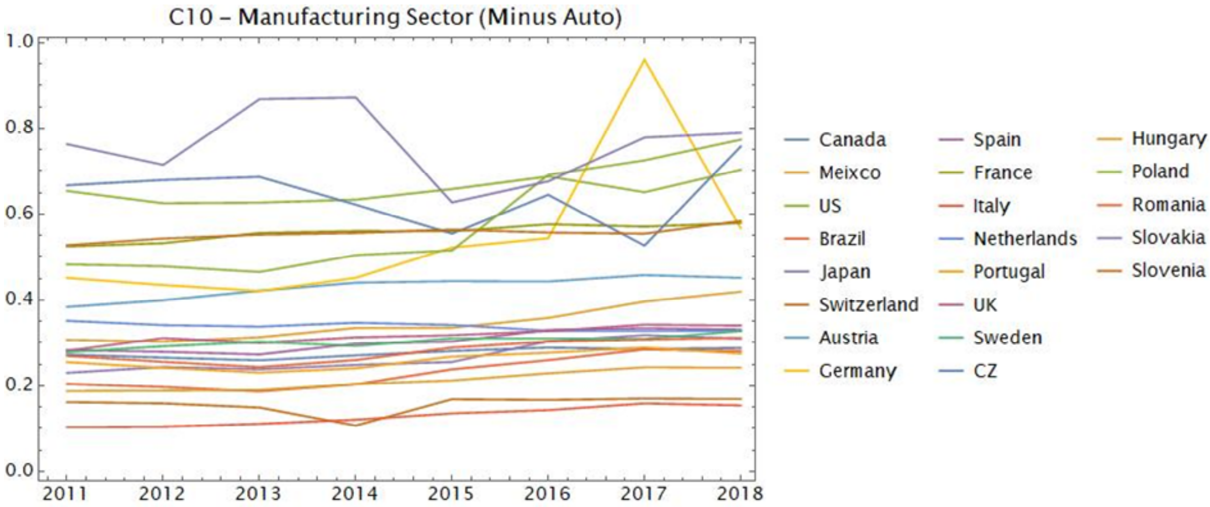
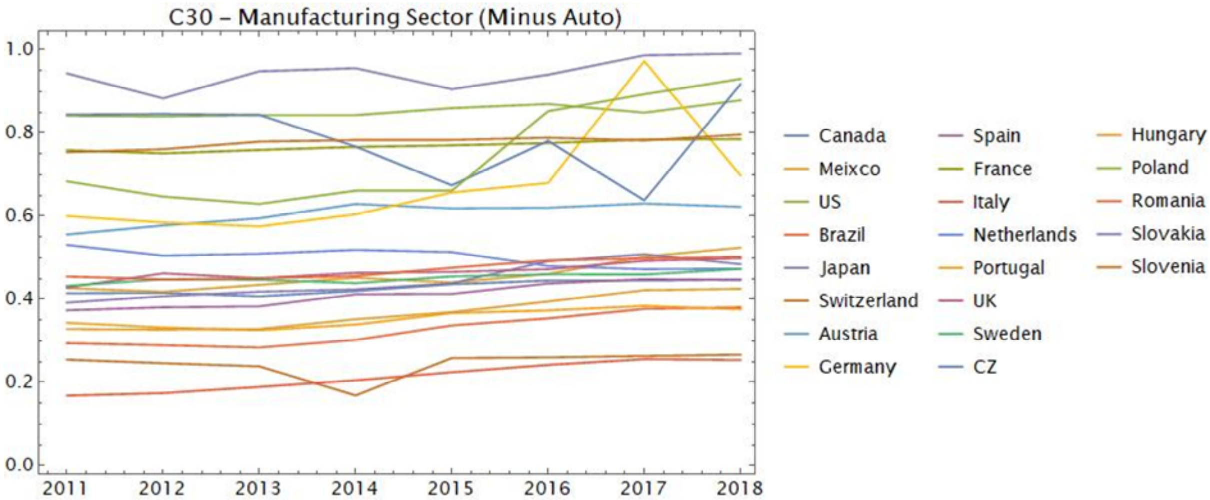


Figure 13: Concentration measures Manufacturing Sector (c30)



Equally, the „class-view" is hardly helpful in the case of general manufacturing. Every country seems to see decreasing concentration rates, except for France.

Table 13: Class view Concentration in the Manufacturing Sector

	2011	2012	2013	2014	2015	2016	2017	2018
Low (c10<0.5)	{US, Brazil, Japan, Austria, Germany, Spain, France, Italy, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Brazil, Japan, Austria, Germany, Spain, France, Italy, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Brazil, Japan, Austria, Germany, Spain, France, Italy, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Japan, Austria, Germany, Spain, France, Italy, Portugal, United Kingdom, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Japan, Austria, Germany, Spain, France, Italy, Portugal, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Japan, Austria, Germany, Spain, France, Italy, Portugal, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Japan, Austria, Germany, Spain, France, Italy, Portugal, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}	{US, Japan, Austria, Germany, Spain, France, Italy, Portugal, Sweden, CZ, Hungary, Poland, Slovakia, Slovenia}
Mid (c10>0.5<0.8)	{Canada, Mexico, Switzerland, Netherlands, Romania}	{Canada, Mexico, Switzerland, Netherlands, Romania}	{Canada, Switzerland, Netherlands, Romania}	{Canada, Brazil, Switzerland, Netherlands, Romania}	{Canada, Mexico, Brazil, Switzerland, Netherlands, United Kingdom, Romania}	{Canada, Mexico, Brazil, Switzerland, Netherlands, United Kingdom, Romania}	{Canada, Mexico, Brazil, Switzerland, Netherlands, Romania}	{Canada, Mexico, Brazil, Switzerland, Netherlands, United Kingdom, Romania}
High (c10>0.8	{}	{}	{Mexico}	{Mexico}	{}	{}	{United Kingdom}	{}

Table 14:CAGRs c10 by Country Manufacturing

Country	CAGR CONC AUTO	Country	CAGR CONC AUTO
Brazil	-6.51374	**US**	-2.05849
Italy	-5.60008	**Switzerland**	-1.79826

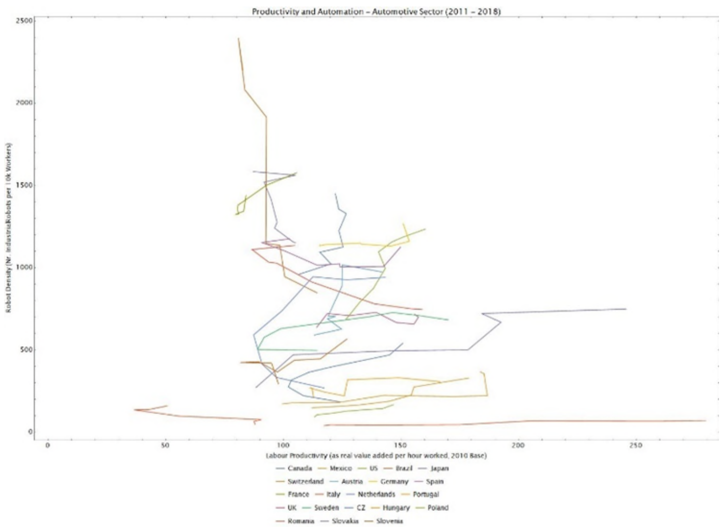
Poland	-4.40836	**Canada**	-1.44747
Slovakia	-4.37259	**Netherlands**	-1.4067
Hungary	-4.13556	**Spain**	-1.06672
Japan	-3.56998	**Romania**	-1.03051
UK	-3.20401	**Slovenia**	-0.777163
Germany	-2.69513	**CZ**	-0.620554
Austria	-2.30164	**Mexico**	-0.482861
Sweden	-2.2866	**France**	0.966851
Portugal	-2.19798		

4.3. Paired Scatterplots

As another in-between step towards inferential analysis, variable pairs are plotted against each other in paired scatterplots. In very clear cases, this can already reveal much. In cases, where the relationship is not entirely linear, as seems to be the case below, or rather more complicated, such scatterplots arguably reveal little.

Productivity and Automation in the Automotive Sector

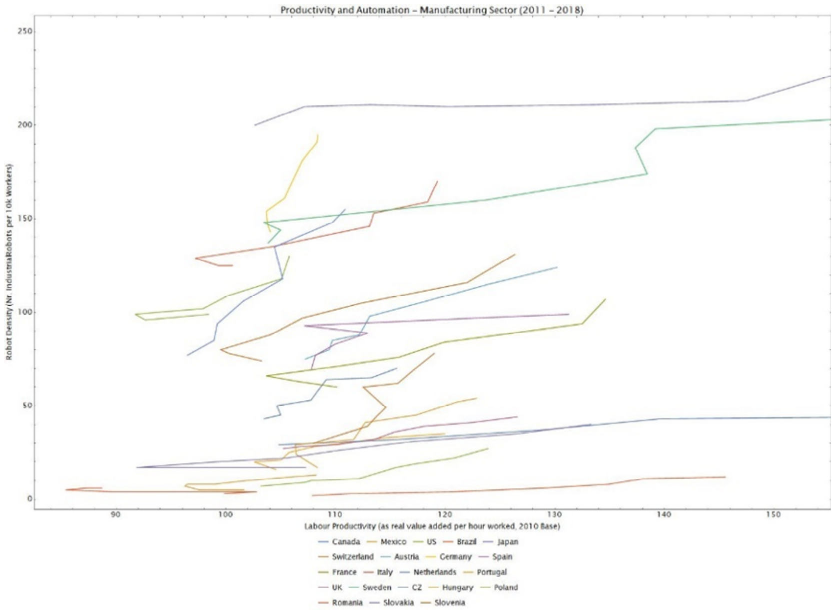
Figure 14: Productivity and Automation in the Automotive Sector



While there appears to be somewhat of a relation between rising robot-density and labour-productivity, this relation is not as clear as expected in the case of the automotive sector.

Productivity and Automation in the Manufacturing Sector

Figure 15: Productivity and Automation in the Manufacturing Sector

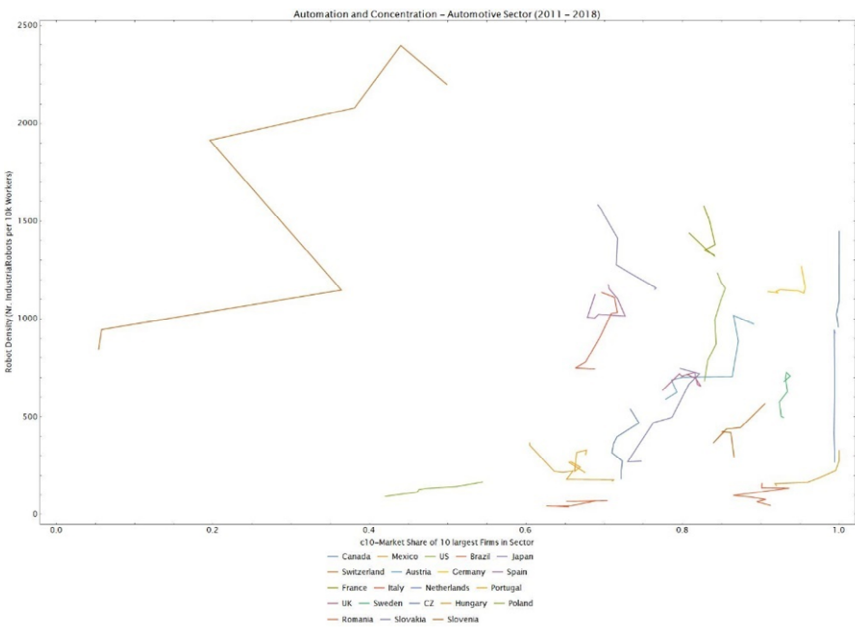


The relationship between productivity and robot-densiuty appears much more clearly positive and linear in the manufacturing sector.

Automation and Concentration in the Automotive Sector

Pairing robot-density and concentration together for the automotive sector seems to show somewhat of a positive relation. In particular the crowding in the lower right corner illustrates the high concentration levels generally. Inferential analysis will reveal if the positive upwards trend is statistically significant or merely a visual distortion and the assessment that independent of fixed concentration level, robot-density has decrease in most automotive sectors.

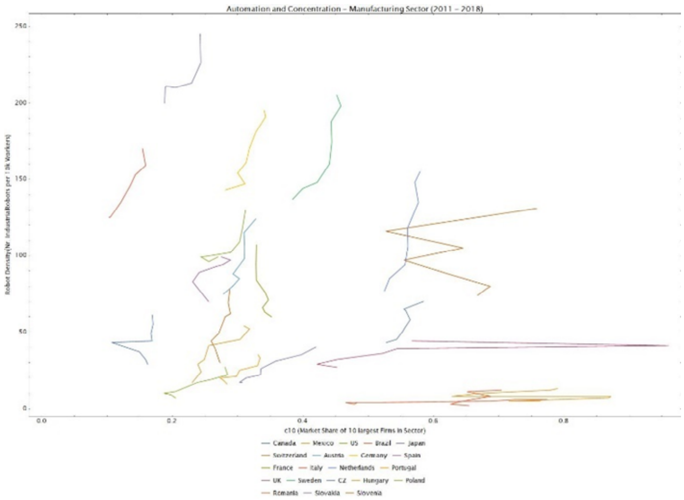
Figure 16: Automation and Concentration in the Automotive Sector



Automation and Concentration in the Manufacturing Sector

Again, the relation appears more straight forward in the case of manufacturing, where robot-density and concentration seem to be positively related.

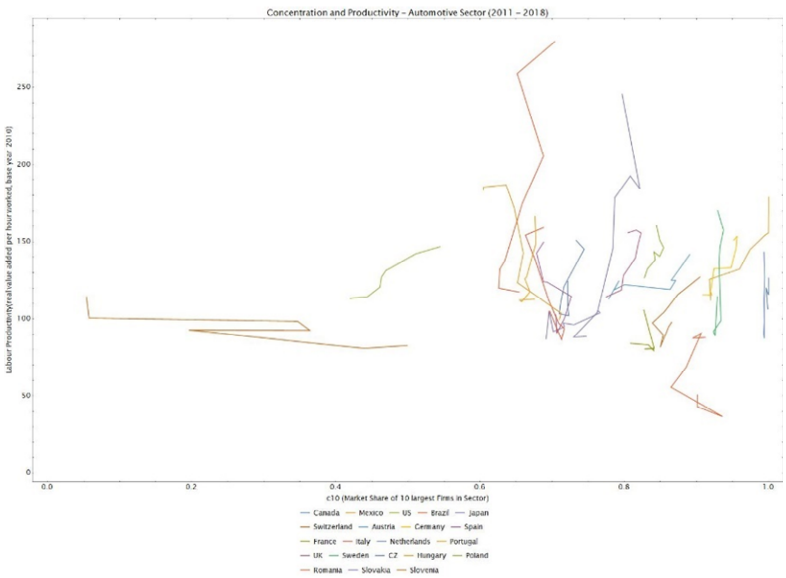
Figure 17: Automation and Concentration in the Manufacturing Sector



Concentration and Productivity in the Automotive Sector

Relating concentration to labour-productivity in the automotive sector again appears to show a sligh positive relation, which may prove statistically insignificant, however, and could merely show steadily concentrated sectors increasing in productivity. In either case a question how the fact that automotive sectors are already highly concentrated as is plays into these results.

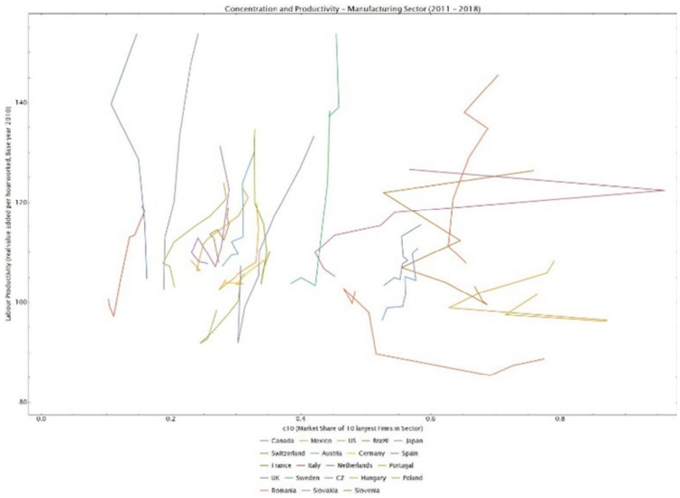
Figure 18: Concentration and Productivity, Automotive Sector



Concentration and Productivity in the Manufacturing Sector

In the case of the manufacturing sector there does not appear to be significant movement towards the upper right corner, which would indicate a significant positive relationship.

Figure 19: Concentration and Productivity in the Manufacturing Sector



4.4. Conclusions Descriptive Analysis

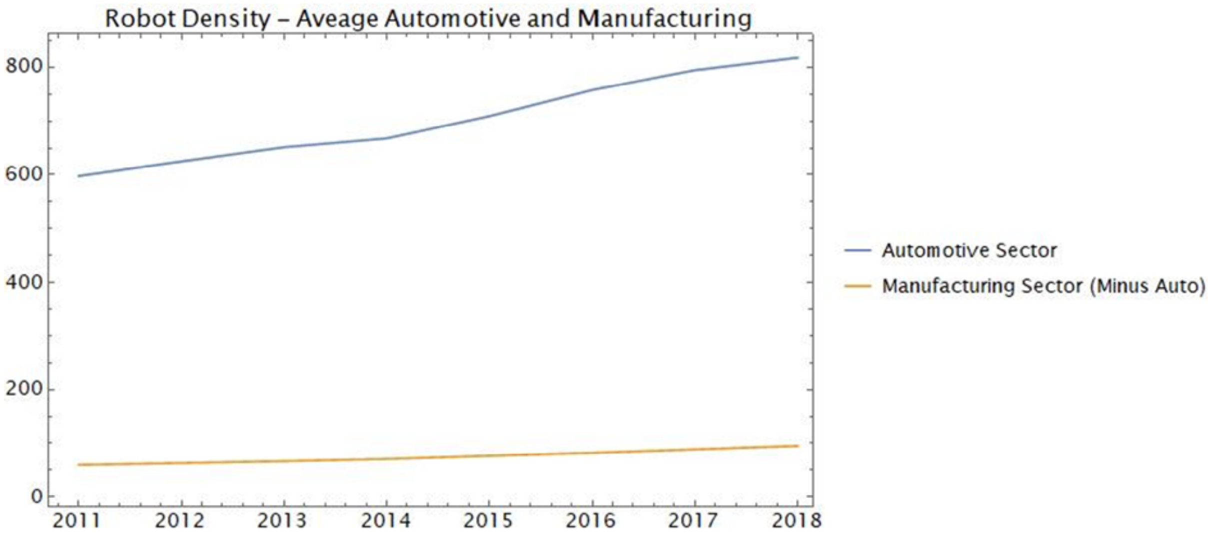
It can thus be concluded from a descriptive perspective that the automotive sector has seen a general increase in the number of industrial robots per 10.000 workers between 2011 and 2018, for most countries in the sample. This general trend excludes the notable cases of Italy, Japan and France, all large automotive countries in their own right. The general trend of increase is also not uniform, and thus does not a convergence-trend, but rather one of segmentation showing large differences between automotive sectors. There is thus a fragmentation between high and low levels of robot-density, as well as high and low increases in the same. The developments of labour-productivity suggest a similar picture, with most countries seeing an increase and only a select few a decrease. Noticeably, the automotive sector of France is the only one which saw both between 2011 and 2018: decreasing robot-density as well as decreasing labour-productivity. Concentration in the automotive sector is at prestigiously high levels throughout the entire time period. This level of concentration further increases with the "n" in c-measures. Overall, concentration shows marginal signs of decrease. The extent of this decrease, however, is very small and thus an overall, general trend should not be identified.

Comparing these developments to those in the "general manufacturing sectors" of countries, naturally a statistical abstraction and excluding values for the automotive sector, (Nace rev. 2., D-29), shows at points similar at others opposite directions. It also shows that the greatest difference lies not between countries, but between sectors within countries. For example, While robot-density has exclusively been increasing for the manufacturing sectors of all countries in the sample, crucially it must be noted, however, that this increase plays out on an entirely different level than in the automotive sector (manufacturing showing robot-densities at about 1/10 of the automotive sector). While the level cannot be assessed for labour-productivity, as it takes the form of relative self-referential values here, the trend seems to be significantly flatter than in the automotive sector, nonetheless increasing, however. Another severe difference of levels, however, can be found in the concentration levels of manufacturing, which appear to be much lower in the manufacturing sector. It is essential to consider here, however, that this result may simply be driven by the abstraction of calculating concentration within "the" manufacturing sector. It is highly unlikely that industrial sub-sectors would be in direct competition with one another (say a cement producer and a manufacturer of bread). This means, that by collecting the largest manufacturing companies of a country together within one “manufacturing sector” (NACE Rev. 2 D) there is the very real danger of losing track of counterfactuals on the sub-sectoral level. To use the above example again, the revenue of a producer of bread in the UK may account for 90% of the total revenue of the sub-sector of bread-production, but when this observation is thrown into comparison with manufacturers of cement, cars, machinery or electronics, its revenue may appear to be in the mid-range, suggesting just another average sized firm, and thus represent a low share of total revenue, reducing the overall degree of estimated concentration, even though the producer is a de-facto monopolist. As a robustness check concentration measures will be calculated anew, based on an averaging of sub-sectoral concentration measures.

Another fact to consider, in particular later analysis, is that it is only the most highly automated countries which show a negative annual growth rate in robot density of their automotive sectors, perhaps suggesting that a plateau-effect or signs of stagnation. More generally, in particular looking at the developments of labour-productivity, it seems that descriptively, effects are more pronounced and “unequally distributed” in the automotive sector than general manufacturing. Except for individual cases, there does not seem to be much of a “paradox” in either the automotive or general manufacturing sectors. Productivity has been increasing, not in large bounds and certainly not to the extent that automation-theorists have foreseen, but also not in specifically stagnating dimensions. This may already lead to the preliminary hypothesis that the diagnosis of “productivity paradox” may simply not apply to manufacturing and in particular not to automotive-manufacturing. Services and agriculture are obviously not spoken to here, but it wouldn’t be surprising the developments especially in services would drive productivity stagnation, as this lies within the nature of the sector itself. Considering that the service sector, despite the continuing relevance of manufacturing argued for in the introduction, represents the largest economic sector in all developed economies, it would be reasonable that productivity stagnation could be identified for entire economies. In contrast, there are many more countries which fall into a “high” category of labour-productivity growth in the automotive sector in 2018, than in general manufacturing, again suggesting a special trajectory. Within the developments of the automotive sector it is also clear however, that differences in class between countries exist and persist. In particular the changes between 2015 and 2018 are interesting here, as mentioned above. The caveat with reading these tables is certainly, however, that the changes listed only represent the relative changes of countries to themselves, meaning there are no absolute values which would allow for groupings to be established outside or alternative to “growth dynamics”. Still, while general manufacturing shows less overall growth of productivity, its growth also appears steadier and almost predictably linear, as most economic theory on productivity would have it. The movements of the manufacturing sectors of countries are also much closer to one another, than in the automotive sector. This may also already be hinting towards the global production structure of the automotive industry which consisting / low labour production capabilities, and other regions where labour-costs are relatively low, thus, automation low and productivity not as amenable to increases. Despite the wider gap in the automotive sector, it does not appear reasonable to speak of an overall “productivity paradox”, even less so in general manufacturing. This assessment does not deny the fact, however, that most of the productivity gains are realised in certain countries, while others fall behind and individuals are reduced to negative growth rates. Equally, the take-away regarding the development of sectoral concentration is that while automotive sector(s) are much more highly-concentration than generalised manufacturing (and this concentration increases with the number of companies suggesting a pareto-distribution of revenues), both cases seem to be somewhat steady in their levels. And again, while technically the movement throughout all sectors and countries shows a negative sign, the corresponding values are so small that it hardly justifies speaking of a significant “trend”. I would thus suggest that concentrations levels are steady in both cases, however show much higher levels in the automotive sector. Complicating factors such as the international production structure of the automotive sector as well as the statistical “fiction” of manufacturing are not included in this assessment, however. While the results from the descriptive analysis appear quite clear, the same cannot be said about the exploratory scatter-plots. What does appear quite certain about them is that the interrelations of the variables in question are at the very least not straightforward, direct or overly linear. This does not mean that there is no relation, merely that is it not “clean”, which, however, can also not be expected in the analysis of economic variables.

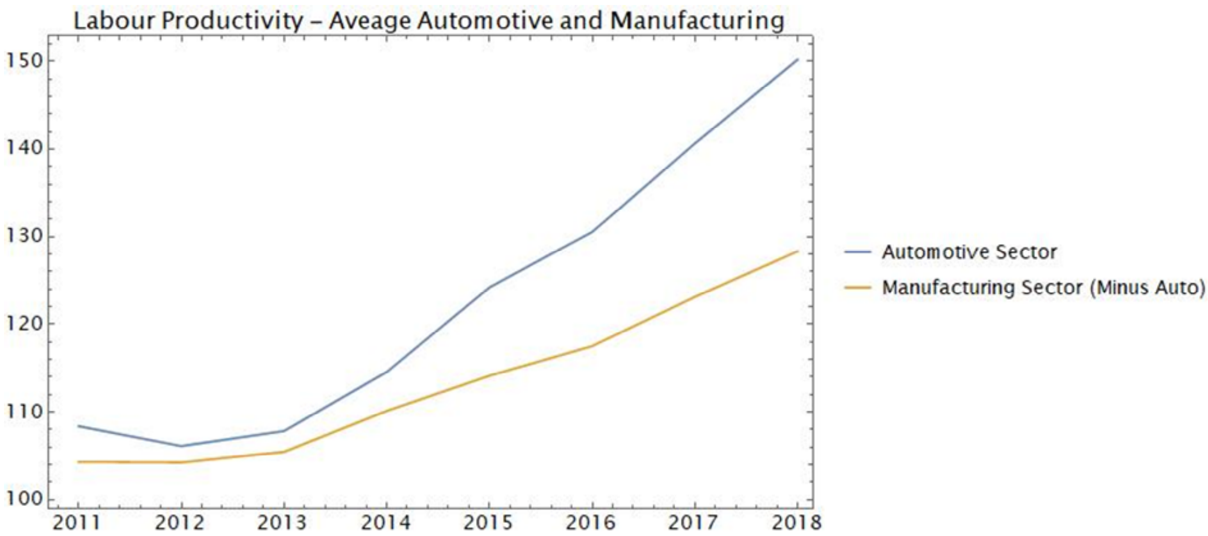
The central take-aways, derived from descriptive analysis can be reinforced by taking a look at the developments of the averages of all countries’ automotive and manufacturing sectors.

Figure 20: Average Robot-Density of country panel Automotive and Manufacturing Sectors



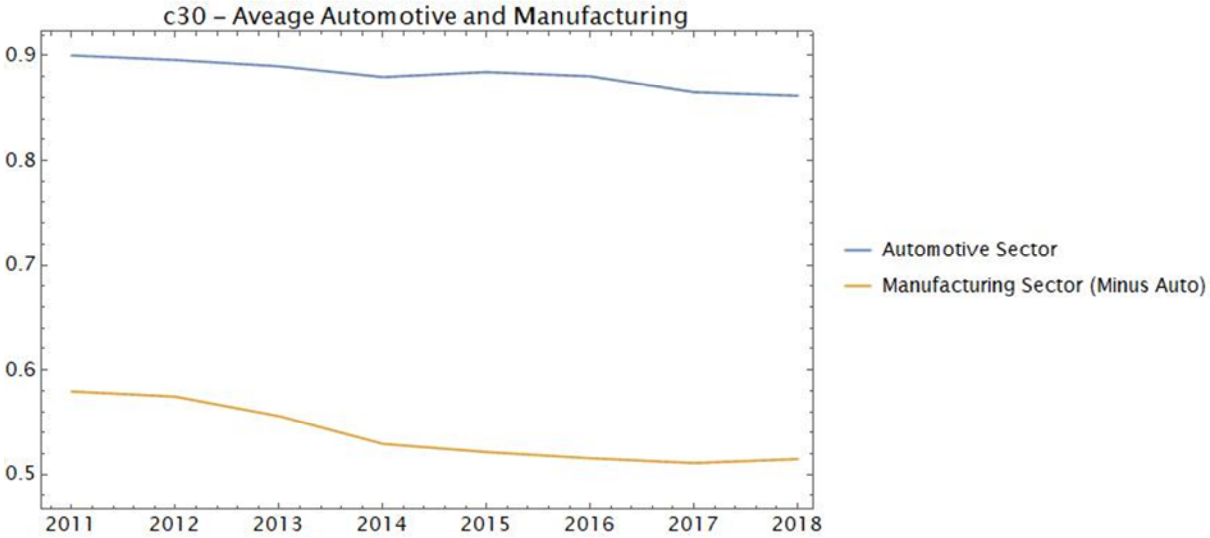
Again, the difference in level of robot-density between the automotive and manufacturing sector is striking. Nicely visible in this representation of averages, is also the difference in slope of both lines, indicating the relatively larger growth rates of the automotive sector.

Figure 21: Average Labour-Productivity of country panel Automotive and Manufacturing Sectors



The view of country-averages of labour-productivity equally reinforces the position developed above. While there is, on average, an increase in both automotive and manufacturing sectors, the level of automotive manufacturing is higher, and the slope steeper.

Figure 22: Average c30 of country panel Automotive and Manufacturing Sectors



Finally, also concentration averages between countries show the above diagnosis in clear terms. The level of concentration is much higher in the automotive sector than in manufacturing. Both show a declining tendency, which, in particular in the case of the automotive sector, however, appears only very marginal (although the average-view exacerbates its effects compared to the view of individual countries).

It is thus these take-aways which will be carried over into inferential analysis as well as the interpretation of its results. A more disaggregated view of paired scatter-plots for each individual country can also be found in the appendix (figures xx through xx). For the study of the developments in individual countries, for where such an interest exists, these are instructive. While it is too early here for definitive conclusions, seeing as inferential analysis has not been conducted yet, it is important to keep the stakes in mind. If we find, for example, that robot-density does not affect productivity, questions must be asked about the conception and purpose of technology not just in economic theory but also practical use in production and the way that automation progresses or does not. If sectoral concentration significantly affects productivity, this will force other fundamental questions such as the role of competition in technological diffusion and industrial production as such. If increasing robot-density does prove to be a significant factor in explaining developments of labour-productivity, this brings into focus notions and positions on technological displacement. Empirical knowledge about these factors, as laid out in earlier chapters, in particular in their institutional variation, represents a prerequisite for drilling down into the specifics of technological displacement in the Austrian automotive sector specifically, which is to follow in substantive chapters 2 and 3.

5. Selection of Model Specification

Before comparing and discussing the relative merits of different model specifications, and why the final model-variant was chosen, it is important to note the following aspects. The output for these regressions has been produced in R, the code for which is attached. Most data wrangling and descriptive work has been done in Mathematica, however, the code for which is also attached. In addition, while the dependent variable for this chapter has been designated as labour-productivity, it is not unreasonable to question if not robot-density should have been chosen, as it technically relates more the research tension in the overall dissertation. After all, if we were to engage the factors explaining the ratio of machines to workers, wouldn't we directly address the interrelation of automation and employment? This is, after all, also the choice of most contributions in economics. The answer is yes and no. The reasoning is certainly not absurd, however, the metric of robot-density is merely a smaller part of much larger bricolage of data and metrics to consider in discussing employment, which is why this engagement has been relegated to chapter 2. As outlined above, labour-productivity itself is already intimately related to questions of employment anyway, plus this preliminary focus allows the integration of an additional prevalent debate, namely on the "productivity paradox", as outlined above. In addition, estimating only changes in employment based on robot numbers appears quite mystifying, *in particular* when conducted in the form of a regression analysis. Nonetheless, among the four discussed specifications below, 2 are with the dependent variable of robot-density, for completeness' sake.

The empirical method for analysis is intentionally kept relatively simple. Regarding the more specific questions surrounding the estimation strategy here chosen, several issues can be anticipated/considered ex ante.

1. *Endogeneity*. The interrelation of all three variables in question is theoretically overdetermined and thus co-dependent. Meaning, concentration is likely to be influenced by automation as well as the development of labour-productivity and vice-versa, as discussed in the theory section of this chapter. The problem in formal statistical terms of "co-determination" of explanatory variables or "simultaneity," is a problem of endogeneity. Engaging this problem could either take the course of arguing why the equation of the specification is nonetheless convincing or to find a methodological fix. Regarding the first, it can bemaitained that why no general direction of effects may be determined beyond doubt, historically specific sectors fo an economy are likely to have definite relations say, between automation technology and productivity and productivity and concentration. Meaning, the theoretical overdetermination may be much reduced in significance in specific empirical instances. Of the latter, two possibilities come to mind: time-lagged variables or instrumental variables. Using time-lagged variables, would mean regressing todays labour-productivity on the concentration and automation of previous periods, as todays productivity should not be affected by yesterday's values of concentration and automation. Such a lag is included in the final model, however, while it mitigates the problem it does not solve it, which is why considerations in the use of instrumental variables are ongoing.
2. *Lag of effects that are to be estimated*. We may have to consider that that effects-of labour-productivity we aim to determine, only occur with some time lag.
3. *Multicolinearity*. As is often the case in econometrics models, the explanatory variables in question are not strictly acting independently but influence each other, as do most economic variables. More specifically and in distinction from endogeneity, multicolinearity means that

the explanatory variables are correlated with each other. This might, for example, be the case regarding labour-productivity and robot-density due to their likely correlated denominators of number of workers and hours worked. If we increase the number of workers, the hours worked might also increase, although not necessarily, of course. To address this interaction terms are added in the estimation, in the hope of disentangling single and joint effects.

4. *Aggregation of industry classifications*. This problem, while strictly not one of estimation strategy, has already been outlined above. Collecting all of the manufacturing sub-sectors into one general "manufacturing" sector is arguably too high a level of aggregation to capture "true" concentration dynamics. Thus, changes in concentration in different sectors might primarily reflect structural changes between sectors, with single sectors simply seeing larger growth than others. The solution here is to include robustness tests using more disaggregated sectors. A related limitation or complication already anticipated is the inherent global structure of automotive firms, the interrelation of global conglomerates, their production sites and sales markets, making the complete statistical capture of revenues and appropriate concentration measures unlikely. This means that background knowledge is required regarding the interpretation of data and results. This, however, does not represent a major issue for the dissertation as a whole, as the chosen approach of substantive chapter 2 precisely builds on such contextual knowledge.
5. *Omitted variable bias/missing controls*. In order to avoid omitted variable bias, given the study of concentration, "capital intensity" is introduced as control in the regression. Otherwise the option cannot be excluded that changes in capital intensity may also affect concentration, as larger capital requirements lead to scale effects and entry barriers. Capital-intensity is also relevant from a theoretical point of view here, as for example in Kaldor's growth-equation, the growth-rate of labour-productivity depends on the growth-rate of capital-intensity.

To reiterate, fixed effects estimators are obtained by demeaning all variables leading to a reduced form, where all variables are adjusted for the mean of each country over time and for the mean of all sectors over time. To deal with heteroskedasticity, autocorrelation and serial correlation Driscoll - Kraay standard error correction is used. The resulting model is presented below in four specifications: 1 and 2: LP as dependent variable. One period lag standardized HHI on labour productivity; regress each of the one - period lagged concentration indicators individually on labour productivity, as well as robot-density, while controlling for capital intensity. 3 and 4: the same, with robot-density as dependent variable. The method of analysis of the below models is pre-defined by the use of multivariate regression methods, with usual emphasis on p-values, the value of R^2 and strength and direction of Beta coefficients.

A first model variation has as dependent variable labour-productivity and only different measures of sectoral concentration as explanatory variables, which are also lagged by one period.

Model Variation 1

Table 15: Regression output Model Variant 1

Regression results: Lag=1

	Dependent variable:							
	Dependent Variable: Labour productivity							
	Manufacturing				Automotive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(HHI, l)	-0.001				0.003^{*}			
	(0.001)				(0.002)			
lag(C3, l)		-14.543^{**}				52.052^{**}		
		(7.254)				(23.027)		
lag(C10, l)			-28.464^{***}				86.073^{***}	
			(6.918)				(25.394)	
lag(C30, l)				-37.565^{***}				95.368^{***}
				(8.604)				(30.836)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.:	146	146	146	146	147	147	147	147
R-squared	0.003	0.008	0.03	0.046	0.002	0.018	0.027	0.021
Adj. R-squared	-0.225	-0.219	-0.192	-0.172	-0.224	-0.205	-0.194	-0.201
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

While all c-measures are significant, the HHI is not. The reason for this is unclear. The other notable result of this model is that in the manufacturing sector, concentration reduces labour-productivity, and increasingly so, with increasing concentration. For the automotive sector, however, the opposite is the case, meaning that on average, concentration drives productivity. What is causing this turn of sign of the Beta-coefficients will be a central question for analysis. The positive effect on productivity of concentration, in the automotive sector is also twice as large as the reducing effect discernible in manufacturing.

Model Variation 2

Variation two keep the general structure of model 1, but adds robot-density as explanatory variable.

Table 16: Regression Output Model Variant 2

Regression results: Lag=1

	Dependent variable:							
	Dependent Variable: Labour productivity							
	Manufacturing				Automotive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(HHI, l)	-0.001				0.003			
	(0.001)				(0.002)			
lag(C3, l)		-13.999^{**}				41.756		
		(6.469)				(25.212)		
lag(C10, l)			-27.617^{***}				64.825^{*}	
			(6.109)				(33.059)	
lag(C30, l)				-35.964^{***}				64.831^{*}
				(8.320)				(37.161)
lag(robden, l)	0.102^{**}	0.101^{**}	0.091^{***}	0.056	-0.017^{***}	-0.015^{***}	-0.011^{*}	-0.012^{**}
	(0.041)	(0.040)	(0.035)	(0.036)	(0.002)	(0.004)	(0.006)	(0.006)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.:	146	146	146	146	147	147	147	147
R-squared	0.01	0.015	0.036	0.049	0.023	0.033	0.035	0.03
Adj. R-squared	-0.227	-0.221	-0.195	-0.179	-0.208	-0.196	-0.194	-0.2
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$			

Again, the HHI remains uninterpretable. Concentration remains significant, although speaking in terms of p-values, greatly reduced in the automotive sector. While the direction, or the sign of the beta coefficients, stays the same for both manufacturing and the automotive sector, the size of the coefficient is reduced for the latter. Robot-density is significant in combination with all concentration measures and both automotive and manufacturing. Two things stand out here: first, the sign of the beta-coefficients is exactly the opposite from those of concentration measures with a positive sign in manufacturing and a negative one in automotive. Secondly, the effect appears to be much larger in the case of the automotive sector, close to a factor of 10. This means that according to this model-variant, higher concentration decreases labour-productivity in the manufacturing sector, while higher robot-density increases productivity. In the automotive sector, the opposite is the case, and concentration increase productivity (although hardly significant) while robot-density decreases labour-productivity (although the size of this effect appears very small as well).

Model Variation 3

Switching the dependent Variable to robot-density now with only the explanatory variable of concentration measures gives the following results.

Table 17: Regression Output Model Variant 3

Regression results: Lag=1

	Dependent variable:							
	Dependent Variable: Robot Density							
	Manufacturing				Automotive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(HHI, l)	-0.002				-0.019			
	(0.002)				(0.027)			
lag(C3, l)		-8.117				-682.673^{***}		
		(7.442)				(153.734)		
lag(C10, l)			-10.260				$-1,771.144^{***}$	
			(6.269)				(435.654)	
lag(C30, l)				-29.466^{**}				$-2,321.800^{***}$
				(12.277)				(666.667)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.:	146	146	146	146	147	147	147	147
R-squared	0.006	0.003	0.005	0.037	0.001	0.049	0.178	0.191
Adj. R-squared	-0.222	-0.225	-0.223	-0.184	-0.226	-0.167	-0.009	0.008
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Lagged concentration measures appear for the most part to be relevant for the automotive sector with higher concentration greatly reducing robot-density. Coefficients for the case of manufacturing also show a negative sign, however the effect being relatively small and not significant except for the c30. Keeping this configuration steady but introducing labour-productivity as additional explanatory variable gives the following result.

Model Variation 4

Table 18: Regression output Model Variant 4

Regression results: Lag=1								
	Dependent variable:							
	Dependent Variable: Robot Density							
	Manufacturing				Automotive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(HHI, l)	-0.001				-0.017			
	(0.001)				(0.026)			
lag(C3, l)		-4.855				-621.366***		
		(7.009)				(149.392)		
lag(C10, l)			-5.572				-1,679.281***	
			(5.182)				(447.250)	
lag(C30, l)				-24.412**				-2,214.995***
				(10.455)				(677.154)
lag(lab_prod, l)	0.182***	0.182***	0.180***	0.159***	-1.600***	-1.398***	-0.896***	-0.988***
	(0.038)	(0.037)	(0.033)	(0.024)	(0.102)	(0.122)	(0.266)	(0.260)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.:	146	146	146	146	147	147	147	147
R-squared	0.045	0.043	0.044	0.066	0.036	0.075	0.188	0.204
Adj. R-squared	-0.183	-0.186	-0.185	-0.157	-0.192	-0.144	-0.004	0.015
Note:						*p<0.1; **p<0.05; ***p<0.01		

Introducing labour-productivity to the estimation changes almost nothing in direction, size and significance of the concentration beta coefficients for the case of manufacturing as well as for the automotive sector. Also here, however, the direction of the, all significant beta coefficients for labour-productivity, changes from a positive direction in manufacturing to a negative one in automotive. This means that while labour-productivity affects the number of robots per 10.000 workers positively in manufacturing, it reduces it in the automotive sector. Again, the size of this effect is about 10-times larger for the automotive sector.

Given all this, it appears most worthwhile to take mode variant 2 under closer consideration. Not only because it represents the fullest version of the formulated interest of this chapter in explaning labour-productivity, but also since its results appear to be the most promising in terms of worthwhile interpretation.

6. Discussion of Results of Variant 2

Laying, therefore, the focus on the specification variant 2, which takes labour-productivity as dependent and lagged concentration indices as well as robot-density as explanatory variables, to reiterate, gives the following results

Table 11: Regression results Model Variant 2

Regression results: Lag=1

	Dependent variable:							
	Dependent Variable: Labour productivity							
	Manufacturing				Automotive			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lag(HHI, l)	-0.001				0.003			
	(0.001)				(0.002)			
lag(C3, l)		-13.999**				41.756		
		(6.469)				(25.212)		
lag(C10, l)			-27.617***				64.825*	
			(6.109)				(33.059)	
lag(C30, l)				-35.964***				64.831*
				(8.320)				(37.161)
lag(robden, l)	0.102**	0.101**	0.091***	0.056	-0.017***	-0.015***	-0.011*	-0.012**
	(0.041)	(0.040)	(0.035)	(0.036)	(0.002)	(0.004)	(0.006)	(0.006)
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.:	146	146	146	146	147	147	147	147
R-squared	0.01	0.015	0.036	0.049	0.023	0.033	0.035	0.03
Adj. R-squared	-0.227	-0.221	-0.195	-0.179	-0.208	-0.196	-0.194	-0.2
Note:					*p<0.1; **p<0.05; ***p<0.01			

In manufacturing (as always, excluding the automotive sub-sector D-29 (Nace rev. 2)), concentration has a negative effect on productivity. This effect gets bigger with increasing c-measures. Hence: for each 1% that the largest 30 companies in manufacturing gain in market share, real value added per hour worked is reduced on average by 36% compared to its baseline in 2010 (this result is certainly also driven by the very small variation in concentration). Robot density has a positive effect on productivity, however, with each robot per 10.000 workers increasing productivity by 0.056% meaning that 100 robots per 10k workers, or introducing 1 robot in an average 100 worker facility, increases valued added per hour worked, on average, by 5,6%.

In the automotive sector these effects are mirrored: concentration has a positive effect on productivity (although less statistically significant but with a greater effect). Hence, each 1% increase of the market share by the largest 30 companies, on average, increases real value added per hour worked by 65%, on average and compared to its 2010 baseline. Robot-density on the other hand has a negative effect on productivity, with each robot per 10k workers reducing productivity by 0.012%, as compared to the 2010 baseline. This effect is around 4 times smaller than in manufacturing (for the models using c30s).

It is the results for the automotive sector, which are counterintuitive here. As outlined in section 2, we would expect robots to increase productivity, and while concentration can be argued to both decrease productivity or increase it, theoretically, in dominant standard economic theory it *must* decrease. Why then is the opposite of the expected explanation the case? And why only for the automotive sector? Manufacturing seems to follow the expected path. The switching of signs for concentration and productivity could at least be accounted for theoretically, as theories for both are available, the drag on productivity through robot-density in the automotive sector, however, makes no sense theoretically. These results themselves thus present somewhat of a puzzle with the central question at its core being: what about the automotive industry warrants these different results? Approaching this from the side of the descriptives of section 4, we remember that the primary difference between the automotive and general manufacturing sector lay in the *levels* of the values of the variables in question. Robot-density has been rising in both the Automotive sector and General Manufacturing, the levels at which this increase takes place are about 10x higher in Automotive manufacturing, however. The same is true for concentration measures: the levels are much higher in the Automotive sector, but both the automotive and Manufacturing sector show the same tendency, namely, a slight decrease. Finally, both Automotive sector and General manufacturing show rising tendencies in labour-productivity, with the automotive sector showing a wider spread, and thus sharper increases and lower falls (the level cannot be assessed per se as LP is based on relative to its values in 2010). Hence, the tendencies of the manufacturing and automotive sectors are the same. However, a significant difference in the descriptive data lies in the *levels* of these trends. More precisely, therefore, the question to be answered becomes: *why are the levels of automation and concentration so different in the automotive sector compared to general manufacturing? And what is the mechanism that turns these higher levels into different effects on productivity?* Or putting it more generally again for simplicity's sake:

(1) Why does robot density reduce labor productivity in the automotive sector?

(2) Why does concentration increase labor productivity in the automotive sector?

It appears reasonable to discuss the potential answers to these questions first in separation, before considering their possible interrelation.

Ad 1.: *Why is robot-density affecting labour-productivity negatively in the Automotive Sector(s)?*

a. "Too much" automation and diminishing returns

Knowing that the level of robot-density is about 10x higher in the automotive sector than general manufacturing, an explanation of the negative effects (which are in any case very small and around 10x smaller than the positive coefficients estimated for manufacturing) could be theorize that industrial robots are already used to such an extent in Automotive manufacturing that productivity gains based on their use are only very marginal, even *reducing* it at points. The negative effect of robot-density on productivity may thus be the result of diminishing to negative returns on production processes in Automotive manufacturing, which might be "too automated" or have reached a state of "automation saturation". The open question given this explanation is certainly why then robots would still be implemented at all? We can determine that they are, given the increase of robot-density. Taking the smallness of the effect seriously may thus allow us to speak of a situation of "automation-productivity stagnation" in the automotive sector, rather than a strictly decreasing effect.

b. The increasing number of robots is of a new generation, which is not (yet) increasing productivity

Following certain arguments in the debate on the productivity paradox, it may be the case that the productivity effects of robots introduced in the automotive sector simply lag behind their implementation. They could also be of a new generation (for example “lightweight” robots etc.), and differ in their form and function from those robots introduced in the manufacturing sector, and in the past in the automotive sector. These new robots may have not yet been efficiently integrated into production, producing either lagged effects, which cannot yet be seen, temporary net-productivity losses and stagnation, or are not designed for productivity-increases in the first place. Usually new industrial technologies are spearheaded in automotive production, making this an imaginable scenario, however how could we then explain the rise of labour-productivity? This is obviously also the question if we assumed that newly installed robots are not meant to increase labour-productivity per se, but rather to control and increase surveillance or other purposes not directly increasing productivity. In addition, there is hardly any explanation why increasing control should not equally be represented in productivity increases. This explanation would thus assume that all the national automotive sectors in the sample behave uniformly and have the same strategies and level of investments, that the purpose of robots is not for increasing productivity, and that somehow increased control and supervision would not affect productivity. Fulfilling all of the above conditions appears quite unlikely.

c. Business Cycles and Capacity Utilization

It is also important to consider that the indicator at play here is not the absolute number of robots in production, but the relation of robots to workers. Thus, increasing robot-density means that more robots have been introduced per worker. This does not say anything about the dynamics of workers per se, however. Theoretically we could thus also find that labour-productivity decreases because, for business cycle reasons, more people are hired for production, reducing labour-productivity. This is unlikely, however, for two reasons: first, we know that robot density has been increasing, not decreasing. Secondly, it is unlikely that highly-automated production processes in the automotive sector would be amenable to a 1:1 exchange of machinery to living labour. It is also important to mention that a positive relationship between automation and productivity does not necessarily imply labor-saving effects of technology, as higher output could simply be produced. A more reasonable avenue in line with business-cycle considerations would be that new robots are being bought and installed, but perhaps they are not being used in production because a downturn of the business cycle has reduced demand and the high fixed costs of using the robots makes it less costly to simply not use them, decreasing labour-productivity despite a rising number of robots.

d. Increase in service employment outweighs automation and its productivity increases

Perhaps, while there are new robots being introduced in new facilities, say in Germany, tendencies in the industry may be to for some reason to also extend employment, however not directly in production, but rather in “production-near”-services, which are still counted in automotive labour-productivity and employment. Since workers in services are inherently not very amenable to productivity increases, this may reduce overall productivity of the sector, despite increasing numbers of industrial robots, which are themselves productivity increasing. For this to be true this would have had to happen in many automotive sectors of the sample, however, to such an extent that they dampen the effects of regular productivity increasing robots. Then again, the negative effect is quite small and, in a sense, closer to “stagnation” than a negative trend.

e. Differing Underlying Typologies of automotive sectors makes the averaging in the results confusing

Another plausible explanation lies in the fragmented international character and global production networks of automotive production. Meaning, the typology of different automotive sectors with different emphases, which are integrated into one commodity chain, may result in very different automation/productivity trajectories for each country. For example, robots may be introduced in Germany and there increase productivity, at the same time, however, in CZ or Slovakia hardly any robots are used, and productivity is comparably low. Perhaps these labour-intensive automotive sectors have increased in size and thus reduced average productivity overall. This would mean again, however, that those countries which use an increasing number of robots would have to be so large as to offset the fact that other countries are hardly using robots, and still produce a significant rising tendency in the automotive sector as a whole, while at the same time keeping overall labour-productivity steady/slightly decreasing. Thus, as we know that both LP and Automation have been rising overall, perhaps the inferential result is confusing as it mixes, for example, two separate trends in automotive manufacturing: those who increase productivity and robots; and those who stagnate in both (perhaps because of low labour costs). The "on average" inferential estimation result may simply be glossing over this difference.

Ad 2.: ***Why is the relation of concentration and labor productivity positive in the automotive sector but not in other manufacturing?***

a. Oligopolistic Struggles

While this second puzzle is the easier one, as literature can be drawn upon to explain the effects, thought on it is still warranted. One starting point is that strong international competition, over decades, has resulted in an oligopolistic, global structure of the automotive sector. High degrees of automation are not just interesting therefore because of the complex nature of its production process, and corresponding high labour costs (and thus historical strength of labour-organisation), but also in the fight for market shares with other oligopolies. This may drive the productivity increasing effects of concentration in automotive manufacturing, whereas other manufacturing is much more nationally bound and thereby subjected perhaps to less intense competitive struggles. Especially given few possibilities to extend the market under conditions of stagnation, technological investment, or an automation arms-race, may have become the central lever for competitive struggles in the automotive sector. There are conditions in automotive production which would reinforce this intuition: huge requirements of capital and technological knowledge which effectively bars any new company from entering the sector, except perhaps in specialized supplier production. Hence, while concentration has increased productivity, by forcing the competitive development of technology, and vice versa, perhaps it has driven automation to such a point where it does not significantly increase productivity anymore. This could be called an "over-investment", where oligopolistic competition forces firms to invest in further robots without there being much productivity gain. It is also interesting to note that the highest robot-density rates (excluding outliers) still represent a ratio of 1,5 robots to 10 workers. This means that even in the most highly automated sectors of automotive manufacturing, which is itself the most highly automated manufacturing sub-sector, there are still plenty of human workers in production. This does not exclude the possibility that automation may already be "too high", however.

b. Verdoorn's Law and Economies of Scale

With growing output grows productivity, even without any particular technological development. The Automotive sector may simply have developed to a stage of industrial production, highly concentrated and thus productive, while other industrial sub-sectors lag behind. The extent to which this applies to other manufacturing sectors may simply be (still) lower.

c. Market position begets productivity and productivity begets market position (Manufacturing Superstar Firm thesis)

A variant of the above: Productive firms hold large market shares, giving them resources to increase productivity to defend those shares. The increased productivity then allows them increase their shares etc.

d. International Production leaving only the most automated parts of production in the concentrated global North

Automotive manufacture may particularly lend itself to global commodity chains, either for historical reasons or the nature of its product and production process. These chains can be better controlled and made use of through large size, explaining high automation, high concentration and high productivity- (although puzzle 1 suggests that automation should be decreasing productivity). Other industrial sectors may be much more closely tied to (and fettered) by national conditions and different accumulation regimes. They are thus more idiosyncratic and not as much subject to the international pressures and thus investments as the automotive sector.

e. Statistical Differences

The results may be explained by the fact that the automotive industries cannot be captured appropriately by national statistics as they are widespread and globally dispersed in production facilities and headquarters, sales markets etc. producing distorted aggregates. It may also be, that the average of manufacturing has significantly lower levels of robot density and concentration, because single sectors drag the average down. For example, a mining operation requires huge capital-intensity, natural monopolies almost, leading to likely low competition, while productivity and automation may have been stagnating, as there are only so many ways to move rock. A factory which produces food, on the hand, is a much simpler and thus less capital intensive-enterprise. Competition is likely to be higher and, perhaps, productivity more easily increased. Perhaps the averages above are dragged down by certain industries, creating a false picture. Measures of "manufacturing" may in this sense be a distorting abstraction.

Conclusion

Drawing the interpretation to its narrow form again of asking why the levels of automation and concentration are so different sector as compared to general manufacturing, and what mechanism turns these higher levels into different effects on productivity, the following explanations appear as the most plausible.

1. Concentration and productivity: Global oligopolies have created a specific situation in the automotive sector over decades, which has forced the increase of productivity alongside concentration (either by virtue of this concentration itself, such as Verdoorn's law or more intensified technological global competition). The result being that on average more concentrated automotive sectors are also more productive.
2. Robot-density and labour-productivity: The negative effect of robot-density on labour-productivity is like to be based in the inner-differences of national automotive sectors and their positions in a global commodity chain. This assessment may further interact with other effects such as diminishing returns to automation.

7. Limitations and Robustness

There are several limitations of these results which must be pointed out, equally, the robustness checks regarding the reliability of these results must also be illustrated.

7.1. Limitations

The above results are constrained in their generalizability on the one hand, by only relying on one manufacturing sub-sector-automotive manufacturing- and on the other hand, as at several points discussed in this chapter, the aggregation to a generalized "manufacturing" sector, in comparison to it. The results also illustrate the importance of analyzing the dynamics of automation, productivity and concentration in each sub-sector for each country, in a specific period of time. Even then, this might prove to large an aggregation, and to truly understand empirical variation of these interplays, the sectors to be analyzed would probably need to go as specific as 4-digit NACE rev. 2 levels. This would, on the other hand, mean to produce specific results, which significantly lose power in their generalizability. This is, however, a central tension of social science generally, and the comparisons/combination of quantitative and qualitative methods specifically.

A second limitation lies in the unfortunate shortening of the used time-series. In particular the constrain of Orbis data to ten years from access has curtailed potentials significantly. The early end to the collection efforts of The Conference Board in 2018, as well as missing entire countries of interest, has also put an unfortunate limit on the number of observations for the estimation. While it is not likely that the results would massively change, a longer time-series may have produced more clearly demarcated effects and directions of coefficients. Plus, the data may have shown radical breaks, or moments of crisis and industrial reorganization which may have been interesting for interpretation.

This ties in with the issue of the generally low quality of Orbis data. As has been illustrated in section three, Orbis is, comparatively speaking, nonetheless the best, most suitable and most widely used database for sectoral concentration analysis. However, this does not change the fact of massive amounts of "n.a."'s in its data. While in most cases a large enough amount of observations could be recovered, in particular from the largest companies, which are the most likely to have shown values and are also the most central for concentration measures, a frustrating extent of "observation loss" cannot be ignored. See table x for the extent of this loss by each step of data extraction and preparation.

Third, a significant limitation of this research as it appears now also lies in the insufficiency of "national" economic sectors as categories of analysis. At least since the 1980s the fact of economic organization, in particular in the automotive sector, has been of global commodity chains. Cars bought in the UK are not just produced by UK manufacturers for the UK public, there are complex international interrelations which must be considered, in particular due to ongoing mergers and acquisitions.

Finally, fourth, a set of limitations lies in the statistical issues inherent in econometric estimation meaning, problems such as endogeneity and multicollinearity. While they are not out of the ordinary, they should be kept in mind as constant reminder of the volatility of econometric estimations and that estimation results should be regraded with appropriate skepticism and relativization.

7.2. Robustness

Most points of checking the robustness of these results relate to alternative data sources. One such approach would be, instead of using the pre-calculated metric of robot-density, to calculate it manually based on a combination of IFR data and national employment data from multiple other sources. Table 14 also shows alternative sources for labour-productivity and their constraints, which might be used. Equally, labour-productivity measures could also be constructed manually. In addition, the use of the database COMPNET for different concentration is of interest. Another option would be to increase the variance in the estimation by including another sub-sector which is likely to have lower degrees of automation. Finally, instead of calculating the concentration indices as they have been for the above analysis, it would be possible to calculate concentration indices for each sub-sector, and then take their average. This may change the view, while of course not "solving" the fundamental problem that concentration within each sub-sector is a different animal. Another possibility, would be to use a variation of variables, for example other measures of (labour)productivity as well as the growth-rates of indices rather than their absolute values. Potentially also other lags could be included.

8. Chapter Conclusions and how to proceed

Thus, the central findings and conclusions to be carried over into the analyses of the following substantive chapters are the following:

1. Automation has undoubtedly been progressing and the use of machinery relative to human workers has increased between 2011 to 2018 for most countries of the sample, both in the automotive and manufacturing sector. However, this progression seems a far cry from the revolutionary bouts postulated by commentators. The fact of the matter appears closer to a steady increase in specific and steady form.
2. The developments of productivity are hardly paradox for industrial production (for the time and country selection of this chapter). Labour-productivity is neither particularly stagnating in the automotive or manufacturing sector. For individual cases the developments vary of course, but overall a steady increase is determinable, the one in the automotive sector being distinctly sharper than that in manufacturing. The "productivity paradox", thus appears to not apply to industrial production. This then means that, given that the empirical assessments are correct, it is a "problem" of the service and perhaps agricultural sectors.
3. The development of the third variable in question, sectoral concentration, shows marginal decreases in both sectors, which, however, seeing the smallness of their changes, hardly constitute a "trend". Concentration continues at a very high level in the automotive sector,

and at a reduced level in manufacturing, although at several points in this chapter the question of statistical aggregation has been raised regarding these calculations.

4. Regarding the questions raised by the interpretation of model variant 2, namely why the levels of both concentration and automation are so different from generalized manufacturing, and by what mechanism this difference translates into different effects on productivity, the following explanations appeared most plausible: First, regarding the positive interrelation of concentration and productivity in the automotive sector, the history of the later has led to intense global competition forcing simultaneous concentration and productivity increases. The productivity increases qua concentration are certainly the expanded capacities for technological development but also mere facts of output-extension as classically described in Verdoorn's law. The negative relation between robot-density and labour-productivity, is also likely to depend to some degree on the global structure of production processes in the automotive sector and typological differences between national automotive sectors, their position in global value chains and different labour-use regimes, all of which may very well run parallel to processes of (present) diminishing returns of automation.

The central conclusion then, to carry forward into the overall analysis of this dissertation and the following substantive chapters, and in particular from the results of the regression analysis, is that it is precisely that which has emerged as central difference in the automotive sector rand generalized manufacturing, which must be the starting point of further analysis of the automotive sector: its global structure of production, or rather an understanding of the local and national variations of its production and labour regimes. While the factor of employment has not yet been added to these considerations, it appears that the processes of de-industrialization and the use of industrial robots in the automotive sector, are not as straightforward as assumed. A better understanding of the oligopolistic structure of the automotive sector, and in particular its representation in national production and labour-use regimes, must be achieved, and with it an understanding of the contemporary economic issues associated with it, such as stagnation. Since employment and its development are multi-dimensionally overdetermined, the following chapter will focus on one sector, in one country. Building on the answers to these research questions, a further focus on the still open gap of technological displacement in Austrian manufacturing is possible. The dynamics uncovered in this chapter are important for moving on to the labor-displacing effects in one particular industrial sector in one country: Automotive manufacturing in Austria.

9. Appendix

Figure 23: Directed acyclic graph of the Technology, market concentration, and productivity nexus (Ferschli et al., 2021)

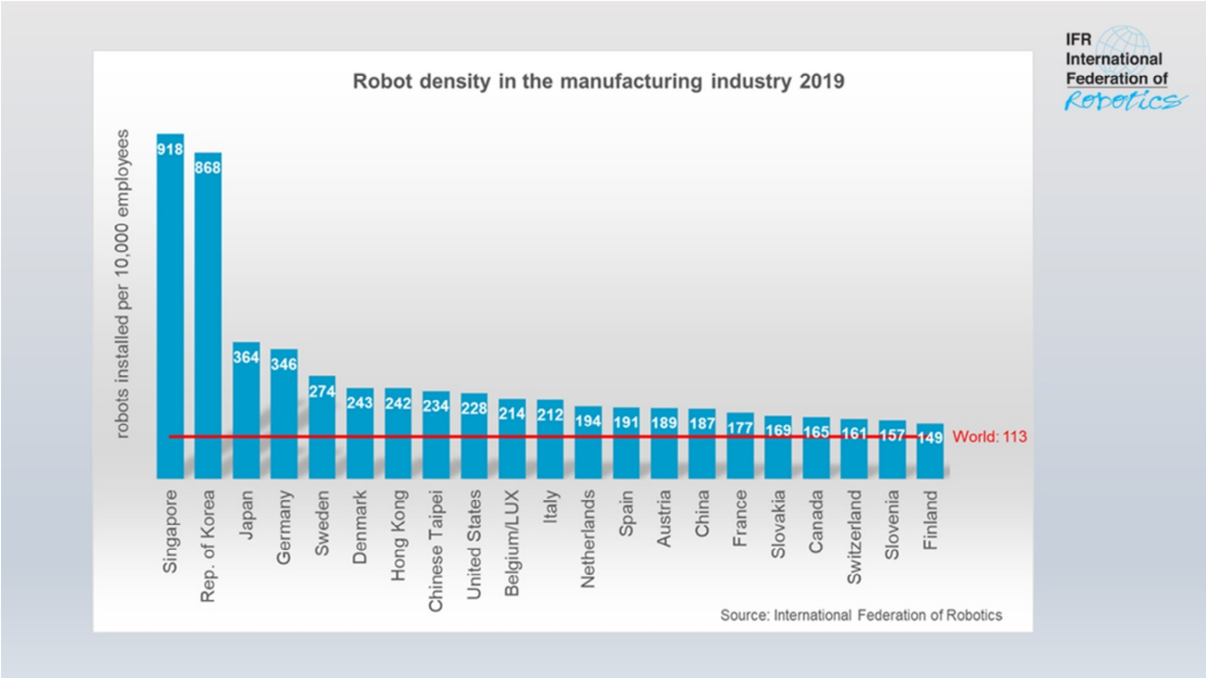


Figure 24: Ranking of Robot Density in manufacturing, 2019; Source IFR

Table 19: Avaialability Overview Robot Stock and Installations IFR

	Automotive Sector, Installations and Stock of Robots	All Industries (Manufacturing), Installations and Stock of Robots
AUT	2004-2019	1993-2019
GER	1993-2019	1993-2019
JPN	1993-2019	1993-2019
CHIN	2006-2019	1999-2019
US	2004-2019	1993-2019
UK	1993-2019	1993-2019

Figure 25: Robot Density Manufacturing Sector 2010-2019

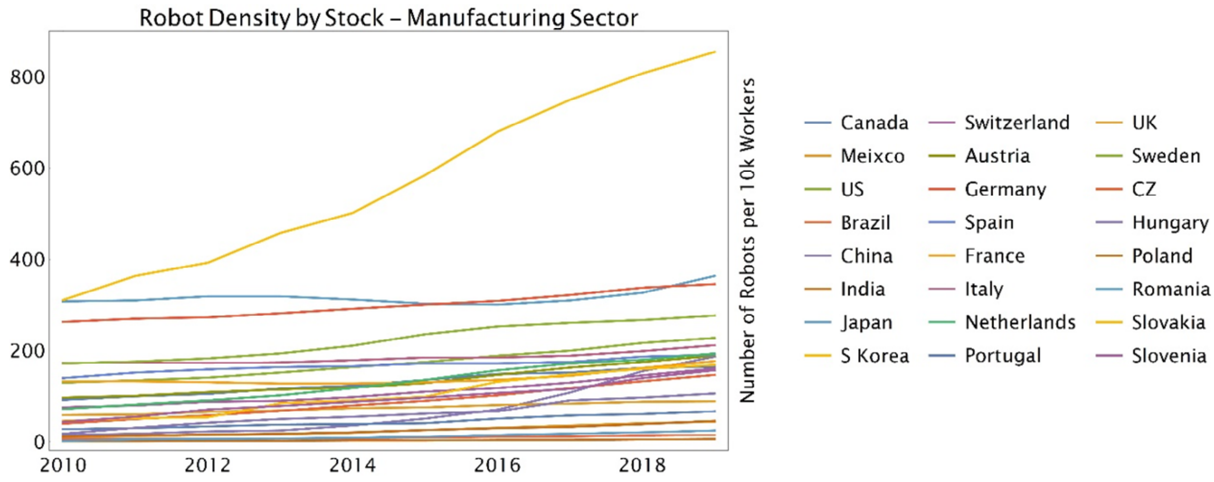


Figure 26: Robot Density Automotive Sector 2010-2019

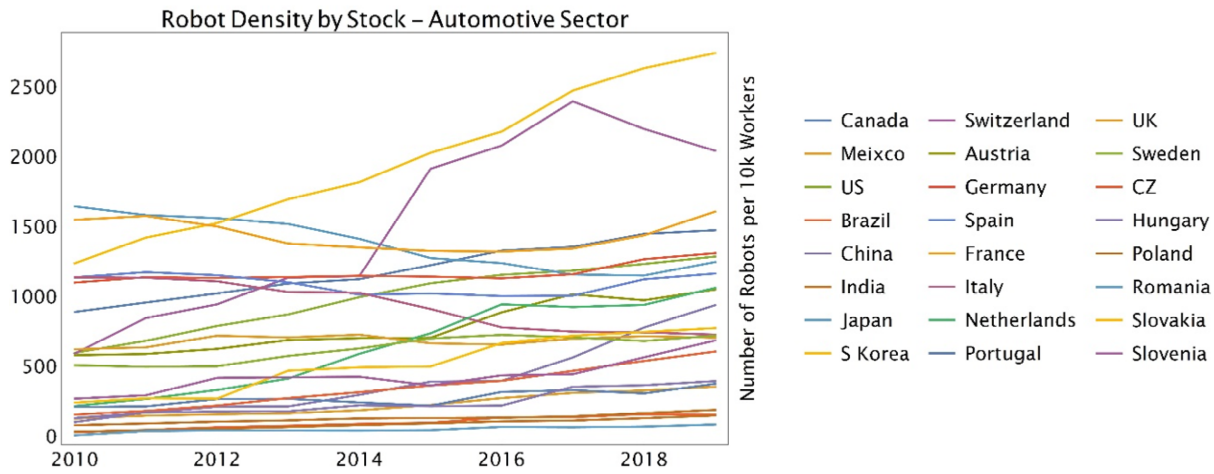


Figure 27: Robot Density Manufacturing Sector (Excluding Automotive) 2010-2019

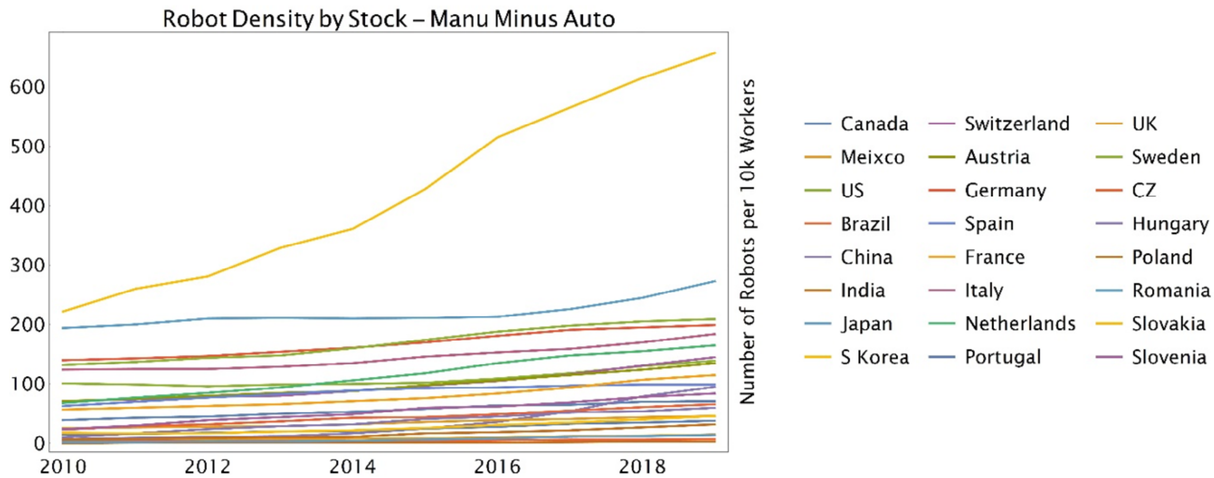


Figure 28: c10 Automotive Sector 2011-2019

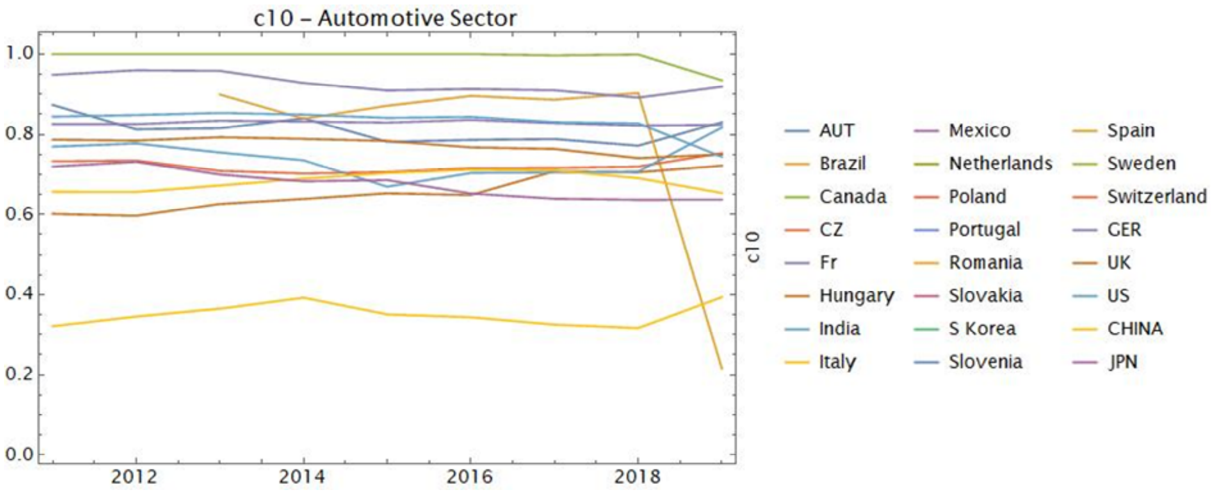


Figure 29: c10 Manufacturing Sector 2011-2019

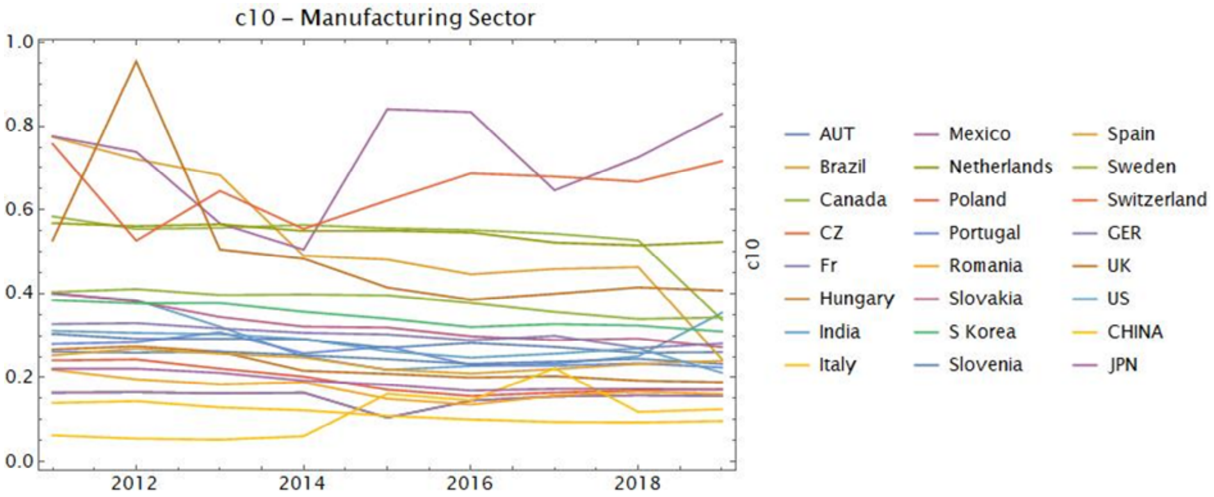


Table 20:Example Automotive Sector 2019 - Valid Observation Degradation Orbis

2019 Automotive	Theoretical Observations in Orbis	Observations Exported	NA's among Exported	Lost through Accounting Consolidation	Used for calculation
Austria					
Brazil					
Canada					
Czech-Republic					
France					
Germany					
Hungary					
Italy					

Japan					
Mexico					
Netherlands					
Poland					
Portugal					
Romania					
Slovenia					
Slovakia					
Spain					
Sweden					
Switzerland					
United Kingdom					
United States					

Table 21: Example Manufacturing Sector 2019 - Valid Observation Degradation Orbis

2019 Manufacturing	Theoretical Observations in Orbis	Observations Exported	NA's among Exported	Lost through Accounting Consolidation	Used for calculation
Austria					
Brazil					
Canada					
Czech-Republic					
France					
Germany					
Hungary					
Italy					
Japan					
Mexico					
Netherlands					
Poland					
Portugal					

Romania					
Slovenia					
Slovakia					
Spain					
Sweden					
Switzerland					
United Kingdom					
United States					

Figure 30

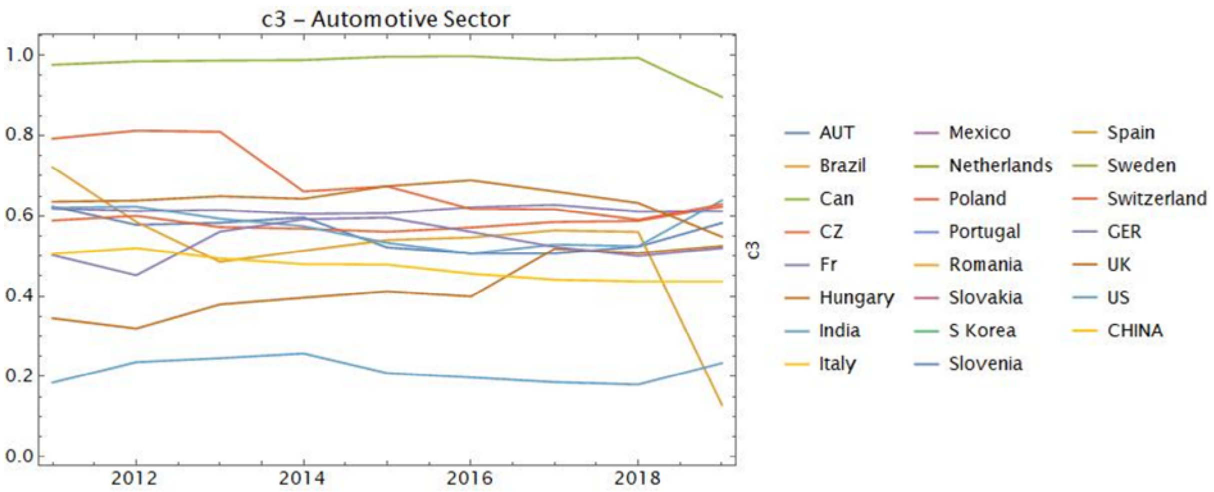


Figure 31

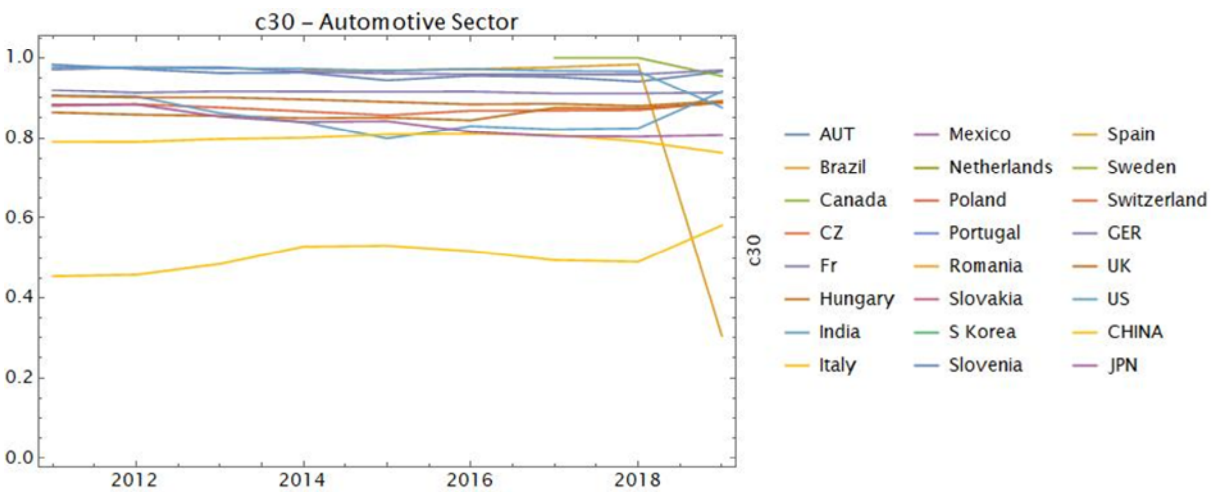


Figure 32

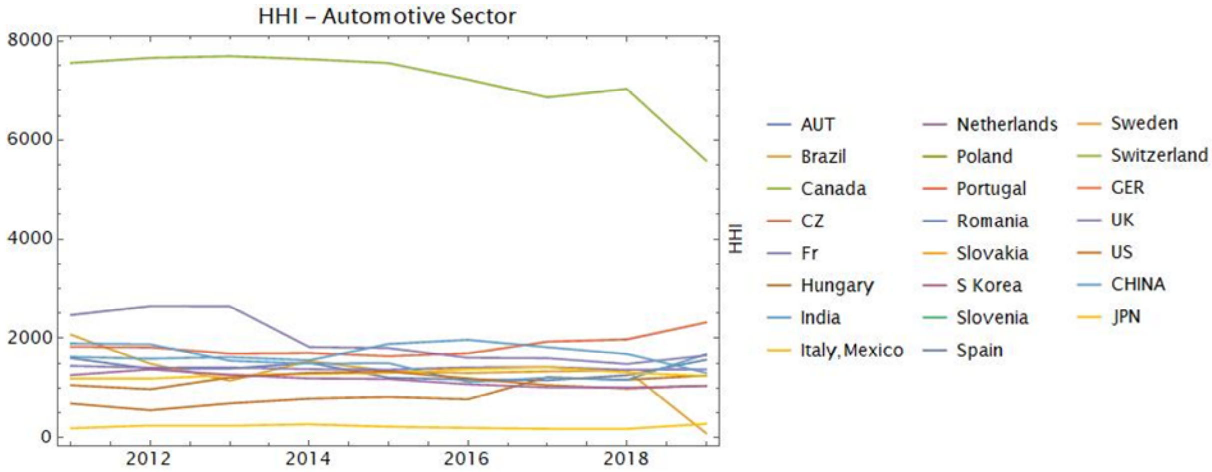


Figure 33

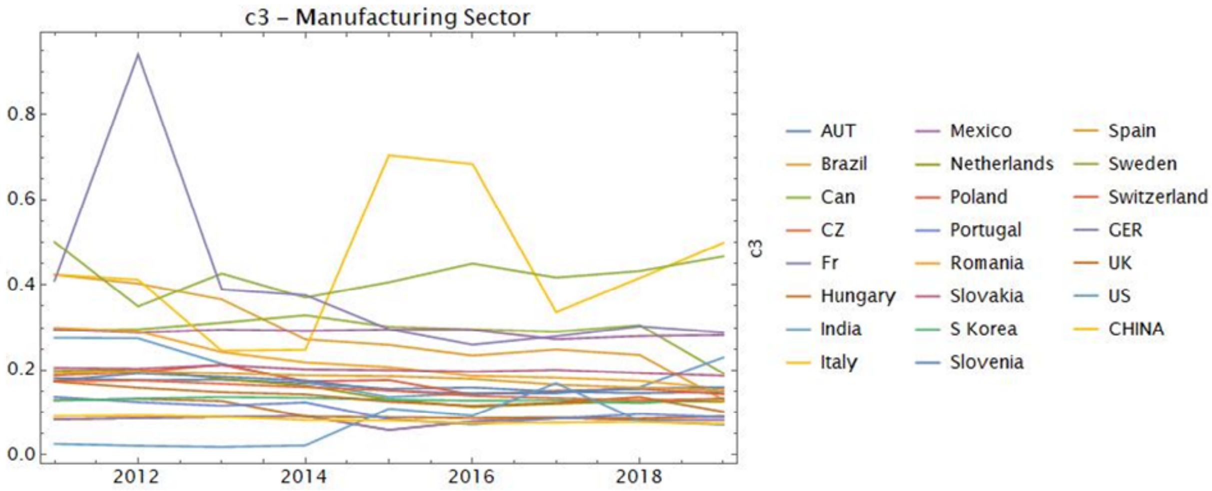


Figure 34

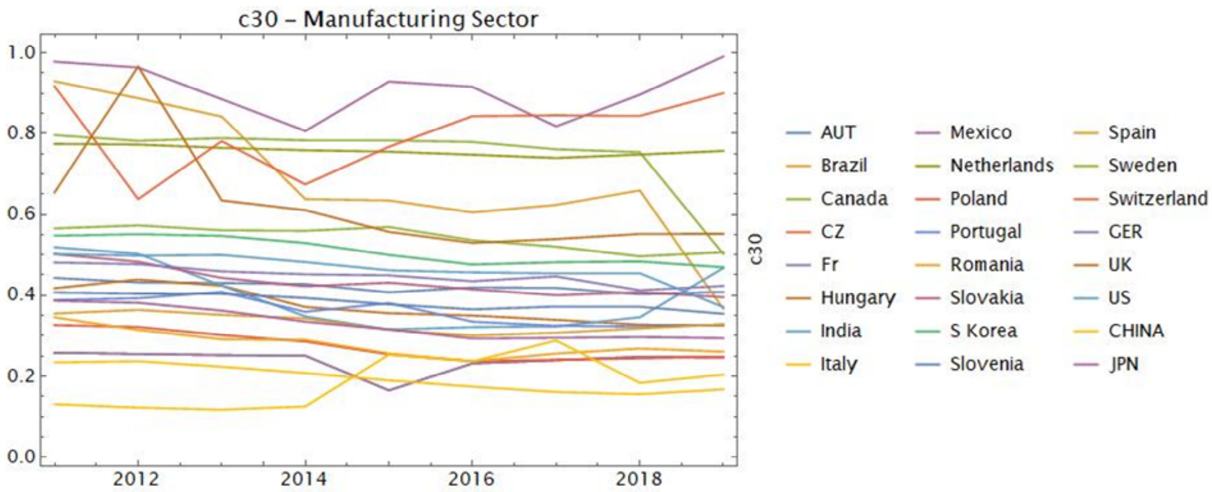


Figure 35

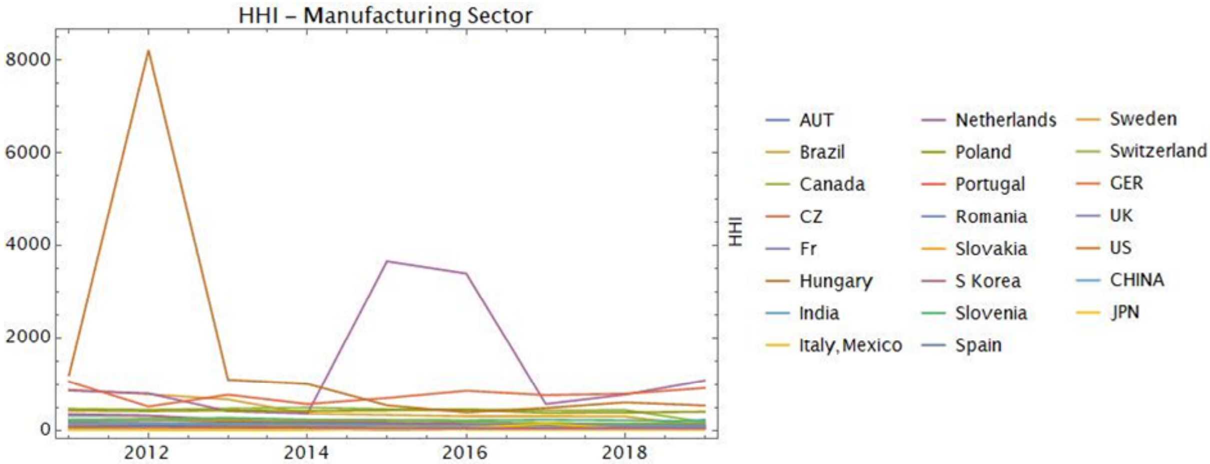


Figure 36: Real Value added Per Hour Worked Automotive 1995-2018

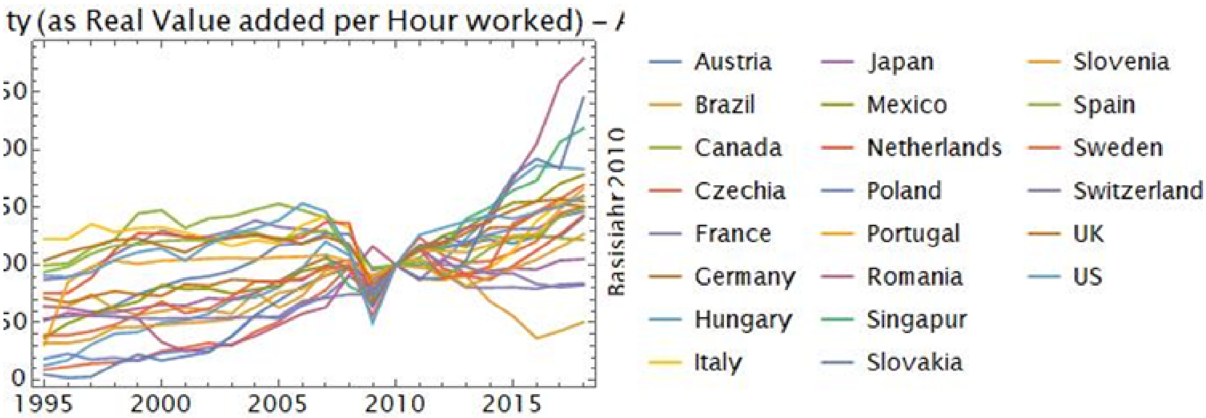
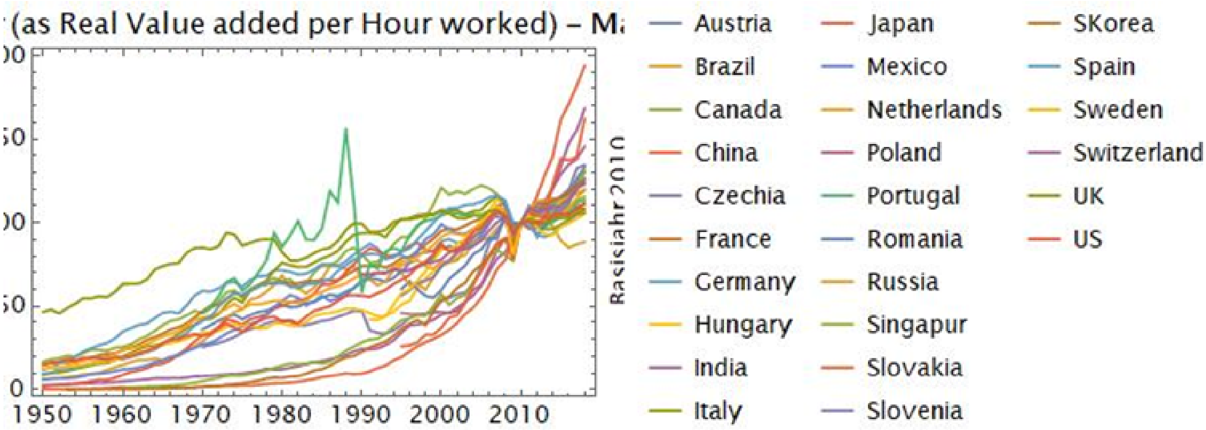
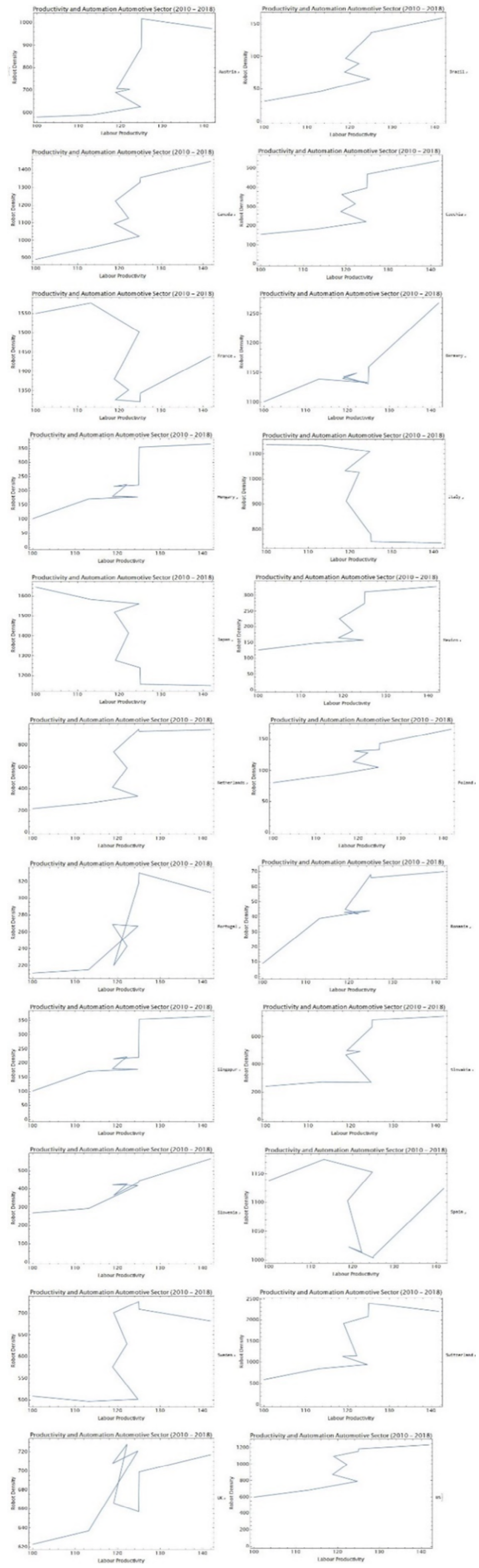


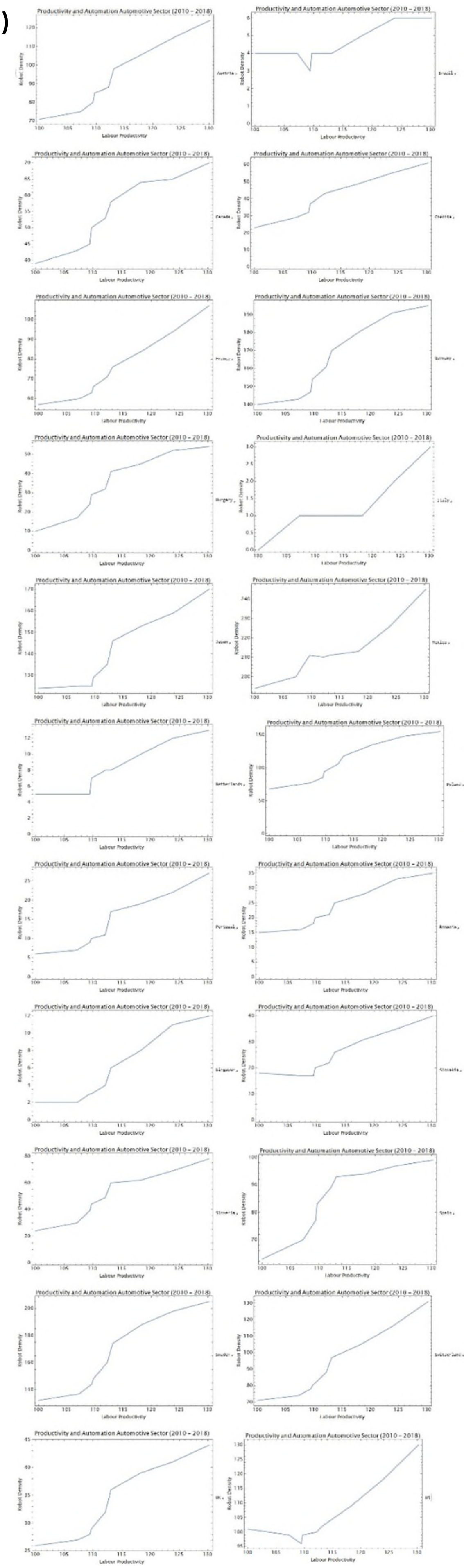
Figure 37: Real Value adder Per Hour Worked Manufacturing 1950-2018



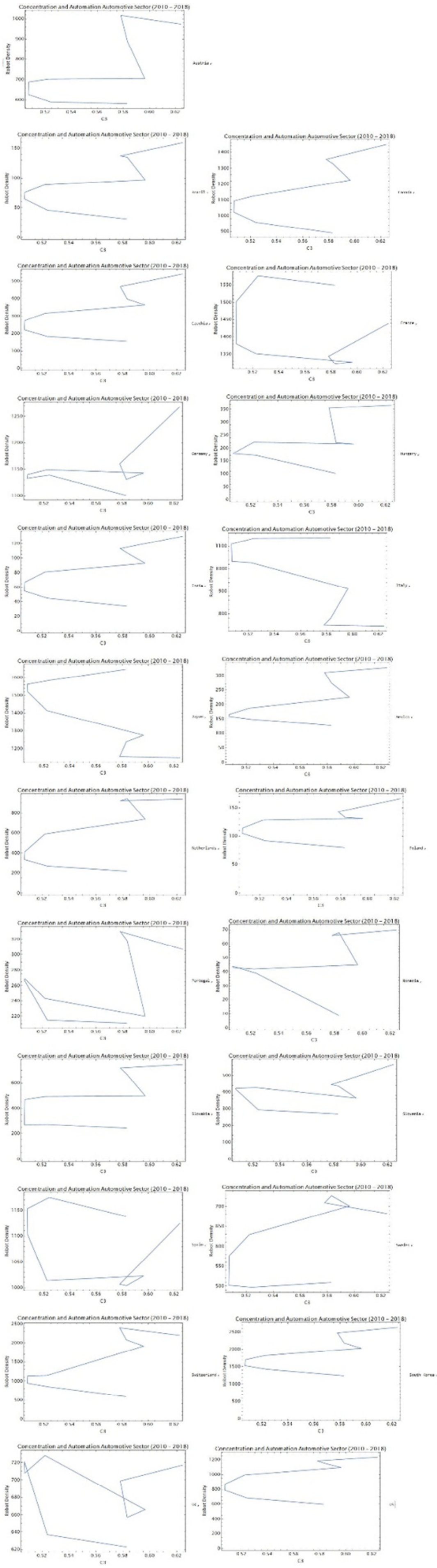
PRODUCTIVITY AND AUTOMATION AUTOMOTIVE



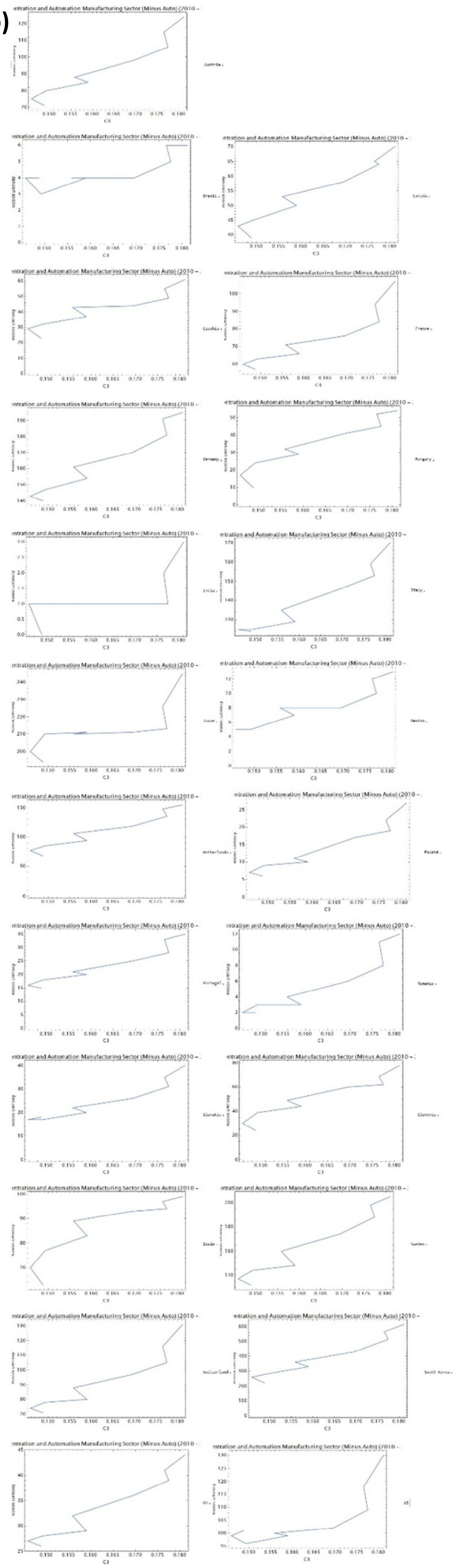
Productivity and Automation Manufacturing (Minus Auto)



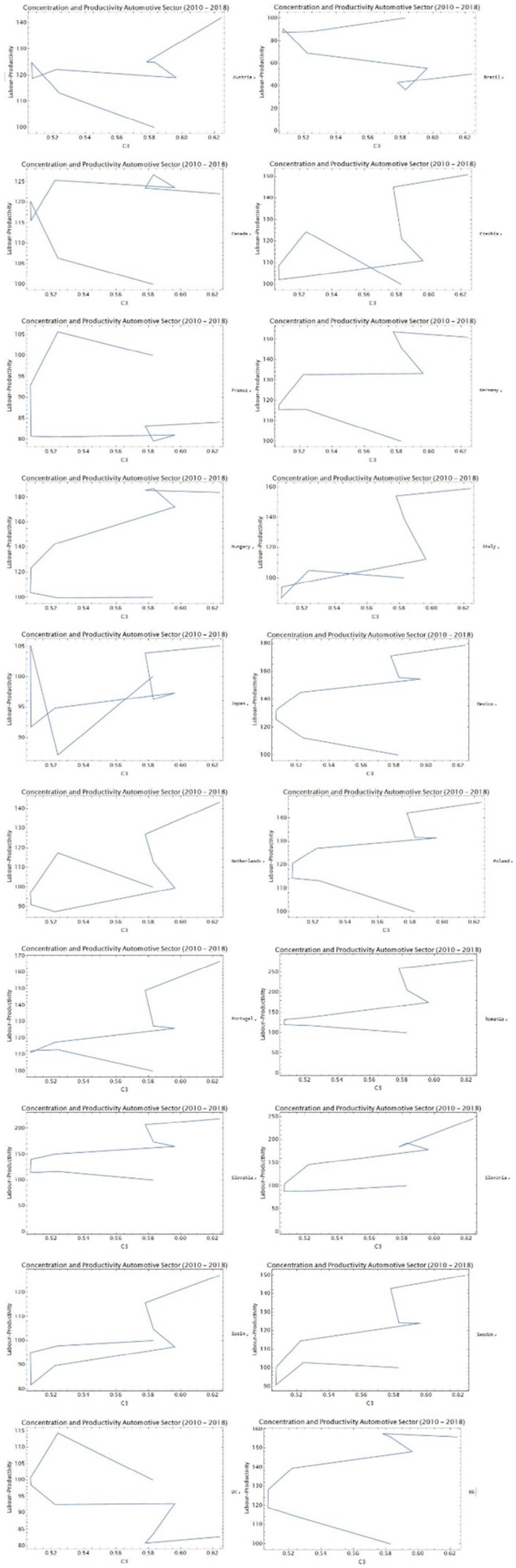
Automation and Concentration Automotive



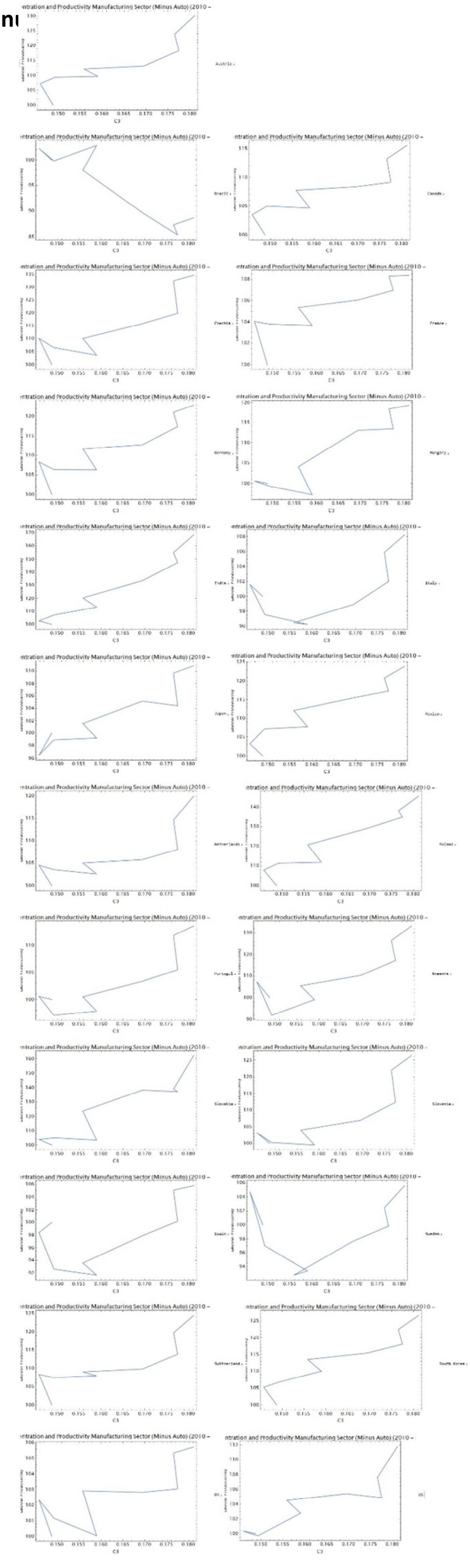
Automation and Concentration Manufacturing (Minus Auto)



Concentration and Productivity Automotive



Concentration and Productivity Manufacturing (Minu



Beschränkungen Daten zu Employment Zahlen bei eigenständiger berechnung Robot-Density:

Table 22 : Data Constraints in Manual Robot Density Calculations

Employment Daten für Robot-Density[14]	**Datenquelle**	**Datenform**	**Problem**
AUT	Eurostat LFSA 1992-2008 (NACE 1); 2008-2020 (NACE 2)	In Tsd. , Arbeiter in Herstellung von Kraftwagen und Kraftwagenteilen	Übergang NACE 1 zu 2 2008
GER	Wie AUT	Wie AUT	Wie AUT
JPN	Statistics of Japan Labour Force Survey; 2006-2020	Employees in Manufacturing of Transportation Equipment in 10k, Japan Standard Industrial Classification (JSIC)	**Transport Equipment nicht gleich Automotive Manufacturing; Klassifikation**
CHIN	Chinese Statistical Yearbooks, 2008-2018 (einzeln durchforstet)	In 10Tsd., Arbeiter, NIC (National Industrial Classification of all Economic Activities)	**Ab 2011 nicht mehr „automobile" sonder Transport Equipment manufacture. Nicht Deckungsgleich. +NA's für 2013;2014. Jährlich wechselnde Klassifikation und Datenverfügbarkeit**
US	ILO, 2003-2019	ISIC Rev 4, Level 2: 29, In thousands	ISIC Rev 4, NACE Rev 2 harmonisieren.
UK	Wie AUT	Wie AUT	Wie AUT

Labour-Producitivity source alternatives

Table 23: Alternative Labour-Productivity Sources

Database	**Was**	**Länder**	**Level**	**Range**
ILO	Annual growth rate of output per worker	All Countries	Country	2001-2019

EUROSTAT	Labour productivity per person employed and hour worked	Only European Countries	Country	2005-2019
OECD 1	Aannul Growth Rate Value Added per hour worked	AUT,GER, UK,US	Manufacture Transport Equipment	AUT (1996); GER(2003); UK(1990);US(1990)
OECD 2	Annual Growth Gross Value Added per hour worked	AUT,GER;UK	Manufacturing	1996-2020
The Conference Board TED 2	Annual Growth of Total Factor Productivity	All	Country	1990-2019
The Conference Board TED 1	Labor productivity per hour worked in 2020 international dollars, converted using Purchasing Power Parities	All	Country	1950-2021 JPN,US,AUT,GER-1950 China ab 1970
The Conference Board TED Regions	Growth of labor productivity per hour worked, percent change	US,UK;JPN,CHINA	Country	2006-2021
The Conference Board - International Comparisons of Manufacturing Productivity and & Unit Labor Cost https://www.conference-board.org/ilcprogram/	**Real Value Added per hour worked (and much more)**	**All (-China)**	**Country, Manufacturing, Sub-sectors (ISIC Rev 4 29: Manufacture of Motor-Vehicles)**	**1950 Einzeljahre aufwärts für manufacturing** **1995-2018 Für Automotive (für einheitlich, einzlene Länder auch früher) //Als Index (ref 2010) sowohl als Level**

Table 24: Publications on Concentration and their data bases

Publication	Research on	Data Source	Data used for
Weche und Wambach 2018	Development of Concentration in Europe	Orbis	Calculation of Markups, 2007-2015, firm observations from 17 of the EU 28
Weche and Wagner 2020	Concentration and Digitalisaiton in Manufacturing	Cost Structure Surveys	Calculation of Markups 2005-2013, manufacturing industries Germany
Stiebale et al. 2020	Concentration and Automation rise in Manufacturing	IFR and Orbis	Mark up calculations for six European countries 2004-2013
Ponattu et al. 2018	Concentration, Digitalisaiton and the Wage Share	Orbis	Sectoral concentration 2008 and 2016
De loeker and eckhout 2017	Rising market concentration and macro-ecnomic consequences	Compustat	Calculaiton of Markup 1980 to 2014
Cavalleri et al 2019	Concentration in the Euro are	Orbis	Calculation of Markups 1980 to 2014
Bighelli et al 2020	Concentration and Productivity in Europe	Compnet	2008-2016
Autor et al. 2019	Concentration and fall of labour-share	Among others Orbis	Markups six european countries 1980-2014

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