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Industrial robot population density and the neoclassical growth model

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Abstract

Neoclassical economic growth model theory identifies technology as a key promotor of productivity and long-run economic growth. Theory and literature on the subject has grown significantly since Robert Solow's seminal work in 1956. Notwithstanding the substantial literature, gaps remain in several aspects, including the establishment of suitable metrics that can be applied to assess the impact and influence of certain technologies, and in particular industrial robots, on the modern economy.

Given these gaps in knowledge, the aim of this study was to support exploratory research that has found industrial robot density, as a proxy for technology and automation, to be a relevant metric that correlates with productivity and economic growth. Decision and policy makers aiming to improve manufacturing productivity and economic development should find this metric and the associated analysis beneficial in achieving a better understanding of forces that influence economic performance. This research was quantitative by design, and used inferential analysis of data from diverse countries. The suitability of industrial robot density as an econometric measure was tested with statistical methods.

Strong statistical correlations were found between industrial robot density, productivity and economic growth in the manufacturing sector. These findings supported existing growth theory quantitatively, while addressing limitations in previous research by using a larger sample that included developing countries for the first time.

Keywords

Industrial robot density; productivity; neoclassical economic growth; automation; econometrics

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Masters of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out his research.

Johan le Roux

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CEP	Centre for Economic Performance
GDP	Gross Domestic Product
IFR	International Federation of Robotics
ISIC	International Standard Industrial Classification
ISO	International Organization for Standardization
OECD	Organisation for Economic Co-operation and Development
TFP	Total Factor Productivity

1. Introduction to Research Problem

1.1. Research Title

Industrial robot population growth and the neoclassical growth model.

1.2. Technology and Productivity in the Manufacturing Sector Economy

Automation, technological innovation and increased productivity in the manufacturing sector are fundamental factors that are linked to the neoclassical economic growth model. One only has to reflect back on the economic impact of the industrial revolution following the invention of steam engine technology in the 18th century to realize the great impact technological advances have had on the manufacturing sector and the world economy as a whole. Were the number of steam engines employed per country measured, recorded and used to make business investment decisions and to explain and predict economic growth during the industrial revolution? Are industrial robots our modern day steam engines, and can a statistical evaluation of new robotic installations be shown to have strong correlation with productivity increases and economic growth?

The impact of robotic automation on the economy is certainly contemporary and topical. The Financial Times (2016) featured a four-day series on the robot economy, titled: “Robots: Friend or Foe”. Topics covered were: The Robot Economy, Living with Robots, Working with Robots and The Human/Robot Future. Waters and Bradshaw (2016) reported that the robot market (manufacturing, sales and installations) would reach $135bn by 2019, and that patents covering robot technology have recently soared. While these periodical articles are not necessarily suitable for a literature review, it does indicate that this proposed research covers a topic that is current and relevant. This again supports the need for the proposed study, which will not be based on opinion or speculation, but a quantitative study on actual secondary data.

The so-called Fourth Industrial Revolution was also a primary topic of the 2016 World Economic Forum in Davos Switzerland. Klaus Schwab, founder and executive chairman of the World Economic Forum discussed the first (water and steam mechanisation), the second (electric power) and the third (electronics and information technologies) industrial revolutions. He further introduced the current fourth industrial revolution as a fusion of technologies that could increase global income levels and benefit mankind, as reported by Trudeau (2016). Key amongst these technologies are advances being made in robotics and the way robots are integrated with emerging technologies.

Industrial robots are increasingly being used to substitute for labour and to increase productivity (Autor, 2015; Mokyr, Vickers & Ziebarth, 2015; Krone, 2014). The increased use of industrial robots, defined through industrial robot density, was shown to correlate with increased economic growth in the recent exploratory empirical study of 17 developed countries (Graetz & Michaels, 2015).

Industrial robot density is a parameter derived from actual industrial robot installations reported annually by the International Federation of Robotics' statistical department and is defined as the number of industrial robots per 10 000 industrial workers. A thorough literature review identified that there is a need to substantiate industrial robot density as an indicator and key promotor of economic growth in developed economies, and to expand the correlation between robot density and productivity and gross domestic product contribution to emerging economies. The potential to expand Graetz and Michaels' (2015) findings to emerging economies is supported by Rodrik (2012), where he found cross-country convergence of improvements in productivity when comparing developed and developing countries' productivity. This suggests that developing countries should achieve comparatively high rates of productivity improvement when introducing benchmark technologies.

The relevance of robotics in improving productivity and enabling economic growth was expressed by Chinese President Xi Jinping in a speech in 2014 when he called for a "robot revolution", affirming automation's key role in raising productivity in China (Chan, 2015), thus further supporting the relevance and need for this research. In 2013, 36 560 Robots were installed in China, 59 per cent more than in 2012 (International Federation of Robotics, 2014), followed by further growth of 56 per cent in 2014 (International Federation of Robotics, 2015). This rapid growth could be explained by national policies implemented by the Jinping government to stimulate the proliferation of industrial robotic installations.

This research aims to show that industrial robot density is an ideal metric to track the pace of the revolution, as emerging technologies in fields such as artificial intelligence, advanced multiple axis motion, sensing technologies, connectivity, nanotechnology, biotechnology, materials science, energy storage, and quantum computing are actively integrated into robot and manufacturing technologies.

To put the scale of the robot industry into perspective, consider that the total number of new industrial robot installations was 229,261 in 2014 (International Federation of Robotics, 2015). This was 29 per cent more than in 2013, and by far the highest level of new installations ever recorded for one year. These new installations brought the total of installed operational industrial robots to 1,480,800 (International Federation of Robotics, 2015) at the end of 2014. Comparing this growth rate of 29 per cent to the estimated global human population growth rate of just over one per cent per annum (United States Census Bureau, 2016), the significance of the comparative growth rates and the economic impact of the accelerated growth in the industrial robot population cannot be underestimated.

1.3. Research Problem

Automation, mechanisation and the implementation of new technologies as a key promotor of long-run economic growth is a well-established concept (Dowrick & Rogers, 2002). Identifying simple metrics to determine the significant correlation between technology, productivity and economic contribution in the manufacturing sector remains a problem. Empirically measuring and evaluating the levels and extent of technology in the manufacturing sector through industrial robot density and its relation to productivity and economic growth was done recently for the first time by Graetz and Michaels (2015).

Investigating and confirming that the accurately measured and reported trends of industrial robot installations is a valid proxy or indicator for automation and technology in the industrial sector will be invaluable for accurate econometric analysis. Due to the technological nature of industrial robots, installations in manufacturing facilities are not done in isolation from related technology. A typical robot installation is integrated with peripheral automation system installations, such as programmable logic controllers, computer based control, monitoring systems and industrial information technology networks. The significance of this integrated nature of automated industrial installations to this study is that industrial robots represent more than just the pieces of equipment, but can be used as a valid indicator for the level and intensity of automation and technology utilized in the respective manufacturing economies.

1.4. Research Objective

The aim of this quantitative study will be to identify and quantify the correlation of the statistical relationship between robot density, productivity and economic growth, with specific focus on including developing countries. The statistical significance, and applicability as a metric or indicator of economic growth models of this research analysis and findings will be investigated.

This study of industrial robot density in relation to productivity and manufacturing sector economic value added could establish it as an economic metric. This new metric may be useful to organisational, industrial and national policy decision makers aiming to analyse productivity and make technology investment decisions on company, industry and national levels.

The author contends that there is an academic and economic need to identify simple, available metrics to accurately evaluate the level and efficacy of technology in the industrial sector. If proven significant, such metrics would be beneficial to economists, analysts and policy makers.

Furthermore, this research aims to show that industrial robot density is an accurate, relevant metric and key promotor of increased productivity and the resulting economic growth in the secondary economic sector, across developed and developing countries.

The extent of correlation will thus determine whether robot density trends can be used as a manufacturing sector economic indicator, similar to the agricultural machinery, tractors per 100 square kilometres of arable land (denoted by AGRMACH) indicator tracked by the World Bank (2016). The similarity between industrial robots and agricultural machinery is that in each case human labour is replaced by technology in order to increase productivity and economic contribution.

1.5. Academic Motivation

The principle of diminishing marginal productivity gains on new robot installations in developed countries was identified as a limitation by Graetz and Michaels (2015). The authors remarked that recent evidence suggested that robots were increasingly used in developing countries, and that the contribution to growth might be even greater than shown in developed countries. Data limitations were cited as the reason for the shortcoming in the research.

Identifying reliable and accurate metrics in order to determine the relationship between technology, productivity and economic contribution on a global scale, thus including developing countries, remains an area to which research can contribute.

This study will explore and expand on the exploratory research titled: “Robots at Work”. In this research, Graetz and Michaels (2015) evaluated the economic and productivity impact of industrial robots based on data from 17 developed countries covering the period from 1993 to 2007. Their conclusion was that the increased deployment of industrial robots contributed 10 per cent of annual aggregate economic growth rate (Graetz & Michaels, 2015).

It is thus proposed that there is a need to explore the research with a more recent and complete dataset, covering 38 countries and data up to 2014. It is specifically relevant to evaluate the co-variance in developing countries, where increasing industrial robot density has not yet reached the plateau of diminishing returns. This study will utilise the available data to fill the void and explore the identified research opportunity.

1.6. Report Outline

This report continues in Chapter 2 with an overview of the relevant theory and literature concerning economic growth theory, productivity, industrial robot density the effect of increased industrial robot density on labour and unemployment, technology indicators, stages of country development and research methodology. This is followed by Chapter 3 that covers the research questions and propositions, and Chapter 4 where the research methodology is presented. Research results are presented in Chapter 5 and discussed in Chapter 6. The research will conclude with Chapter 7 where the findings, management implications, limitations and suggestions for future research will be presented.

2. Literature Review

2.1. Introduction to the Literature Review

The literature review is divided into four distinct sections: Economic growth, productivity, industrial robot density, the effect on labour, technology indicators and stage of development and methodologies used for analysis. Lastly, it concludes with salient observations to consolidate the literature review.

2.2. The Solow Residual and the Neoclassical Economic Growth Model

Burda and Severgnini (2014) stated that for half a century the Solow decomposition and residual theory have been used to define and measure the productivity component of growth in economics and management. The work by Solow (1957) remains influential, as it broke the limitations of the contemporary and restrictive labour and capital input growth models of the period.

In Robert Solow's (1956) seminal essay: "A Contribution to the Theory of Economic Growth", he supposed that the single composite product is produced by labour and capital, and that in a new growth model it should be possible to substitute labour with capital. The so-called Solow residual can be explained by the phenomenon where the growth rate in output exceeds that of the growth rate of inputs (Ten Raa, 2011). This paved the way for the inclusion of productivity as a metric included in long-run economic growth theory, and in this context, why the increased productivity achieved through ever advancing robotic technologies and rate of implementation are important to study. Robert Solow's research was core to theoretical concepts of which the Solow residual, total factor productivity (TFP), the Solow decomposition and the neoclassical growth model were relevant to this research.

Robert Solow's (1956) seminal essay introduced the framework for the development of the neoclassical growth model. In theory, it is well established that productivity is a key enabler of long-run economic growth (Autor, 2015; Krone, 2014; Mokyr et al., 2015). Bernard and Durlauf (1996) described the technological growth component as exogenous technical change, and advances in robot technology forms an integral part of recent technological growth. Similarly, Gourinchas and Jeanne (2013) argued that according to the neoclassical growth model, growth is driven by an exogenous productivity path. Furthermore, each countries' productivity path in relation to the world technology frontier determines capital flows into the country. The consequence of this is that when developing countries embrace new technologies in order to improve productivity, the neoclassical model postulates that foreign direct investment into the country should increase.

Halsmayer (2014) concluded on Roberts Solow's growth theory that while he was not the first to show that economic growth was not entirely dependent on capital accumulation and labour input, Solow was the first to have clearly articulated the residual, which is referred to as the productivity component and explained shifts in the production function. This study identified industrial robots as a quantifiable metric that represents the capital employed to utilise technology in order to increase productivity.

Conversely, Petrin, White and Reiter (2011), analysed the aggregate Solow residual by isolating the aggregate plant resource reallocation and aggregate technical efficiency aspects of productivity growth. On average, reallocation of resources was responsible for more of the growth than technical efficiency. In essence, they found that doing the right things is more important than doing things right. While the findings made by Petrin et al. (2011) might be interpreted as downplaying technological efficiency, both organisational and technological efficiency remains the optimal goal.

As Ten Raa (2011) concluded, industries may achieve increased productivity growth through technical progress or by through organisational efficiency and that the combined performance remains consistent with the Solow residual and Malmquist productivity indices.

The role of technology to improve productivity was evident in Crafts (2015) assessment when he reviewed economic growth in the United Kingdom over the past 30 years: "The information, communication and technology (ICT) revolution did deliver and, as a pleasant surprise, the UK turned out to be much better at exploiting its opportunities than had been the case with Fordist manufacturing" (p. 236).

The Solow decomposition and resultant neoclassical growth model is the theoretical framework for the suitability of industrial robot density as an accurate metric and enabler of economic growth within long-run economic growth theory framework.

2.3. Manufacturing Sector Productivity

For the purpose of this study, the author chose to use one of the most basic definitions and measurements of productivity, namely the ratio of value added to the number of workers in the manufacturing industry per country. According to Brandt, Van Biesebroeck and Zhang (2012) this was the most widely used measure of labour productivity. An advantage to using this measure was that it could be derived from the raw secondary data sourced from the World Bank and the International Labour Organisation, and that the respective data could be sourced from the same databases for the 38 countries in the sample. This prevented any bias that could have emanated from different data sources, which would have negatively impacted this correlational study.

Calver (2015) analysed the comparison between gross output based productivity and value added based productivity growth measurements, and warned that while the methods are comparable in the short term, differences are observed over longer periods. Based on his conclusion that researchers should be wary of combining these two methods when comparing productivity across countries or regions, this study will standardise on the value added productivity measure for all countries in the sample.

The gross value added at current basic prices and the total number of persons engaged were also used by Mihai and Jivan (2014) in their comparative study of productivity measurements across five European countries. This method concurred with the work of Brandt et al. (2012), and supported the selection of productivity measurement used in this research.

Below follows a review of contemporary views and measurement of productivity and how it is impacted by advances in technology. While some of the productivity measurements, such as total factor productivity, were not used in this study, the theory, research findings and general principles regarding productivity in the broader sense remained applicable to this study.

Baldwin and Teulings (2014) defined total factor productivity as a weighted average of the ratio of output to labour input and the ratio of output to capital input, where both types of inputs are adjusted for quality changes. The difference between single-factor and multi-factor productivity, of which total factor productivity is an example, was explained by Lieberman and Kang (2008). Multi-factor productivity ratios take into account the weighted averages of multiple inputs. They identified labour productivity, or value added per worker hour, as used in their study as the most simplified and widely used method, but also combined it with other weighted input factors to yield multi-factor productivity. Lieberman and Kang (2008) continued the explaining the difficulty in calculating the often arbitrarily measured capital, material and energy inputs, and stated that: "Unlike labour productivity, capital productivity is not directly interpretable as an indicator of economic welfare, but it does provide an indicator of the efficiency of resource use" (p. 11).

Calculating multi-factor weightings and productivity ratios per company, industry and country is thus a complex matter, open to subjectivity, and not ideal for a comparative study such as this one. Subsequently, single factor labour productivity, namely value added per unit of labour unit as described by Mihai and Jivan (2014), Brandt et al. (2012) and Lieberman and Kang (2008) was used for this study.

The so-called productivity paradox was presented by Brynjolfsson and Hitt (1998), the paradox discussed was the weak correlation between information technology investments and productivity in the United States since 1973. Productivity stagnated despite the rapid growth in computing power stemming from Moore's law, and wide adoption of computers. One explanation for this was that not all information technology investment was aimed at cutting costs or improving productivity, and that quality and customer service were identified is the primary reasons for these investments. The reasons for investing in industrial robots today are, however, overwhelmingly focussed on cost reduction and productivity increases. Pratt (2015) proposed that robotics is a technology that might improve productivity at an ever faster rate than previous technological advances, to the point where it might disrupt the economy as the industrial revolution disrupted the textile industry two centuries ago. It is thus doubtful that a study of industrial robotics and productivity should face challenges similar to the productivity paradox of the information technology sector discussed by Brynjolfsson and Hitt (1998).

Theoretically, the increase in total factor productivity yielded a high long-run growth of an economy (Oh, Heshmati, & Lööf, 2012). Factors enabling productivity improvements included product and process technology, skills and innovativeness. Of relevance to this study is that industrial robot density has been identified as an accurate, measurable parameter for process technology in the manufacturing sector.

As found by Rodrik (2012), and applied by Inklaar and Diewert (2015), productivity in the non-traded industries is convergent across countries. The phenomenon of cross country technology convergence was quantified by Dowrick and Rogers (2002) at 3.4 per cent per annum. This quantified convergence implied that a country's technological development level will catch up with the global technology benchmark within 20 years. The consequence is that improvements in productivity are not restricted to certain countries, and that the macro-economic trends in productivity spans borders. Furthermore, Inklaar and Diewert (2015) concluded that during the 2007-2011 period, the world market TFP growth slowed from 1.1 per cent to 0.6 per cent, and was caused by the contraction of the traded sector. Conversely, during the same period the non-traded sector TFP expanded by 2.6 per cent per year from 2007 to 2011. This indicates the growth potential in the nontraded manufacturing industries and could result in increased global productivity growth, specifically in developing countries.

While Rodrik (2012) addressed cross country productivity convergence, Solow (2001) expressed scepticism over applying growth theory regressions across multiple countries, especially when developed industrialized countries, and developing countries were being compared. His view seems problematic for this study, but Solow (2001), however maintained that productivity remains a valid metric for long-run economic growth, regardless whether the driver of productivity change was technical or non-technical. Therefore, the theory of increased productivity associated with increased use of new technology holds true for the purpose of this study.

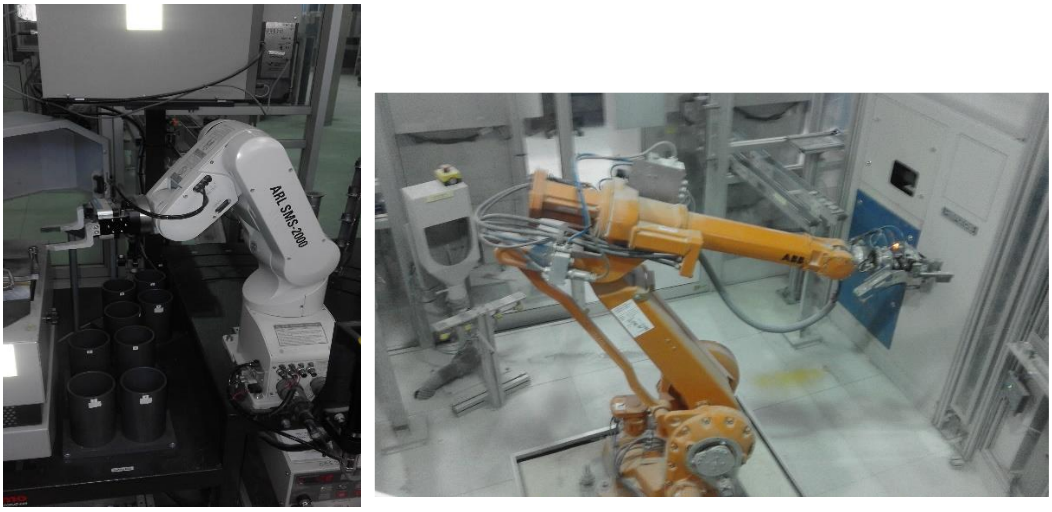
2.4. Industrial Robot Density

Firstly, a clear definition of exactly what is understood of industrial robots is required. Below follows the official definition of industrial robots by ISO 8373:2012:

"An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (ISO, 2012, p.3).

Elaborating on this formal definition, one can describe industrial robots as computer controlled machines that perform designated manipulation tasks in three or more planes. Industrial robots are typically installed in factories and industrial plants as part of greater automation systems. Industrial robots are not service robots, which are popularly portrayed as android-like robots that interact with humans, talk and perform cleaning or similar tasks. For illustration purposes, Figure 1 shows typical examples of industrial robots.

Figure 1. Typical examples of industrial robots.



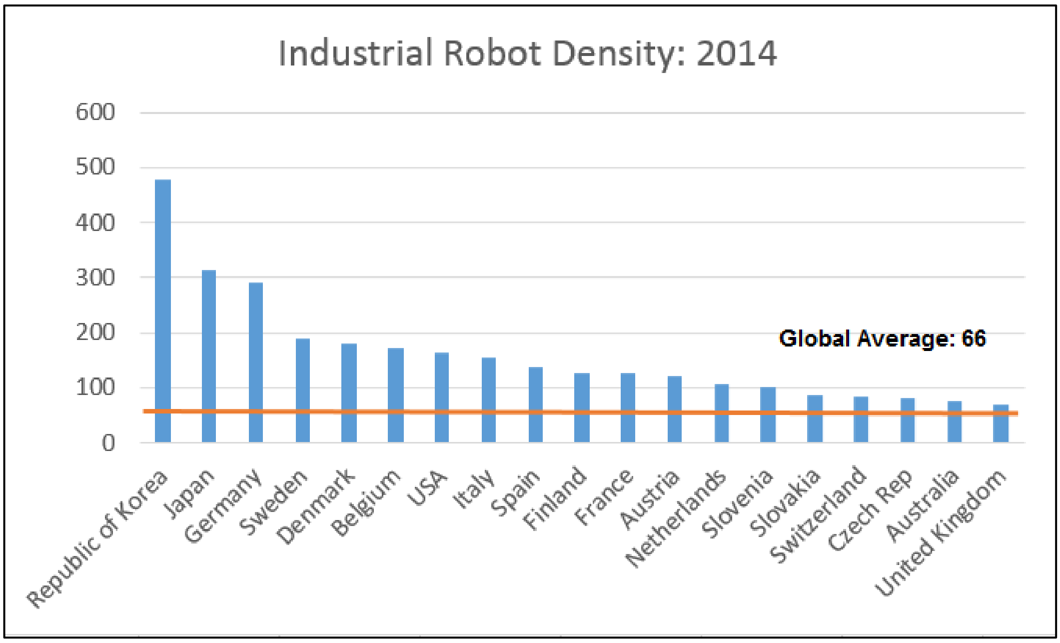
Source: Authors own.

The global supply of industrial robots is accurately monitored and published annually in the publication *World Robotics Industrial Robots* by the International Federation of Robotics' Statistical Department. The general parameter of interest was industrial robot density per country, which was reported as the number of industrial robots per 10 000 industrial workers in each specific country.

Multipurpose industrial robot density per country are depicted in Figure 2 and Figure 3, sorted from the highest to the lowest density. In 2014, the Republic of Korea (also referred to as South Korea) had the highest industrial robot density at 478 per 10 000 employees in the manufacturing industry, and the total number of industrial robots installed at the end of 2014 was 176 833 (International Federation of Robotics, 2015).

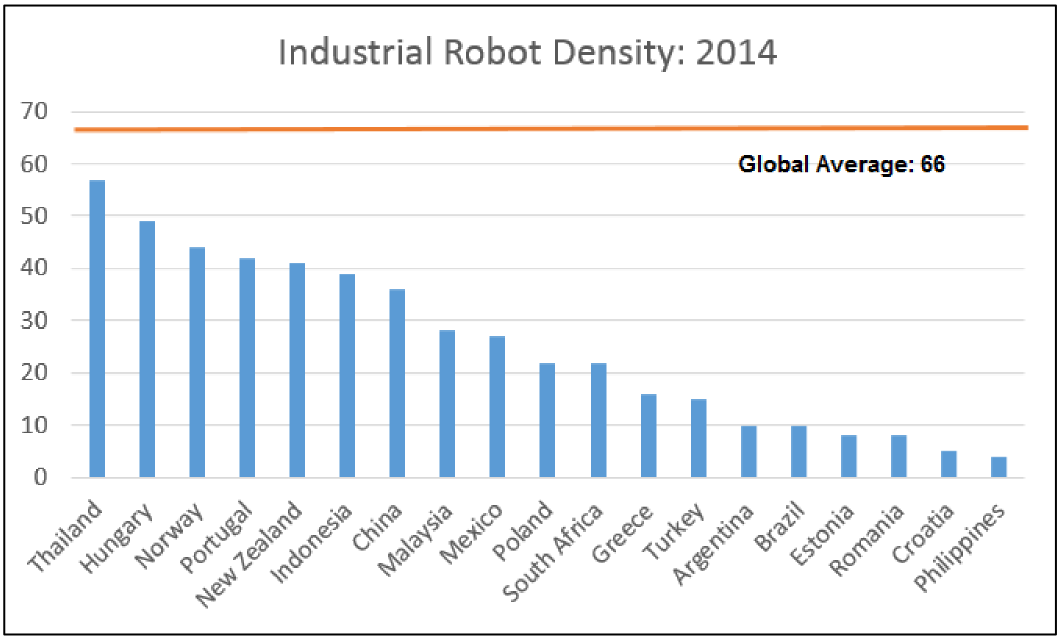
In comparison, South Africa had a robot density of 22 per 10 000 employees in the manufacturing industry and 3 452 in total (International Federation of Robotics, 2015). Iran ranked the lowest with a total of only 590 installed robots at a density of 2 industrial robots per 10 000 employees.

Figure 2. Number of industrial robots per 10,000 employees.



Source: Adapted from International Federation of Robotics (2015) data.

Figure 3. Number of industrial robots per 10,000 employees (continued).



Adapted from International Federation of Robotics (2015).

This valuable source of data was first used in exploratory academic research to correlate industrial robot density to increases in productivity and value-added by Georg Greatz, assistant professor at the Department of Economics at Uppsala University, Sweden and Guy Michaels, Research Associate at the Centre for Economic Performance, London School of Economics and Political Science in 2015, CEP Discussion Paper No 1335.

A gap identified in this research was that Graetz and Michaels only evaluated industrialized developed countries from Europe, Australia, South Korea and the United States. This research proposal contends that similar work is of specific relevance and importance to developing countries, where opportunities for robot applications in manufacturing industries and potential for economic growth is higher than the previously studied developed counties.

In his article, “Increasing Workforce Productivity: Smarter People and Machines”, Krone (2014) argued that increased productivity gave companies and countries a competitive economic advantage. Of further significance was that the pace of technological innovation was increasing (Brynjolfsson & McAfee, 2011), and in the current global market conditions, it is imperative that technological progress and its effect on economies are measured and predicted if possible. This research will explore the potential to develop increasing industrial robot density as a metric for increased application of technology, productivity and economic growth, especially in developing countries which were not included in Graetz and Michaels’ (2015) study.

2.5. The Effect of Increased Industrial Robot Density on Labour

Arguments against technology and automation have been raised over two centuries, Autor (2015), in his aptly named article: “Why Are There Still So Many Jobs? The History and Future of Workplace Automation” investigated the Luddite-like concerns that automation and robots destroyed jobs. He concluded that while robots do in most cases substitute for human labour, these are mostly unskilled labour performing menial tasks. Autor (2015) further emphasised that robots did in fact compliment labour, improved productivity and stimulated the economy which in turn created more employment. The phenomenon also allowed labourers to acquire skills in order to gain middle and higher levels of employment that required a mixture of tasks from across the skills spectrum.

Seemingly opposing this view, Kristal (2013) showed that labours' share of production output declined by six per cent, and that this was due to the increasing levels of computerisation, automation, and robots. This benefited capitalists and highly skilled workers more than labourers. Substantiating this view, Milkman (1997) found that at a General Motors automobile assembly plant in North America, production workers were reduced by approximately a third when the plant was technologically modernized.

The following interesting viewpoint was raised by Mokyr et al. (2015). In a hypothetical case where labour was totally substituted by automation, it might become necessary for the holders of capital, or government, to supplement the income of some classes of workers through wealth distribution. While the labour implications were not the focus of this research, it is noteworthy that the potential of automation to create wealth in future could be so great that the need for wealth redistribution to the unemployed is foreseen.

Brynjolfsson and McAfee (2012) also concluded that technology may substitute for human labour in ever increasing instances, which may be good for business but not individuals who lose their jobs. However, computers (technology, robots) are not good at many things and human skills will remain in demand. Brynjolfsson and McAfee (2012) further identified general skills that humans should attain and utilize to use computers, rather than compete against them. These identified skills generally had creativity in common, and included: applied mathematics and statistics, negotiation and group dynamics, creative writing, framing problems and solving open-ended problems, persuasion and human interaction, and nurturing.

This was comparable to the opinion of Crafts (2015) when he stated: "Tasks which will probably not be susceptible to computerization are those involving perception and manipulation, creative intelligence, or social intelligence" (p. 235). This indicates that not all theorists fear that robots will be taking over most human jobs.

While the effect of automation and robotics in particular on rates of employment is contemporary and of great importance, it will not have a direct impact on this study, as the data used will represent economic performance and not the specific socio-economic factors such as unemployment and income disparity.

2.6. Technology Indicators and Economic Growth

The principle of specific technologies or deployment of technological equipment as economic growth indicators or metrics is well established. An example that is functionally similar to the prospect for using industrial robots as an economic growth indicator in the manufacturing sector is the established use of agricultural machinery and tractors per 100 square kilometres of arable land economic indicator, as monitored and reported by the World Bank and represented by the acronym AGRMACH. The relevance of agricultural machinery and tractors are clear in the article by Alston and Pardey (2014), in which they attributed the increase in agricultural productivity to the increased use of agricultural machinery and tractors.

This was corroborated by Khan, Khan, Zaman, and Khan (2014) in their study of relieving rural poverty and economic growth in Pakistan. They found that variance decomposition analysis showed that the agricultural machinery and tractors per 100 square kilometres exerted the largest positive degree of influence on economic growth in the rural economy. This conclusion lends credibility to the potential of industrial robots to be a useful indicator for economic growth in the manufacturing sector. Agricultural machinery and tractors are similar to industrial robots, in that in both cases sizable investments in technology are made for the purpose of improving productivity in a specific economic sector, and sales and deployment of the equipment are accurately recorded and reported for use by analysts and researchers.

2.7. Stage of Development

The stage of development of each country as defined by the United Nations (2014) publication, *World Economic Situation and Prospects 2014,* were used to classify each of the 38 countries in the research sample as either developed or developing. The Development Policy and Analysis Division of the Department of Economic and Social Affairs of the United Nations Secretariat based the country classification on basic economic country conditions (United Nations, 2014).

This classification will be used to observe whether the statistical correlation between industrial robot density and worker productivity as shown by Graetz and Michaels (2015) for 17 developed countries also holds for the 11 developing countries included in this research.

2.8. Methodologies Used for Analysis

This quantitative, descriptive, relational statistical study of industrial robot density versus industrial worker productivity and total manufacturing value added per country, using secondary data, was done using correlation and linear regression techniques. This research design used similar techniques to that of the research by Mihai and Jivan (2014), Khan et al. (2014) and Alston and Pardey (2014).

The Pearson's correlation method was specifically used by Mihai and Jivan (2012), in a similar study determine the correlation strength between productivity and gross output and gross domestic product per capita, and the correlation between different types of productivity measurements. The interpretation of the Pearson's correlation results (r) and coefficient of determination (r^2) were based on guidelines provided by Cohen (1998). The guidelines for interpretation of the Pearson's correlation coefficient values greater than 0.3 were regarded as moderate, values greater than 0.5 large or strong linear associations.

Baird and Bieber (2016) proposed the use of the least squared estimate of the slope of the independent variable predictive of the dependent variable, and is the answer to the research question, "how is the independent variable predictive of the dependent variable". In this study, the regression of industrial robot density is proposed to be predictive of productivity and manufacturing value added respectively. The respective slopes, or β, were proposed to be positive for the management proposition in this study. The proposition tested whether the variability in industrial robot density is associated positively with the variability in productivity and manufacturing value added respectively.

Confidence intervals were constructed at the 95 per cent confidence interval, with p at 0.05. The calculated p-values were evaluated, as it is a measure of the significance of the relationship between the predictor and response variables, and answers the question: "Is the statistical relationship between x and y, as given by the regression equation, a genuine relationship or is it due purely to chance?" (Wegner, 2012, p. 311). For the purpose of this research, p-values less than 0.05 were interpreted as significant at a confidence interval of 95 per cent. With the significance level set at for $p < 0.05$, there was only a 5 per cent chance of making a Type I error of rejecting a true null hypothesis.

Notably, Greenland et al. (2016) raised concerns about the misinterpretations of p values and confidence intervals. They proposed the view that the p value should be interpreted as a statistical summary of the compatibility between the observed data and what was predicted if the entire statistical model were known. Furthermore, the p value should be seen as simply indicating the degree to which the data conforms to the correlation predicted by the null hypothesis and the other assumptions used in the model. Thus a p value of $p < 0.05$ shows that the data are not similar to what the null hypothesis predicted they should be, and that the null hypothesis can be rejected in favour of the alternative hypothesis (Greenland et al., 2016, p. 340). The prevalence of making a Type I error of rejecting a true null hypothesis would only be in 5 per cent of cases. It is noteworthy that Greenland et al. (2016) refers to the confidence level not as the chance of making an error, but how often you would have incorrectly rejected a null hypothesis.

2.9. Literature Review Conclusion

The literature reviewed gave theoretical evidence of the role of productivity and technology in the neoclassical growth model. Literature on the quantification or measurement of the level or extent of productivity promoting technologies used in the manufacturing sectors remains sparse. Graetz and Michaels (2016) showed for the first time that industrial robot density could be such a suitable metric for productivity improvements. Unfortunately, their study was limited to developed countries, and a need for further research to validate the findings for developing countries was stated.

The literature review revealed the increased rate of new industrial robot installations, and as comment, and indeed reaction, from leaders in the global economy. While seemingly conflicting views on the effect of this phenomenon on labour was observed, this impact was not the core focus of this research. The literature review and this research certainly focussed on the effect of industrial robots as proxy and metric for wider industrial technology, and as a key promotor of productivity and long-run economic growth.

3. Research Propositions and Hypotheses

3.1. Introduction

Research propositions are represented through the following:

- Annual variations in industrial robot density correlate positively with changes in industrial sector worker productivity per country.
- Annual variations in industrial robot density correlate positively with changes in the industrial sector value added per country.
- The above correlations should be positive and applicable to developed as well as developing countries.

The statistical relationship between the variables were described using correlation and simple linear regression analysis, and aims to answer the question whether industrial robot density (independent variable) can be used as an economic indicator or metric for industrial worker productivity and manufacturing sector value added to GDP respectively.

3.2. Research Propositions

3.2.1. Proposition one: Robot Density and Productivity

Annual variances in industrial robot density (independent variable) correlates positively with changes in industrial sector worker productivity (dependent variable) per country (n from 1 to 38) over an extended period. The nature of the relationship is to be tested through simple linear regression and co-variance against the following hypotheses and criteria:

Null Hypothesis one:

$H_{0:}$ $\beta_n \leq 0$

The alternate Hypothesis one:

$H_{1:}$ $\beta_n > 0$

The null hypothesis test will be discussed and described according to the following management proposition criteria:

1a) The correlation is statistically significant, $p < 0.05$;

1b) The regression coefficient or slope is positive, $\beta > 0$;

1c) The strength of the statistical relationship is moderate (0.3) to strong (0.5), $r > 0.3$;

1d) The coefficient of determination is moderate (0.09) to strong (0.25),

r2 > 0.09.

3.2.2. Proposition two: Robot Density and Economic Contribution

Annual variances in industrial robot density (independent variable) correlates positively with changes in industrial sector value added (independent variable) per country (n from 1 to 38) over an extended period. The nature of the relationship is to be tested through simple linear regression and co-variance against the following hypotheses and criteria.

Null Hypothesis two:

$H_{0:}$ $\beta_n \leq 0$

The alternate Hypothesis two:

$H_{1:}$ $\beta_n > 0$

The null hypothesis test will be discussed and described according to the following management proposition criteria:

2a) The correlation is statistically significant, $p < 0.05$;

2b) The regression coefficient or slope is positive, $\beta > 0$;

2c) The strength of the statistical relationship is moderate (0.3) to strong (0.5), $r > 0.3$;

2d) The coefficient of determination is moderate (0.09) to strong (0.25),

$r^2 > 0.09$.

3.2.3. Proposition three: Productivity and Stage of Country Development

The positive linear relationship between industrial robot density and worker productivity holds across economies, regardless of the stage of development and economy size. This will be interpreted through observation and analysis of the results Hypothesis one and 2, and supported by deductions from the literature review.

4. Research Methodology

This chapter covers the units of analysis, research methodology, population, sampling methods used, data collection, assumptions, data analysis and limitations of the research.

4.1. Introduction

A quantitative, descriptive, correlational statistical study of industrial robot density versus industrial worker productivity and total manufacturing value added per country using secondary data was done.

The empirical nature of the research propositions allowed the study to test the relevant neoclassical growth theory discussed in Chapter 2 against independent secondary data. Secondary data sourced from the International Federation of Robotics, International Labour Organisation and the World Bank were analysed using co-variation and simple linear regression techniques.

These methods were chosen for their simplicity, following guidelines from Wegner (2012), and are suitable for this research because the aim was not to construct a detailed economic growth model, but to test and describe the relationship between robot density and productivity and economic contribution respectively. This study does not propose that industrial robot density is the only predictor variable for productivity and manufacturing value added, but tests the statistical relationship and significance associated with the outcomes.

The simple linear and correlation analysis will be performed for each of the 38 countries separately, using annual data spanning the ten years from 2005 to 2014 for each of the three variables: industrial robot density, productivity per worker and manufacturing sector value added.

An additional analysis of the combined set of all the countries will also be done and interpreted.

4.2. Units of Analysis

4.2.1. Industrial Robot Density

The first unit of analysis to represent industrial robot prevalence will be the independent variable robot density, defined as the number of industrial robots installed per 10 000 industrial workers per country, reported annually by the International Federation of Robotics.

4.2.2. Manufacturing Value Added

The dependent variable, manufacturing sector contribution to gross domestic product per country is represented by The World Bank indicator: Manufacturing value added (current US$), unique indicator code NV.IND.MANF.CD. The World Bank (2016) defined the parameter as follows:

> Manufacturing refers to industries belonging to ISIC divisions 15-37. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 3. Data are in current U.S. dollars. (Metadata-Indicators section, para. 1).

4.2.3. Manufacturing Worker Productivity

Productivity will be expressed in a simplified form, namely the single-factor productivity measurement of total manufacturing value added figure per country reported by the World Bank divided by the total employees in industry per country reported by the International Labour Organisation.

4.3. Population

“The population of any research study is the complete set of group members that meet the requirements of the study” (Saunders & Lewis, 2012, p. 12). Thus a complete sample would be all countries that have industrial robots installed. For the purpose of this study, all the required data for the entire population was not readily available for all the countries in the world.

4.4. Sampling Method

The researcher considered all 44 countries for which industrial robot density data were available between 2005 and 2014.

The original sample which consisted of 44 were reduced by three , as only countries for which sufficient robot density, total industry workers, and manufacturing value added data for the period were available. The three countries, namely Israel, Canada and Taiwan were excluded due to unavailability of manufacturing value added or sector employment data. Furthermore, Iran, India and the Russian Federation were excluded due to the fact that these countries had a robot density of two or less.

Consequently, the method can be classified as availability sampling, as it excluded countries for which sufficient data was not readily available

The final sample of 38 countries spans developed countries with high robot densities such as Germany, Japan and Finland, to developing countries such as South Africa, Brazil and Malaysia.

The complete list of the 38 countries sampled was as follows:

Argentina, Brazil, Mexico, USA, China, Indonesia, Japan, Malaysia, Philippines, the Republic of Korea, Thailand, Australia, New Zealand, Austria, Belgium, Netherlands, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom and South Africa.

Due to the phenomenon of diminishing returns observed by Graetz and Michaels (2015) on investment in technology such as robotics, the hypotheses results will also be evaluated in terms of their stage of development.

4.5. Data Collection

Worldwide industrial robot density per country was obtained from the publication *World Robotics Industrial Robots 2015*, compiled by the International Federation of Robotics' (IFR) Statistical Department. The reliability and accuracy of the data is the best available on the subject, and according to the International Federation of Robotics (2015):

> The robot statistics are based on consolidated world data reported by robot suppliers as well as on the statistics of the national robot associations of North America (RIA), Japan (JARA), Denmark, (DIRA), Germany (VDMA, R+A), Italy (SIRI), Republic of Korea (KOMMA), Spain(AER), United Kingdom (BARA) and Peoples Republic of China (CRIA)" (p. 1).

The data and report is not open source, and can be purchased at EUR 1200 from the organisation. The price of the publication might well be a contributing factor to the limited quantitative research available on the subject utilising the data.

Manufacturing contribution to gross domestic product per country data for the relevant years was sourced from the World Bank (2016).

The total employees in the industrial sector per country per year data was sourced from the International Labour Organisation.

Manufacturing sector employee productivity was represented by dividing the Manufacturing sector contribution by the total number of industry workers per country.

The reliability and validity of the data is based on the source of the data and verified by comparing data used in the statistic evaluation with original raw data.

4.6. Assumptions

Correlation and linear regressions require that the sets of variables are normally distributed, or close to normal, linear or close to linear and that the variables are homoscedastic.

The suitability of the data for the descriptive statistical methods, co-variance and linear regression, will be verified for normality as per the Ryan–Joiner test. According to de Souza and Junqueira (2005, p. 31), the Ryan-Joiner test is suitable to prove the normal distribution of data regression residuals to verify data for normality and uses two fundamental concepts, the normal probability plot and the correlation coefficient.

All 38 countries sets of data was tested for normal distribution, and results discussed in Chapter 5.

- The relationship between the two variables will be visually inspected for linearity.
- The relationship between the two variables is assumed to be homoscedastic.

4.7. Data description

4.7.1. Industrial Robot Density

These secondary datasets were sourced from the annual publication “World Robotics Industrial Robots 2015” by the International Federation of Robotics’ Statistical Department. The specific independent variable used for this research is industrial robot density, represented as the annual number of installed industrial robots per 10 000 industrial workers per country. The industrial robot density independent variable per country will thus be presented by the ten values for the corresponding periods from 2005 to 2014. The data is continuous and time-series by nature, as it is reported annually.

The sample of countries and industrial robot density data is as per Table 1:

Table 1. Industrial robot density data per country and year

World Robotics Robot density: intsalled industrial robots per 10 000 factory workers per country										
Country	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**
Argentina	2	3	4	6	4	4	7	8	9	10
Brazil	3	3	4	5	5	6	7	8	9	10
Mexico		7	8	10	12	14	16	19	24	27
USA		72	86	109	118	128	133	140	152	164
China	4	5	7	9	11	13	17	18	25	36
Indonesia	0	0	5	6	7	10	15	22	31	39
Japan	367	335	345	366	350	333	328	330	323	314
Malaysia	9	11	12	14	17	18	21	24	26	28
Philippines	1	1	2	2	2	2	2	3	3	4
Republic of Korea	171	194	207	235	230	289	354	389	437	478
Thailand	5	6	9	12	14	23	32	42	49	57
Australia	46	50	52	59	58	63	68	77	77	76
New Zealand	1	3	6	9	14	18	25	30	37	41
Austria	70	72	77	86	92	96	101	111	118	122
Belgium	107	112	112	117	125	122	131	146	169	171
Netherlands	39	45	51	59	66	69	77	85	93	107
Croatia	0	1	1	2	2	2	3	4	4	5
Czech Rep	17	20	26	35	38	39	52	61	72	82
Denmark	75	83	95	118	133	140	150	160	166	180
Estonia	0	0	0	1	3	3	4	5	6	8
Finland	105	108	109	123	130	128	126	123	122	126
France	94	103	109	118	122	124	127	130	125	126
Germany	216	221	236	256	255	254	265	272	282	292
Greece	2	2	3	5	7	9	11	12	13	16
Hungary	5	7	9	13	15	18	30	41	47	49
Italy	137	141	148	158	162	162	164	157	153	155
Norway	34	37	38	41	43	42	43	44	44	44
Poland	3	4	6	9	10	12	15	16	19	22
Portugal	18	20	23	26	29	31	34	38	41	42
Romania	0	0	1	1	2	2	5	6	7	8
Slovakia	12	12	14	19	25	42	48	53	83	88
Slovenia	21	25	32	43	49	55	66	83	90	100
Spain	83	91	97	118	126	130	143	145	141	139
Sweden	119	121	129	153	154	152	164	169	174	190
Switzerland	56	56	59	63	63	63	71	75	79	85
Turkey	1	2	3	5	5	6	8	10	13	15
United Kingdom	53	57	60	64	61	59	58	63	66	71
South Africa	4	6	8	10	11	13	15	16	20	22

Source: Adapted from International Federation of Robotics (2015) data.

4.7.2. Manufacturing Value Added

Manufacturing contribution to gross domestic product per country data for the relevant years was sourced from the World Bank (2016) database, as described as Manufacturing value added (current US$) per country from the manufacturing industries belonging to International Standard Industrial Classification (ISIC) divisions 15-37 by the World Bank (2016). The Manufacturing value added dependent variable per country will thus be presented by the ten values for the corresponding periods from 2005 to 2014. The data is continuous and time-series by nature, as it is reported annually.

An example of the data is as per Table 2. Due to the volume of data and the impracticality of presenting all the raw data here, only data for ten countries for the period of 2005 to 2010 is displayed here. The study was conducted using 38 countries and data spanning 2005 to 2014.

Table 2. Manufacturing value added data example

Country Name	2005	2006	2007	2008	2009	2010
Australia	71,777,928,131	74,072,327,044	79,507,733,375	97,362,578,335	78,490,649,389	91,722,892,627
Austria	55,042,022,137	59,844,762,263	70,522,803,175	74,778,877,984	65,343,803,834	64,878,264,901
Belgium	61,098,122,124	62,248,149,542	71,227,758,007	73,678,043,064	62,032,509,030	63,667,549,669
Switzerland	76,790,328,863	82,313,719,971	92,340,643,036	108,345,112,547	99,261,827,589	107,432,957,331
Estonia	2,063,959,707	2,456,793,376	3,108,431,426	3,337,219,862	2,410,238,955	2,675,218,543
Indonesia	78,349,463,192	100,393,875,817	116,907,767,203	141,916,385,387	142,208,892,017	166,412,396,916
Korea, Rep.	229,169,976,429	253,764,988,236	285,849,032,340	258,554,832,567	234,967,147,768	304,283,770,493
Malaysia	39,543,279,633	44,847,550,134	50,559,784,501	56,689,568,230	48,137,502,483	59,760,019,869
Netherlands	85,163,536,874	88,142,014,804	102,471,940,871	108,245,202,871	90,309,808,280	88,773,509,934
South Africa	41,909,486,893	39,838,874,636	43,005,482,315	41,361,666,586	40,319,789,572	48,994,610,501

Source: Adapted from World Bank (2016) data.

4.7.3. Manufacturing Sector Employee Productivity

This variable was represented by the manufacturing value added data (as above, 4.7.2) divided by the total number of industrial sector workers data, sourced from the International Labour Organisation (2014) database. The manufacturing sector employee productivity dependent variable per country will thus be presented by the ten manufacturing value added per employee values for the corresponding periods from 2005 to 2014. The data is continuous and time series by nature, as it is reported annually.

An example of the manufacturing sector employee productivity data is as per Table 3. Again, due to the volume of data and the impracticality of presenting all the data, only data for one country for the period of 2005 to 2014 was displayed here. The study was conducted using 38 countries.

Table 3. Manufacturing sector employee productivity data

Malaysia	Manufacturing value added	Total industrial workers	Productivity: Manufacturing value added per employee
2005	$ 39,543,279,633	3135688	$ 12,610.72
2006	$ 44,847,550,134	3254847	$ 13,778.70
2007	$ 50,559,784,501	3125788	$ 16,175.05
2008	$ 56,689,568,230	3195656	$ 17,739.57
2009	$ 48,137,502,483	3051203	$ 15,776.57
2010	$ 59,760,019,869	3190819	$ 18,728.74
2011	$ 69,483,006,536	3439265	$ 20,202.87
2012	$ 72,756,410,256	3472614	$ 20,951.48
2013	$ 73,858,262,719	3482802	$ 21,206.56
2014	$ 77,421,247,212	3575105	$ 21,655.66

Source: Authors own, adapted from World Bank (2016) International Labour Organisation (2014) data.

4.8. Data Analysis

4.8.1. Simple Linear Regression

As both independent and dependent variables are continuous data, simple linear regression analyses were performed to describe the statistical relationship between robot density and manufacturing value added contribution to gross domestic product per country.

4.8.1.1. Regression Significance

The p-value is the measure of the significance of the relationship between the predictor and response variables, and answers the question: “Is the statistical relationship between x and y, as given by the regression equation, a genuine relationship or is it due purely to chance?” (Wegner, 2012, p. 311). For the purpose of this research, p-values less than 0.05 were interpreted as significant.

4.8.1.2. Regression Slope

Of specific interest will be the slope (β), or gradient of the regression line. The slope is the least squares estimate of the slope associated with the predictor variable (Baird & Bieber, 2016), and is the answer to the research question, how is industrial robot density predictive of productivity and manufacturing value added respectively. For the research propositions to agree with the neoclassical growth model theory discussed in Chapter 2, positive slopes should be observed.

4.8.2. Correlation Analysis

Correlation analyses were performed to determine the strength of the statistical relationships between robot densities and manufacturing value added contribution to gross domestic product per country respectively, as both independent and dependent variables are continuous data.

4.8.2.1. Pearson's Correlation Coefficient

Of specific interest will be the Pearson's correlation or R. Pearson's correlation coefficient is a measure of the strength of the linear association between two variables, and can range from $-1 \leq r \leq +1$, or from perfectly negative correlation (-1), no correlation (0) or perfectly positive correlation (+1). For the purpose of this study, correlation coefficient values greater than 0.3 were regarded as moderate, correlation coefficient values greater than 0.5 large or strong linear associations (Cohen, 1998).

The selection of the Pearson's correlation method was consistent with the study done by Mihai and Jivan (2012) as observed in the literature review (2.8.).

4.8.2.2. Coefficient of Determination

The coefficient of determination or r squared was used to quantify the proportion of the variance of the response variable accounted for by the variance in the predictor variable. The selection of this method was based on the literature review (2.8.) as proposed by Baird and Bieber (2016).

R squared values range from $0 \leq r^2 \leq 1$, or $0\% \leq r^2 \leq 100\%$. For the purpose of this research Cohen's (1998) guidelines were applied and r^2 values greater than 0.09 or 9 per cent were regarded as moderate and r^2 values greater than 0.25 or 25 per cent were regarded as large or strong.

4.9. Limitations

While there is great potential to use the accurately monitored and reported figures for industrial robot density as a metric or indicator for national and global manufacturing output, the researcher has to highlight some limitations:

- The extent to which the change in robot density correlates or influences manufacturing activity growth depends on the installed base and rate of change thereof per country. As an illustration, the installation of the first robot in Iran would be irrelevant, but installing 1 000 robots per annum would be significant. The implication was that those countries with a negligibly low density of robots were not likely to show meaningful correlations as evaluated according to the hypotheses. Countries with very low industrial robots densities of two or less were Iran, the Russian Federation and India, and were excluded from the sample.

- There are vast numbers of factors that influence manufacturing contribution to each country's gross domestic product and total factor productivity, of which operational efficiency discussed in the literature review is but one. The author does not claim that robot density is the only independent variable and that there is a clear, significant causality between industrial robot density and productivity and sector value added. The intention is to determine whether a strong correlation can be shown, and that industrial robot density is a valid metric indicator of productivity and value added.

- It is unlikely that each and every industrial robot installation succeeds in improving productivity to the extent that increased manufacturing output is realized. It can however be reasonably argued that at a typical installation cost of $75 000 per robot system (Frey & Osborne, 2013), proper project planning and viability studies ensure a high project success rate.

Despite the identified limitations, this research aimed to support the findings of the recent exploratory work done by Graetz and Michaels (2015) on the subject, and may contribute in that it includes evaluation of the critically important developing economies, while doing this with more recent data.

5. Results

5.1. Introduction

This chapter will commence with a description of the sample obtained, followed by data quality evaluation and data transformations. Results for the three propositions will follow sequentially. Proposition one and two will each be divided into sections where the null hypotheses could be rejected or not for the respective countries.

5.2. Description of Sample Obtained

Each of the 38 countries sampled contained datasets consisting of industrial robot density, manufacturing value added and manufacturing value added per employee (productivity). These datasets are in the form of continuous data, containing annual values for the period 2005 to 2014.

While it might be interesting, a description of each countries' datasets falls outside the scope of this research. Results of the statistical analyses performed on all 38 countries (Tables 5-8) and graphical presentation of some results follows in this chapter.

5.3. Data Quality Check for Normality

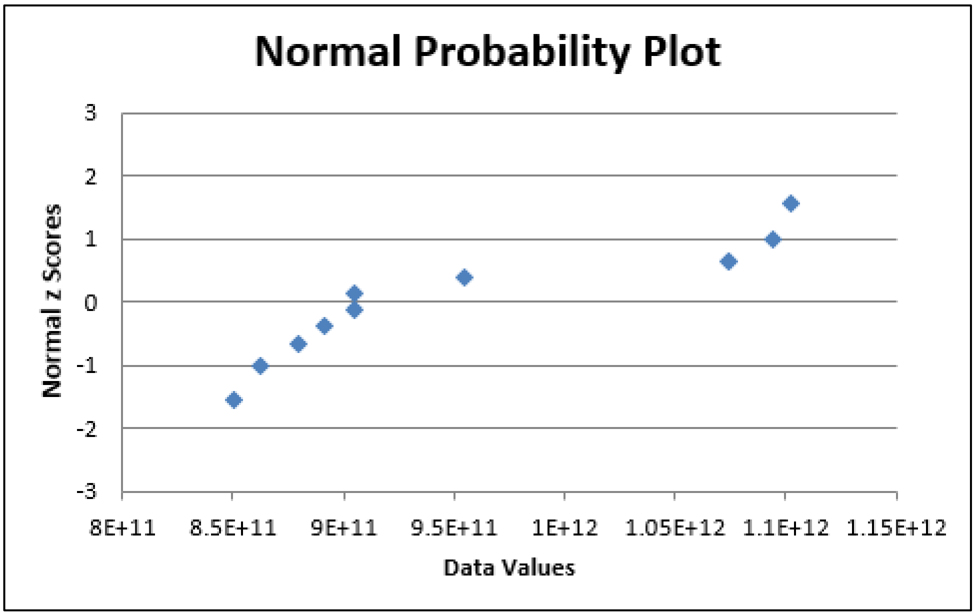
Normality was checked using the Ryan–Joiner test. For data to be deemed normal or near normal, r-calculated should be greater than r-critical. Of the 38 countries' data sets, two were found to have failed the normality test. These were Japan and the Republic of Korea. The r-critical and r-calculated values are displayed in Table 4. The Ryan–Joiner test requirement for normality is that r-calculated is greater than r-critical. The test for normality was not true for Japan and the Republic of Korea, as r-calculated were less than r-critical in both cases as can be seen from the test results in Table 4. This was substantiated by the observation of the normal probability plots are shown in Figure 4 and 5. The normal probability plots for Japan and the Republic of Korea were not close to linear, as opposed to the linear properties observed in Figure 6, the normal probability plot for Estonia manufacturing value added per employee added for illustration purposes.

Table 4. Ryan-Joiner normality test, selected countries.

RYAN-JOINER TEST (FROM THE PLOT)		
Japan	r	0.91
	r CRIT	0.92
	Nearly Normal?	
	FALSE	
South Korea	r	0.91
	r CRIT	0.92
	Nearly Normal?	
	FALSE	
Estonia	r	0.99
	r CRIT	0.92
	Nearly Normal?	
	TRUE	

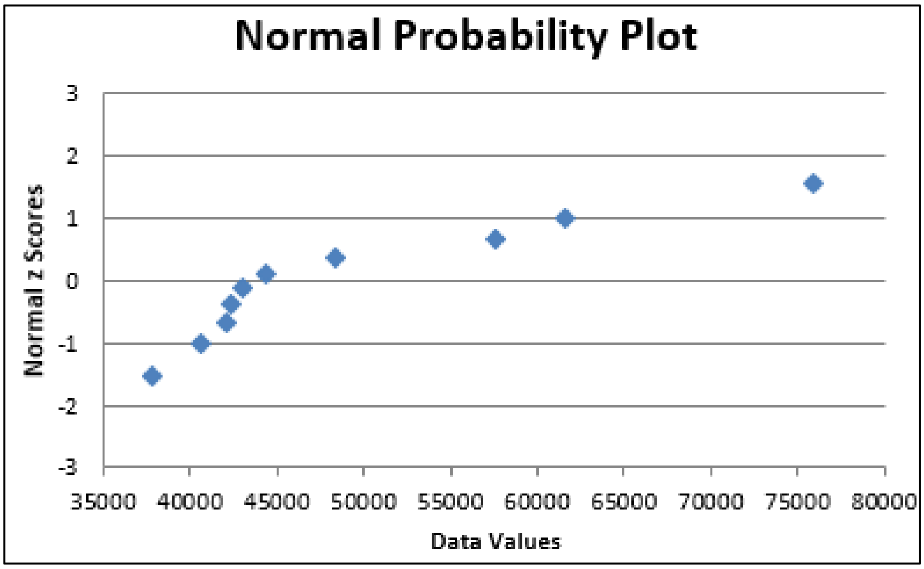
Source: Authors own.

Figure 4. Japan, not normal data for total manufacturing value added



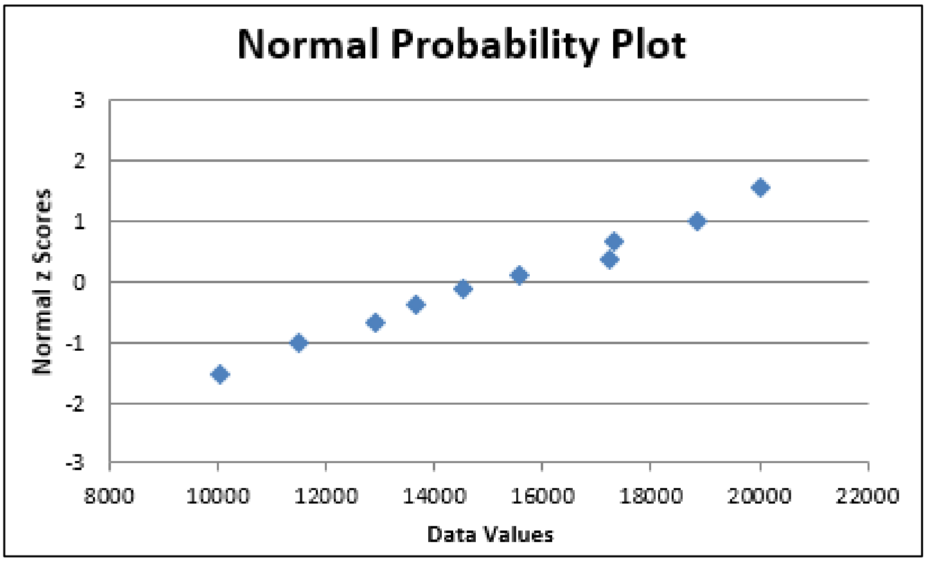
Source: Authors own.

Figure 5. The Republic of Korea, not normal data for productivity.



Source: Authors own.

Figure 6. Estonia normal data for manufacturing value added per employee



Source: Authors own.

The author, however continued to evaluate data for the Republic of Korea and Japan, with the caveat that these two countries will specifically be discussed, as the two cases are relevant in further discussions.

5.4. Data Transformations

No raw sourced data were altered in this research. The only transformations executed were the following:

- The total number of industrial sector workers data sourced from the International Labour Organisation (2014) database were originally represented under the label “Total employment in industry (thousands)”. For statistical evaluation each data value per year and country were multiplied by 1000 to represent the intended true value.

- The manufacturing sector productivity per employee values were calculated from raw sourced data by dividing the manufacturing value added data (4.7.2) by the total number of industrial sector workers data (4.7.3.). This was done for all relevant corresponding country and year data.

5.5. Proposition one: Robot Density and Productivity

As the sample consisted of 38 countries, this section is divided into sub-sections where the Null Hypothesis one could be rejected in favour of the management Proposition one (31 countries), and another where the null hypothesis could not be rejected at the 95 per interval (7 countries).

5.5.1. Null Hypothesis one Rejected: Robot Density and Productivity

$H_{0:}\ \beta_n \leq 0$

Proposition one tested the statistical relationship between annual robot density (independent variable) and industrial worker productivity (dependent variable) data per country over the period from 2005 to 2014.

A total of 38 countries were tested, and the results for 31 countries that met all the requirements to reject the null hypothesis of Proposition one, is presented in Table 5.

The 31 countries, all tested through correlation and linear regression, displayed a positive productivity to industrial robot density slope (β), a strong Pearson’s correlation and a strong coefficient of determination. The respective criteria for the parameters followed the guidelines suggested by Cohen (1998). The results are statistically significant at the 95 per cent confidence interval, with p values less than 0.05.

The 31 countries for which Null Hypothesis one could be rejected in favour of the proposed alternate hypothesis were:

Argentina, Brazil, Mexico, USA, China, Indonesia, Malaysia, Philippines, Thailand, Australia, New Zealand, Belgium, Netherlands, Croatia, Czech Rep, Denmark, Estonia, France, Germany, Greece, Hungary, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom.

Details of the industrial robot density to productivity relationship are summarised according to measure of significance (p), slope (β), Pearson's correlation (r) and coefficient of determination (r^2) in Table 5.

Correlation and regression results in Table 5 are for the respective countries statistical evaluation results where the null hypothesis of Proposition one could be rejected in favour of the management proposition. All p values were less than 0.05 and the slope, or β greater than zero.

Table 5. Proposition one: Robot Density and Productivity, H_0 Rejected

Country	2014 Robot density	Proposition 1a p-Value	Proposition 1b Slope, β	Proposition 1c r	Proposition 1d r^2
Argentina	10	0.01	887	0.71	0.51
Brazil	10	0.02	600	0.64	0.41
Mexico	27	0.00	281	0.82	0.68
USA	164	0.00	218	0.89	0.79
China	25	0.00	418	0.98	0.96
Indonesia	39	0.02	69	0.67	0.45
Malaysia	28	0.00	456	0.94	0.88
Philippines	4	0.00	1470	0.90	0.80
Thailand	57	0.00	97	0.81	0.66
Australia	76	0.00	354	0.86	0.73
New Zealand	41	0.02	349	0.71	0.50
Belgium	171	0.01	155	0.76	0.58
Netherlands	107	0.00	230	0.79	0.62
Croatia	5	0.00	828	0.79	0.63
Czech Rep	82	0.01	107	0.74	0.55
Denmark	180	0.00	231	0.97	0.94
Estonia	8	0.01	1144	0.89	0.79
France	126	0.04	154	0.59	0.35
Germany	292	0.00	196	0.80	0.64
Greece	16	0.00	829	0.86	0.74
Hungary	49	0.01	104	0.73	0.53
Norway	44	0.02	1000	0.67	0.45
Poland	22	0.00	289	0.90	0.81
Portugal	42	0.00	285	0.93	0.87
Romania	7	0.01	104	0.73	0.53
Slovakia	88	0.02	55	0.68	0.46
Slovenia	100	0.00	135	0.85	0.73
Spain	139	0.00	290	0.97	0.93
Sweden	190	0.02	253	0.64	0.41
Switzerland	85	0.00	2125	0.95	0.90
United Kingdom	71	0.01	548	0.75	0.57

Source: Authors own.

5.5.2. Failed to Reject Null Hypothesis one: Robot Density and Productivity

Null Hypothesis one could not be rejected for 7 of the 38 countries evaluated. This means that the management proposition for these countries cannot be accepted at a confidence interval of 95 per cent.

The seven countries for which the management proposition could not be accepted were: Japan, the Republic of Korea, Austria, Finland, Italy, Turkey and South Africa. Results of the statistical evaluation performed are summarised in Table 6 below.

Table 6. Proposition one: Robot Density and Productivity, Failed to Reject H_0

Country	2014 Robot density	Proposition 1a p-Value	Proposition 1b Slope, β	Proposition 1c r	Proposition 1d r^2
Japan	314	0.74	-97	0.23	0.05
Korea, Rep.	478	0.60	-10	0.09	0.01
Austria	122	0.06	151	0.53	0.28
Finland	126	0.71	-183	0.20	0.04
Italy	155	0.08	181	0.48	0.23
Turkey	15	0.06	144	0.52	0.27
South Africa	22	0.22	55	0.28	0.08

Source: Authors own.

Correlation and regression results highlighted in red are where the respective countries statistical evaluation results could not reject the null hypothesis of Proposition one in favour of the management proposition. All p values were greater than 0.05, and three of the countries'' regression slopes were less than zero.

5.6. Proposition two: Robot Density and Economic Contribution

This section is divided into sub-sections where the Null Hypothesis two could be rejected in favour of Management Proposition two (19countries), and another where the null hypothesis could not be rejected at the 95 per cent confidence interval (20 countries).

5.6.1. Null Hypothesis two Rejected: Robot Density and Economic Contribution

$H_0: \beta_n \leq 0$

Proposition two tested the statistical relationship between annual robot density (independent variable) and industrial sector value added per country (dependent variable) data per country over the ten year period from 2005 to 2014. Null Hypothesis two could be rejected in favour of the management proposition for 19 of the 38 countries evaluated at the 95 per cent confidence interval.

The 19 countries for which Null Hypothesis two could be rejected in favour of the proposed alternate hypothesis were:

Argentina, Brazil, Mexico, USA, China, Indonesia, Malaysia, Philippines, The Republic of Korea, Thailand, Australia, Austria, Czech Rep, Estonia, Germany, Norway, Poland, Switzerland and Turkey.

Details of the industrial robot density to industrial sector value added per country statistical evaluation are summarised in terms of measure of significance (p), slope (β), Pearson's correlation (r) and coefficient of determination (r^2) in Table 7:

Correlation and regression results in Table 7 are for the respective countries statistical evaluation results where the null hypothesis of Proposition two could be rejected in favour of the management proposition. All p values were less than 0.05 and the slope or β greater than zero.

Table 7. Proposition two: Robot Density and Economic Contribution, H_0 Rejected

Country	2014 Robot density	Proposition 2a p-Value	Proposition 2b Slope, β	Proposition 2c r	Proposition 2d r^2
Argentina	10	0.01	4289	0.75	0.57
Brazil	10	0.01	16058	0.72	0.51
Mexico	27	0.00	2766	0.81	0.66
USA	164	0.01	2847	0.73	0.54
China	25	0.00	108234	0.98	0.96
Indonesia	39	0.02	1793	0.75	0.56
Malaysia	28	0.00	1944	0.95	0.91
Philippines	4	0.00	11418	0.93	0.86
Korea, Rep.	478	0.00	503	0.96	0.92
Thailand	57	0.00	968	0.88	0.78
Australia	76	0.00	1026	0.88	0.78
Austria	122	0.04	193	0.59	0.35
Czech Rep	82	0.02	185	0.64	0.41
Estonia	8	0.02	210	0.85	0.72
Germany	292	0.00	2292	0.77	0.60
Norway	44	0.02	667	0.67	0.46
Poland	22	0.00	1754	0.85	0.72
Switzerland	85	0.00	1750	0.90	0.81
Turkey	15	0.00	2897	0.83	0.69

Source: Authors own.

5.6.2. Failed to Reject Null Hypothesis two: Robot Density and Economic Contribution

Null Hypothesis two could not be rejected for 19 of the 38 countries evaluated. This means that the management proposition for these countries cannot be accepted with a confidence interval at 95 per cent.

The 19 countries for which the null hypothesis could not be rejected in favour of the management proposition were:

Japan, New Zealand, Belgium, Netherlands, Croatia, Denmark, Finland, France, Greece, Hungary, Italy, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom and South Africa.

Details of the industrial robot density to industrial sector value added per country statistical evaluation are summarised in terms of measure of significance (p), slope (β), Pearson's correlation (r) and coefficient of determination (r^2) as per Table 8.

Correlation and regression results highlighted in red in Table 8 are where the respective countries statistical evaluation results could not reject the null hypothesis of Proposition two in favour of Management Proposition two. All p values were greater than 0.05, and six of the countries' regression slopes were less than zero.

Table 8. Proposition two: Robot Density and Economic Contribution, Failed to Reject H_0

Country	2014 Robot density	Proposition 2a p-Value	Proposition 2b Slope, β	Proposition 2c r	Proposition 2d r^2
Japan	314	0.66	-846	0.15	0.02
New Zealand	41	0.09	96	0.52	0.27
Belgium	171	0.59	-15	0.08	0.01
Netherlands	107	0.44	18	0.05	0.00
Croatia	5	0.42	38	0.07	0.00
Denmark	180	0.07	41	0.51	0.26
Finland	126	0.84	-285	0.35	0.12
France	126	0.26	331	0.23	0.05
Greece	16	0.96	-409	0.59	0.35
Hungary	49	0.15	53	0.37	0.14
Italy	155	0.33	501	0.16	0.03
Portugal	42	0.66	-36	0.15	0.02
Romania	7	0.28	343	0.27	0.07
Slovakia	88	0.08	38	0.48	0.23
Slovenia	100	0.17	12	0.34	0.12
Spain	139	0.71	-160	0.20	0.04
Sweden	190	0.15	126	0.36	0.13
United Kingdom	71	0.17	1594	0.34	0.11
South Africa	22	0.17	206	0.33	0.11

Source: Authors own.

5.7. Proposition three: Stages of Economic Development

This proposition suggests that cursory observation of the combination of all 38 countries' data into one X-Y scatter plot indicates that the relationship between industrial robot density and worker productivity holds across economies, regardless of stage of development and economy size.

Applying the stages of development classification of the United Nations (2014), the 27 countries deemed as developed are:

The United States of America, Japan, Australia, New Zealand, Austria, Belgium, Netherlands, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and The United Kingdom.

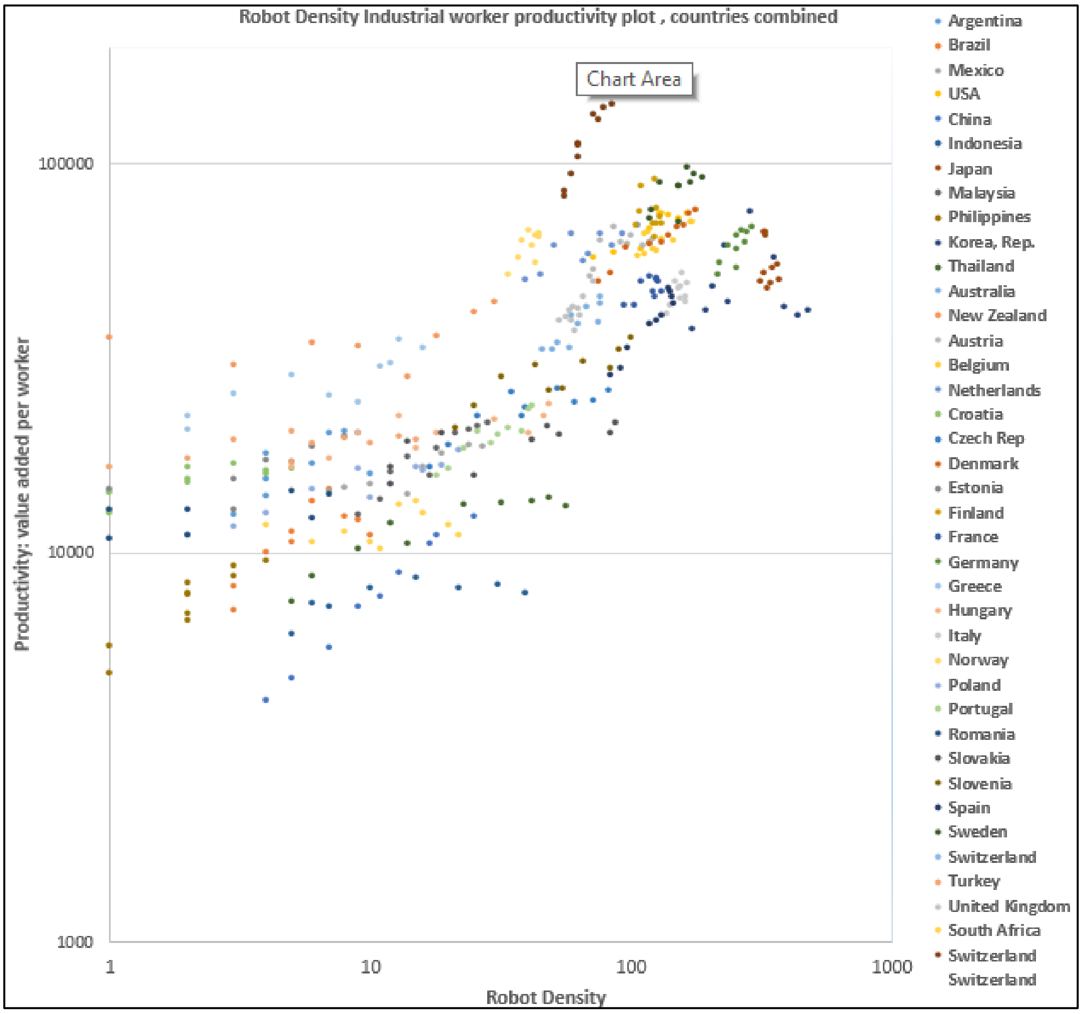
The 11 developing countries are:

Argentina, Brazil, Mexico, China, Indonesia, Malaysia, Philippines, the Republic of Korea, Thailand, Turkey South Africa.

From Table 5 it can be seen that 23 of the 27 developed countries (85 per cent), and 8 of the 11 developing countries (73 per cent) met the requirements to reject the null hypothesis of Proposition one. The proportion of developed and developing countries are of the same order, and satisfies the requirements of the management proposition, in that industrial robot density is positively correlated to industrial worker productivity for both developed and developing countries.

Additionally, from Figure 7, the observation can be made that the general relation is positive across countries, and that there is an evident general increase in value added per worker associated with increases in industrial robot density. Take note that the Y axis (Productivity: value added per worker) is in the logarithmic base ten scale due to the large differences in values between the respective countries.

Figure 7. Combined X-Y scatterplot of all 38 countries.



Source: Authors own.

6. Discussion of Results

6.1. Introduction

In this chapter the results of the statistical analysis in Chapter 5 will be discussed. The discussion will follow the order of discussion of the main propositions, followed by specific interpretations of the relevant statistical parameters, namely correlation significance, regression coefficient or slope, Pearson's correlation and coefficient of determination for each of the propositions respectively.

6.2. Proposition one: Robot Density and Productivity

The management proposition was that there was a moderate to strong positive statistical correlation between annual robot density (independent variable) and industrial worker productivity (dependent variable) data per country over the ten year period from 2005 to 2014. From the results presented in Chapter 5, Table 5, it was found that there was indeed a moderate to very strong and positive correlation between robot density and worker productivity for 31 out of the 38 countries, and that the correlation was significant at the 95 per cent confidence interval.

Of the 7 countries for which Null Hypothesis one could not be rejected, only three, namely Japan, The Republic of South Korea and Finland displayed negative slopes, and the statistical significance was outside the 95 per cent confidence interval. It is possible that these highly developed industrial countries have reached a level of automation at which the marginal returns have become negative, a phenomenon referred to as overcrowding. The scope of this research is however not to make findings of individual countries, but to establish industrial root density as an indicator for manufacturing economic and productivity growth.

For these 31 countries, the findings concur with the views of Autor (2015), Krone (2014) and Mokyr et al. (2015) in that industrial robots are increasingly being used to substitute for labour and to increase productivity. From the analysis one can conclude that the annual increases in industrial robot installations per country moderately to strongly correlate with increased productivity. The outcome is also in alignment with Crafts (2015), where he found that new technology improved productivity in the United Kingdom over a period of 30 years.

The significance of the findings is that the annually published industrial robot density data can be interrogated as a valuable economic indicator for the manufacturing sector. Industrial robot density was found to be an economic metric similar to the Agricultural Machinery and Tractors metric (AGRMACH) reported by the World Bank. The relevance of this metric as an economic indicator for the agricultural sector was evident from the work by Alston and Pardey (2014) and Khan et al. (2014), and from this research it seems likely that industrial root density could fulfil a similar role in the manufacturing sector.

The potential application of this finding is that decision and policy makers at organisational, regional and national levels could use the data and methodology from this research to gain guidance and insight when making investment and manufacturing productivity decisions and investments. Industrial robotics have indeed been elevated to national policy level, referring back to Chapter 1, where robotic was a topic of Chinese President Xi Jinping's speech in 2014 where he called for a "robot revolution" to raise productivity in China (Chan, 2015).

6.2.1. Proposition one: Statistical Significance

The confidence interval for this research was set at the 95 per cent, or $p < 0.05$. The statistical significance requirement was met for 31 of the 38 countries required, Null Hypothesis one was rejected in favour of the management proposition in all 31 cases (Chapter 5 Table 5).

Greenland et al. (2016) refers to the confidence level not as the chance of making an error, but how often you would have incorrectly rejected a null hypothesis. It also infers that it is not true that because the null hypothesis could not be rejected in the cases of the discussed 7 countries, the management proposition is rejected, but rather that a statistical determination at the 95 per cent confidence interval could not be made.

It can thus be concluded that the statistical relationship between industrial robot density and productivity is a genuine relationship, and not due to chance, at a confidence interval of 95 per cent (Wegner, 2012, p. 311). Interpreters could thus have 95 per cent confidence in these results for evaluation.

6.2.2. Proposition one: Regression Coefficient or Slope

An overwhelming 35 of 38, or 92 per cent, of countries displayed a positive regression coefficient, or slope (β), between industrial robot density and industrial worker productivity. Of the 38 countries, 31 displayed positive slopes at a confidence interval of 95 per cent.

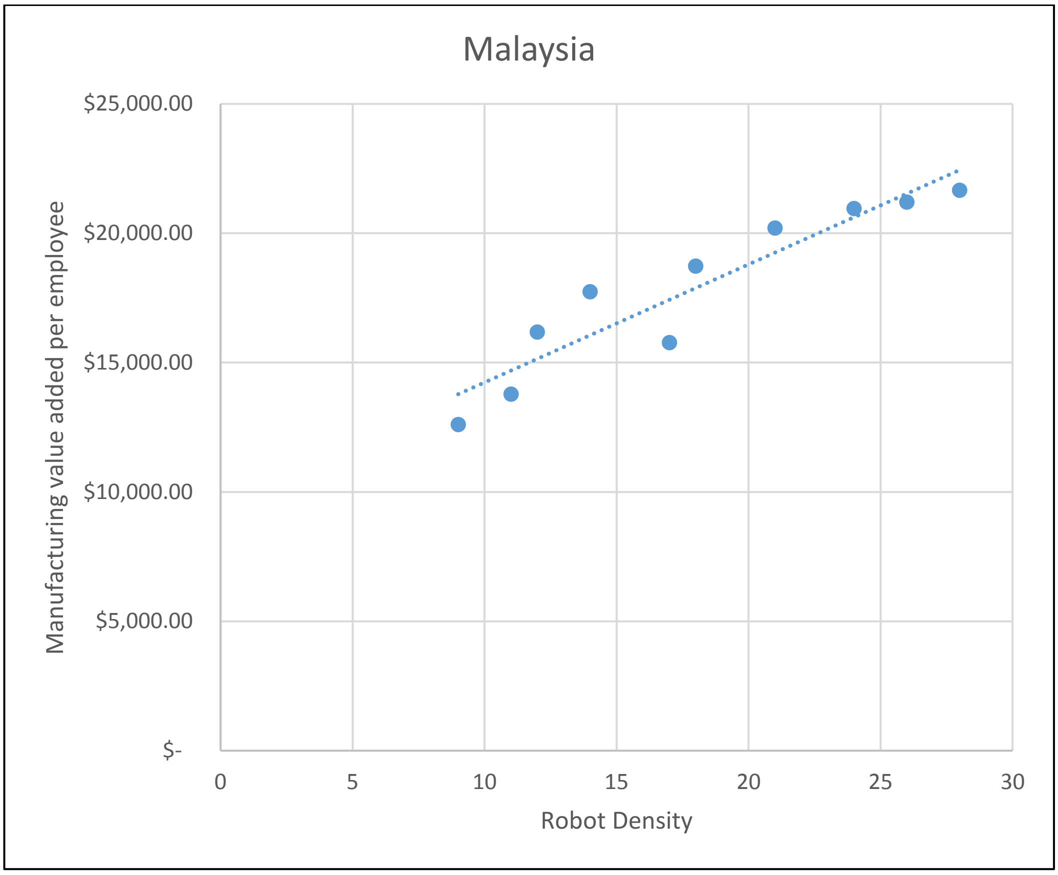
According to Baird and Bieber (2016), the slope is essentially the answer to the research question of how the independent variable is predictive of the dependent variable. For the purpose of this research, it is the answer to Proposition one: How is industrial robot density predictive of productivity and manufacturing value added respectively?

The interpretation is that increases in the density of industrial robots per 10 000 workers is associated with increased worker productivity, or manufacturing value added per employee. The exceptions to this finding were Japan, The Republic of South Korea and Finland. Again, the author suggests that there are specific structural factors such as technology overcrowding, shortage of manual labour due to ageing populations and low unemployment levels in these developed countries. This phenomenon is an area of the study that could be an opportunity for future research.

The average regression coefficient for the 38 countries assessed was 397. This relates to an average increase in manufacturing value added per employee of $397 per additional industrial robot per 10 000 workers. To put this into context, Malaysia (with a slope of 456) will be used to illustrate the implication.

From 2005 to 2014 Malaysia increased their installed base of operational industrial robots from 1695 to 5730, translating to a robot density increase from 9 to 28 per 10 000 workers. Over the corresponding period, manufacturing value added per employee increased from $12 610 to $21 656, as graphically illustrated in Figure 8.

Figure 8. Malaysia Productivity Slope



Source: Authors own.

6.2.3. Proposition one: Pearson's Correlation

It is significant that of the 31 countries for which the correlation analysis was concluded with statistical confidence at 95 per cent, all 31 values for r were greater than the 0.5 suggested by Cohen (1998) as large (Chapter 5 Table 5). In fact, the r values ranged from 0.64 (Brazil), to 0.98 (China).

The interpretation of the Pearson's correlation values are that the linear association between the 31 countries' industrial robot density and industrial worker productivity is not only significant (refer to significance, 6.2.1) and positive (refer to slope, 6.2.2), but the correlation was also found to be strong in nature. This confirmed the findings of Graetz and Michaels (2015) that there is a correlation between increased robot density and higher productivity.

The implication of this finding is that decision makers and analysts of these countries can scrutinize and interpret the industrial robot density and with 95 per cent confidence associate the variance with value added per industrial worker. Industrial robot density as an economic indicator in the manufacturing sector has great potential to be used by decision makers to motivate investment in the application and installation of industrial robots.

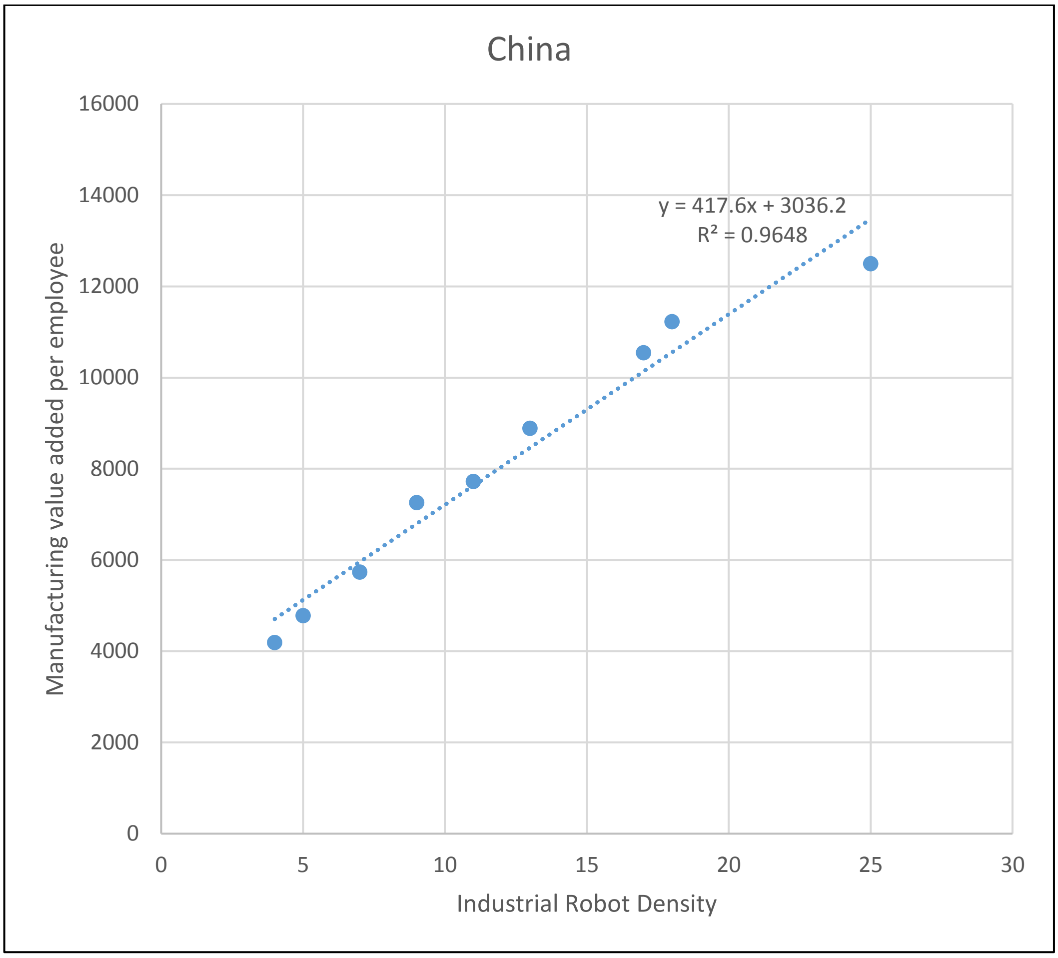
6.2.4. Proposition one: Coefficient of Determination

The coefficient of determination, or r squared, applied to this study quantifies the proportion of the variance of the industrial worker productivity, or response variable, accounted for by the variance in industrial robot density, or predictor variable (Baird & Bieber, 2016).

From Chapter 5 Table 5 it is remarkable to note that all of the 31 countries statistical evaluations that presented with a confidence level at $p < 0.05$, or 95 per cent interval, had r^2 values exceeding the Cohen (1998) suggested criteria of 0.25 as a large coefficient of determination.

The coefficient of determination values ranged from a large 0.41 in the case of Brazil, to a very large 0.96 in the case of China. To illustrate the implication, consider Figure 9, the X Y scatterplot for China with regression equation and r squared values indicated.

Figure 9. China X Y Scatterplot with r squared.



Source: Authors own.

Analysis of the data from Figure 9, with an r squared of 0.96, one can say at the 95 per cent confidence interval that 96 per cent of the manufacturing value added per industrial worker variance in China was explained by the variance in industrial robot density. While causality cannot be claimed, for the period under examination the increases in worker productivity can be explained by the increases in industrial robot density.

6.3. Proposition two: Robot Density and Industrial Sector Value Added

While proposition one dealt with labour productivity in the industrial sector, proposition two statistically analysed the impact of industrial robot density on economic growth, through looking at the economic contribution or manufacturing valued added to gross domestic product per country. The distinction between the two propositions is important. It is possible to achieve increased labour productivity by simply replacing or substituting labour with capital, industrial robots in this case. If this is done while output levels remain flat, labour productivity improved due to lower workers employed, but no positive economic contribution was achieved. Proposition two interrogates this in order to determine if increased industrial robot densities are also associated with increased outputs, or manufacturing value added.

The management proposition held that there was a moderate to strong positive statistical correlation between annual robot density (independent variable) and manufacturing valued added (dependent variable) data per country over the ten year period from 2005 to 2014.

From the results presented in Chapter 5, Table 7, it was found that for the 19 countries for which statistical interpretations could be done at the 95 per cent confidence interval, all 19 displayed a moderate to very strong and positive correlation between robot density and manufacturing valued added to the respective countries gross domestic product.

However statistically significant results for only 19 countries out of the population of 38 showed strong positive correlation between industrial robot density and economic contributions. One could argue that this seems unremarkable in terms of the second management proposition. Nonetheless, it is very important to understand the context of the proposition. Manufacturing economic contribution to national gross domestic product is influenced by a great number of factors, for example macro-economic conditions, supply and demand, input and overhead costs, exchange rate competitiveness, product sector competitiveness et cetera. It would be simplistic to propose that by just installing thousands of industrial robots indiscriminately economic output would be stimulated.

Unsurprisingly, the answer to this conundrum lies in the neoclassical growth theory. Solow (1956) proposed what became known as the Solow Residual, and identified that labour could be substituted by capital, and that technology employed by capital could lead to increased productivity. Ten Raa (2011) found not only is it possible for technology to increase productivity, but that the growth rate in economic output can exceed the growth rate of the inputs. Whether the capital employed is successful in increasing economic output, depends on the design and care taken on a case by case basis.

Notwithstanding the statistical support regarding the management proposition, that the increased use of industrial robots is correlated with economic contribution, one could also approach the argument logically. The relatively substantial cost and complexity of installing each industrial robot, approximated at $75 000 for the current decade (Frey & Osborne, 2013), implies that one should expect that a fairly robust cost benefit exercise is carried out by the investing company prior to installation. The deduction from this assumption is that one could expect only a reasonably small number of unproductive or uneconomical robot installations.

This finding substantiates Graetz and Michaels' (2015) finding that the increased use of industrial robots were shown to have increased economic growth. The similar findings are noteworthy, in that the fairly simple statistical methods employed by this study were very different from the advanced models applied by Graetz and Michaels. The different methods with similar findings gives further credibility to the outcomes.

The potential application of this finding is that it is critical for investors and decision makers, including governments, to consider the potential of increasing industrial robotics investment in order to increase economic contribution from the manufacturing sector. Moreover, industrial robot density as applied as a metric in this study could be useful in making these investment decisions.

6.3.1. Proposition two: Regression Significance

The confidence interval for this research was set at the 95 per cent interval, or p <0.05. The statistical significance requirement for the regression between industrial robot density and manufacturing value added was met for 19 of the 38 countries required, Null Hypothesis two were rejected in favour of the management proposition in all 19 cases (Chapter 5 Table 7).

The theoretical discussion around the statistical implication of the significance is similar to the first proposition and can be referred to as per section 6.2.1 above to prevent repetition.

It can be concluded that the statistical relationship between industrial robot density and manufacturing value added for these countries is a genuine relationship, and not due to chance, at a confidence interval of 95 per cent (Wegner, 2012, p. 311). Evaluators of this data could thus have 95 per cent confidence in these results.

6.3.2. Proposition two: Regression Coefficient or Slope

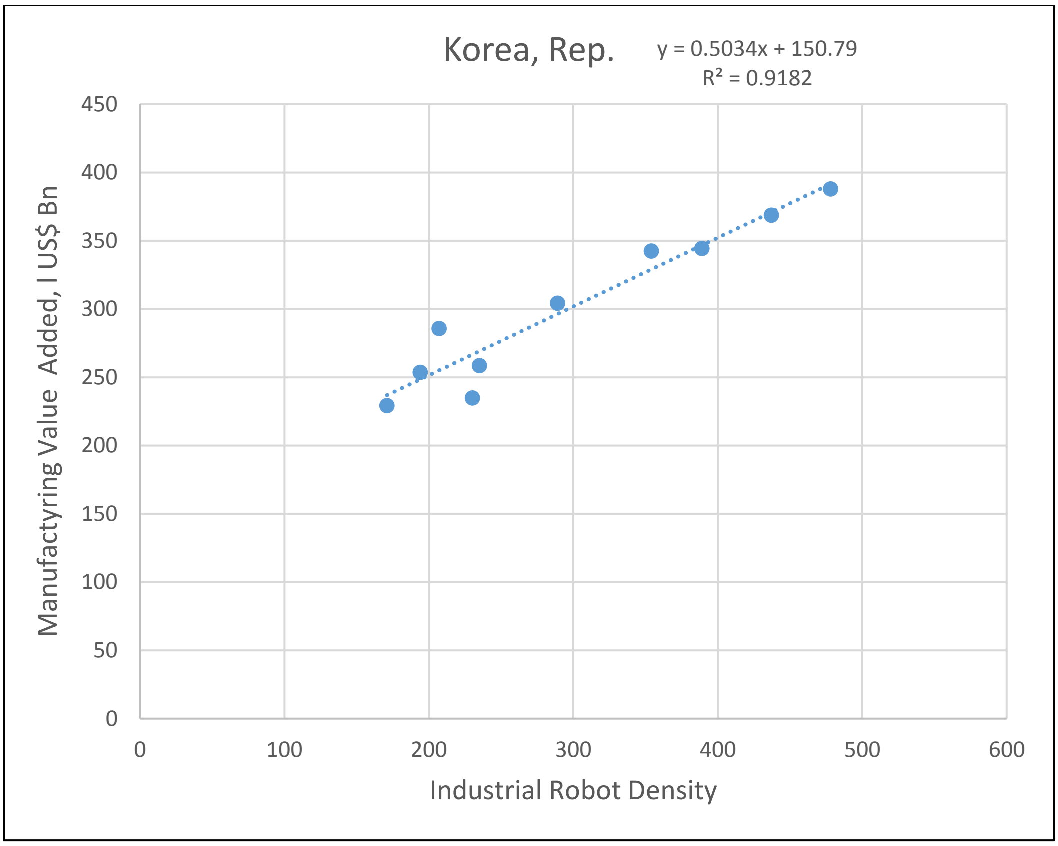
A total of 32 of 38, or 84 per cent (Chapter 5 Table 7 and 8), of countries displayed a positive regression coefficient, or slope (β), between industrial robot density and manufacturing value added. However, of the 38 countries only 19 countries displayed these positive slopes at a confidence interval of 95 per cent.

Applying Baird and Bieber's (2016) definition to this research, the regression coefficient or slope describes how industrial robot density is predictive of manufacturing valued added per country. With regards to Proposition two, for the 19 countries for which statistical inference could be made at the 95 per cent confidence interval, all of these countries displayed a positive slope.

The interpretation is that increases in the density of industrial robots per 10 000 workers is associated with increased manufacturing valued added, or manufacturing contribution to gross domestic product growth. Astoundingly, not a single country displayed negative manufacturing contribution slope when correlated to industrial robot density at the 95 per cent confidence interval.

Even the Republic of South Korea displayed a positive slope for manufacturing value added correlated to industrial robot density (Chapter 5 Table 7). Noteworthy is that the Republic of South Korea, as well as Japan, displayed a negative slope in terms of worker productivity (Chapter 5 Table 6); note that this result is not interpreted at the 95 per cent confidence interval. A possible interpretation in this case is that the country is the most densely populated in terms of industrial robots, and industrial worker productivity could not be shown with confidence to increase with increases in robot density, possibly due to overcrowding and diminishing returns. However, it could be shown with 95 per cent confidence that the manufacturing value added did indeed increase along with increased robot density.

Figure 10. The Republic of Korea, scatterplot with slope.



Source: Authors own.

The average regression coefficient of the Republic of Korea was $503 million US (from Figure 10) and the interpretation is that for each increment of industrial robot density unit (number of industrial robots per 10 000 industrial workers), $503 million US was contributed through manufacturing value added. In the case of the Republic of Korea, one unit of industrial robot density increase comprises of approximately 370 additional industrial robots, at a cost of approximately $280 million US.

6.3.3. Proposition two: Pearson's Correlation

It is significant that of the 19 countries for which the correlation analysis was concluded with the confidence interval at 95 per cent, all 19 values for the Pearson's correlation were greater than 0.5 (Chapter 5 Table 5). This exceeds the suggested criteria of large by Cohen (1998). In fact, the r values ranged from 0.64 (Argentina), to 0.98 (The Czech Republic).

The nature of the Pearson's correlation values is that the linear association between the 19 countries' industrial robot density and manufacturing value added is not only positive (refer to slope, 6.3.1) and significant (refer to significance, 6.3.2), but the correlation was also found to be strong in nature. This confirmed the findings of Graetz and Michaels (2015) that there is a correlation between increased robot density and higher economic growth.

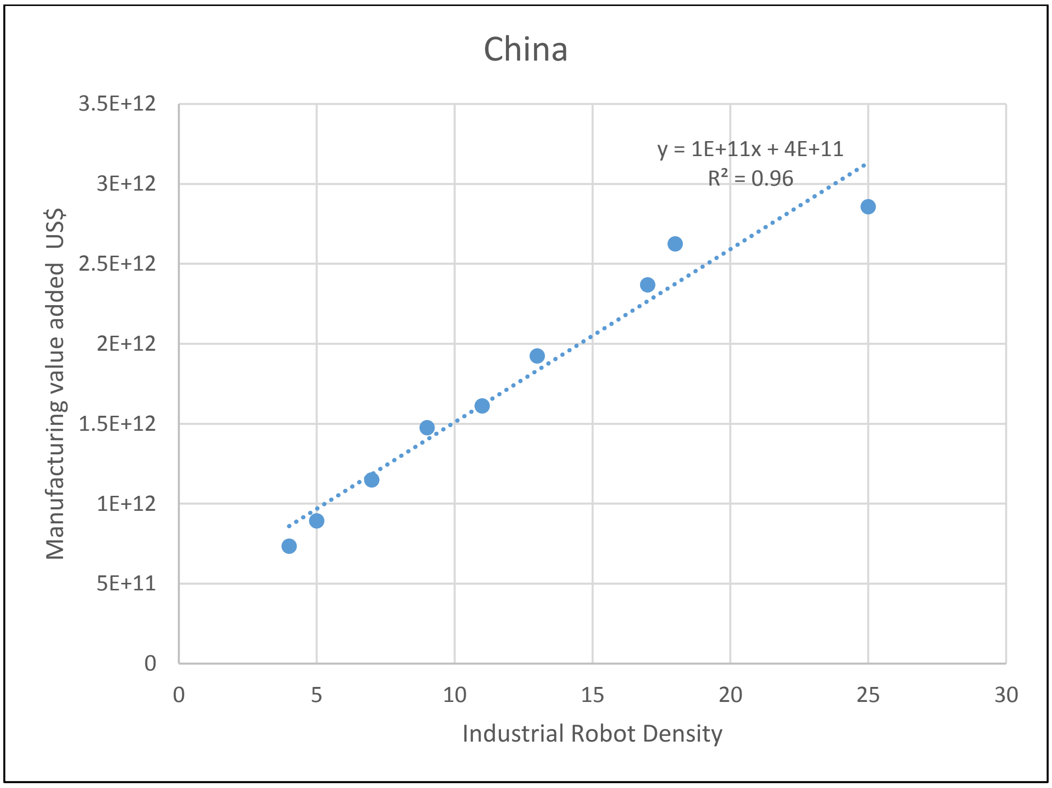
The implication of this finding is that decision makers and analysts of these countries can scrutinize and interpret the industrial robot density and, at the 95 per cent confidence interval, associate the variance with manufacturing value added, or contribution to gross domestic product growth. Industrial robot density as an economic indicator in the manufacturing sector has great potential to be used by decision makers to motivate investment in the application and installation of industrial robots.

6.3.4. Proposition two: Coefficient of Determination

The coefficient of determination, or r squared, applied to this study quantifies the proportion of the variance of the manufacturing value added, or response variable, accounted for by the variance in industrial robot density, or predictor variable (Baird & Bieber, 2016).

From Chapter 5 Table 7 it is remarkable to note that all of the 19 countries with a confidence level at $p < 0.05$, or 95 per cent confidence interval, had r^2 values exceeding the Cohen (1998) suggested criteria of 0.25 as a large coefficient of determination. The coefficient of determination values ranged from a large 0.41 in the case of the Czech Republic, to a very large 0.96 in the case of China. To illustrate the implication, consider Figure 11, the X Y scatterplot for China with regression equation and r squared values indicated.

Figure 11. China X Y scatterplot with r squared, manufacturing value added.



Source: Authors own.

Analysis of the data from Figure 11, with a coefficient of determination of 0.96, one can say, at the 95 per cent confidence interval, that 96 per cent of the total manufacturing value added variance in China was explained by the variance in industrial robot density. While causality cannot be claimed, for the period under examination the increases in manufacturing value added to gross domestic product can be explained by the increases in industrial robot density.

6.4. Proposition three: Stages of Economic Development

Through observation of all 38 countries data combined into one X-Y scatter plot (Figure 7) the finding was that the relationship between industrial robot density and worker productivity did in fact hold across economies and countries, regardless of stage of development and economy size.

This was also evident from analysing Table 5, where both developed and developing countries met the requirements of Proposition one in similar proportions.

The observational finding can thus be made that the statistical relationship between industrial robot density and industrial worker productivity is not only limited to developed countries, but is also applicable to developed countries. This aligns with the cross country convergence theory of Rodrik (2012) and Dowrick and Rogers (2002).

This finding addresses one of the shortcomings identified by Graetz and Michaels (2015), as the sample in their exploratory research only included developed countries.

The implication of this finding is that the identified statistical relationship also holds true for developing countries, and that the research is also of value to these countries' decision makers.

7. Conclusion

7.1. Industrial Robot Density and Worker Productivity

Strong correlation was found between industrial robot density and industrial worker value added per employee. The linear statistical relationship was proven for 31 out of 38 countries at the 95 per cent confidence interval. This finding, that the use of technologies such as industrial robotics, confirms previous research (Autor, 2015; Graetz & Michaels, 2015; Mokyr et al., 2015; Krone, 2014). Furthermore, the role of technology in productivity improvements finding aligns with the Solow residual and neoclassical growth model theory (Burda & Severgnini, 2014, Solow, 1956, Ten Raa, 2011).

The strong correlation showed that industrial robot density, as a promotor of productivity, has potential to be used as a simple economic indicator or metric in the manufacturing sector. This finding is in alignment with similar research by Alston and Pardey (2014) and Khan et al. (2014), conducted in the agricultural sector. The metric used in these studies as an indicator was agricultural machinery and tractors, reported by the World Bank as AGRMACH. In both cases the capital investment in measurable units of plant and equipment, tractors and agricultural machinery and industrial robots, are used to increase productivity and output, and can be used as an indicator for economic activity in the respective sectors.

It was also shown that these findings are not limited to developed countries only, but for the first time also found to be applicable to developing countries.

7.2. Industrial Robot Density and Manufacturing Value Added

The conclusion on the finding of strong correlation between industrial robot density and manufacturing value added is that increased industrial robot density is closely associated with increased contribution, or value added, to gross domestic product per country from the manufacturing sector.

This finding is consistent with neoclassical growth model theory and the Solow residual research done by Bernard and Durlauf (1996), Crafts (2015) and Ten Raa (2011) in terms of the use of technology as an enabler or promoter of long-run economic growth. In terms of using industrial robot density as an economic indicator or metric, this finding corresponds to the exploratory work done by Graetz and

Michaels (2015). Where Graetz and Michaels did their research only on developed OECD countries, this research confirmed the finding for a wider range of countries, and found that the correlation is not only true for developed countries, but also for developing countries.

7.3. Implications for Management

These findings can be very useful to management and decision makers from company to national level, when considering capital investment or policy changes regarding automation and robotics in the manufacturing sector. Industry role players in both developed and developing countries can evaluate the statistical relationship between industrial robot density and productivity and manufacturing value added for the specific country under consideration.

The industrial robot density indicator or metric as researched in this paper can be applied in economic analysis of productivity and growth potential, and assist in making automation investment decisions in the specific countries.

While this research does not claim causality, few economists will claim that they can predict future performance from past trends. However, it is worthwhile to consider the optimal use of historical data and to identify correlations and trends, such as in the case of this study. Moreover, this study is framed within the neoclassical long-run growth theory, and based on numerous peer reviewed articles. Still, the author emphasis that causality has not been proven or inferred statistically.

Considering that the number of installed industrial robots increased at a year-on-year rate of 29 per cent between 2013 and 2014, it is inconceivable to make slight of the impact of industrial robots on the manufacturing sector of the world economy. The author is in agreement with Chinese President Xi Jinping that a robot revolution is underway (Chan, 2015), and this fusion of technologies was termed the fourth industrial revolution by Klaus Schwab, speech as reported by Trudeau (2016), during the World Economic Forum in Davos Switzerland. China is taking the lead in accelerating investment in robotics in the industrial sector, increasing their installed base at a rate of 56 per cent year-on-year by 2014 (International Federation of Robotics, 2015). This increased their industrial robot density from 25 to 36 industrial robots per 10 000 industrial workers.

Monitoring these and other trends from data supplied by the annual International Federation of Robotics report will become increasingly important to role players in the economic and manufacturing sectors, and while this research focussed mainly on industrial robot density, as did Graetz and Michaels (2015), there are many more datasets and trends available from the Federation of Robotics report that warrants further research.

7.4. Limitations of the Research

The research methodology was intentionally based on only one independent variable, namely industrial robot density. It is highly likely that stronger correlation using multiple independent variables can be shown, such as supply and demand conditions, political and macro-economic factors, restrictive labour legislation, cost of capital et cetera. This would require a country by country analysis, and was not within the scope of this research.

The dependent variable used to represent labour productivity, was industrial worker value added per employee. While this is a simple to determine through dividing the manufacturing value added per country by the reported total number of industrial workers reported for the country, there are alternative indicators for productivity. Total factor productivity, estimated as Tornqvist or Malmquist indices are alternatives that are more comprehensive estimators of productivity than the method employed in this study.

This research made use of secondary data sourced from the International Labour Organisation (2014) and The World Bank (2016) databases. It would be of interest to verify this data against independent or alternative sources, such as the World Economic Forum databases amongst others.

While the statistical relationship between industrial robot density and productivity and economic contribution was determined, causality was not determined. However, long-run economic growth through productivity improvements enabled by exogenous technology is covered extensively in literature (Autor, 2015; Bernard & Durlauf, 1996; Krone, 2014; Mokyr et al., 2015). It is conceivable that Granger causality, as used by Khan et al. (2014), might be proven empirically, but this was not attempted or claimed by this study.

The impact of automation and robotics on labour was included as part of the literature review due to the contemporary discussions and academic interest. However, this did not form part of the focus of the quantitative analysis.

Each countries' statistical evaluation could merit individual research, however due to the scope of this work and the fact that the sample consisted of 38 countries, only salient comments regarding some of the countries were made.

7.5. Recommendations for Future Research

This research found strong, positive linear relationships between industrial robot density and industrial worker productivity and manufacturing value added. Further to these findings, value could be added to literature by investigating the covered statistical relationships for causality, perhaps using Granger's causality test and variance decomposition. A comparable method could be used as was proposed in a similar study in agriculture automation by Khan et al. (2014).

Although the scope of this research was limited to the industrial sector, it is likely that a meaningful study covering the services sectors using similar data for service robots could be conducted. Additionally, extensive literature and research is available on the topic of the impact of automation and specifically robots on labour; the International Federation of Robotics' annual report could be a valuable source of data to supplement this with a quantitative research on the subject.

A qualitative study could be done to investigate the suspected phenomenon of diminishing marginal returns, or overcrowding, observed in the analysis of the Republic of South Korea and Japan. These two countries have the highest and second highest industrial robot density respectively (Figure 2 and Table 1), and it is possible that the industries have been saturated with industrial robots, and that additional robots are added due to labour shortages, and not necessarily to improve productivity or increase value added.

Impacts of restrictive labour laws on the potential of industrial robotics to improve productivity should be investigated. An example is South Africa, where it is problematic to reduce labour when the installation of robotics have presented opportunities to do so.

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APPENDIX 1 – ETHICAL CLEARANCE APPROVAL

Dear Mr Johan le Roux

Protocol Number: **Temp2016-01315**

Title: **INDUSTRIAL ROBOT POPULATION DENSITY AND THE NEO-CLASSICAL GROWTH MODEL**

Please be advised that your application for Ethical Clearance has been APPROVED.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards,

Adele Bekker

APPENDIX 2 – IFR APPROVAL LETTER

IFR statistical department

IFR Statistical Department Postfach 710864 DE-60498 Frankfurt / Main

Mr. Johan le Roux

Contact	Nina Kutzbach
Phone	+49-69-6603-1518
Fax	+49-69-6603-2518
E-Mail	nk@worldrobotics.org
Date	06 July 2016

Permission to use IFR data

We grant permission to use IFR data by referring to "IFR World Robotics 2015" to Mr. Johan le Roux for his research as a MBA student at Gordon Institute of Business Science.

i.A. N. Kutzbach

IFR International
Federation of Robotics
c/o VDMA R+A
Lyoner Strasse 18
60528 Frankfurt
Germany

APPENDIX 3 - TURNITIN ORIGINALITY REPORT

Turnitin Originality Report

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