Automation and the Risk of Job Loss: The Case of German Regions

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Abstract
Besides routine tasks, more creative and skillful jobs are increasingly more at risk of automation due to the continuous technological advancements. Policymakers are currently operating in a knowledge vacuum. Therefore, more clarity is needed on the impacts of automation, and especially little is known regarding the spatially contingent implications. This research aimed to discover the relationship between the risk of people losing their jobs, and population density. This relationship is discovered in the context of regions in Germany with the use of an explorative data analysis and a statistical analysis. This study finds a strong negative correlation between population density and the proportion of jobs at high risk of automation. Furthermore, this study concludes that the creativity and diversity of jobs available in more densely populated areas makes them more resilient to automation, and that a higher proportion of higher educated people in a region makes them less susceptible to automation.

1. Introduction

Society is currently undergoing the fourth industrial revolution, referred to as 'Industry 4.0', in which continuous developments in automation driven by advancements in artificial intelligence (AI), the internet of things (IoT), machine learning, and big data will change the dynamics of the labour market (Marengo, 2019). All these technological advancements are increasing the impact of automation, a term referring to the replacement of human labour by machines. In the fourth industrial revolution, the impacts of automation are not limited to low-skill manual and routine jobs, as more cognitive medium and high-skill jobs that involve complex decision-making processes are now at risk of substitution (Marengo, 2019). This 'technological unemployment', as Keynes referred to in 1930 is a controversial case. Some scholars, such as Frey and Osborne (2017), conclude that automation will significantly impact the labour market, estimating 47% of jobs in the US labour market are at high risk of automation. Other OECD reports estimate around 9% of jobs to be at risk as a result of automation developments (Arntz et al., 2016). Additionally, there is a strand of literature that holds a positive outlook on automation developments and their impact on the labour market (Schmidt & Cohen, 2014, Gates et al., 1995). These scholars argue that, just like the other industrial revolutions, the fourth industrial revolution will create new job opportunities alongside the ones that are substituted by automation.

While not all scholars agree on the extent of the impact, most of them understand the need to understand how the continuous developments in automation will affect the dynamics of the labour market. Job loss will not be experienced in the same magnitude everywhere. Previous studies have concluded that the smaller cities and non-core regions are more susceptible to job loss, since larger cities benefit more from agglomeration effects (Frank et al., 2018; Crowley et al., 2021). To my knowledge, the relationship between automation, urbanization and the risk of workers losing their job specifically has only been studied once (Frank et al., 2018). In accordance with other studies that have included urbanization as a component (Crowley et al., 2019, Muro et al., 2019), this research will focus on the relationship between automation, urbanization and the risk of workers losing their job, and additionally cover the impact of the creative class by Florida (2005) and the role of education. Leigh and Kraft (2018) conclude that there is a limited amount of academic knowledge on the spatially contingent implication of automation developments, and further point out that policymakers have to deal with a lack of knowledge about job automation risk at the local level. Therefore, the goal of this study is to improve the understanding of the spatial contingent in job automation. Hopefully, with this study, policymakers are capable of making more grounded decisions regarding job automation.

Given the short timespan this research has, studying the entirety of Europe is too optimistic. Therefore, this study will cover the relationship between urbanization and automation in regions in Germany. Specifically, this study will investigate this relationship at the NUTS-2 level, since this is the lowest scale possible that has data on the location of jobs. The research question following from this is formulated as follows: *How do urbanization, the creativity of jobs, and education impact the risk of workers losing their jobs in regions in Germany?* This research will focus on regions in Germany as the country provides a variety of urbanized and non-urbanized regions. The results of this research can provide useful insights which could be used by governmental organizations for social policy, educational initiatives, and investment strategies. Moreover, the findings of this research could contribute to the body of literature that discusses how the globalizing world changes the disparity between the urban and the rural (Rodríguez-Pose, 2018, Dijkstra et al., 2020).

The remainder of this paper is structured as follows. First, a theoretical framework based on previous academic work will be presented to broaden the understanding of the concepts and provide theories and arguments that can be used to interpret the results. Furthermore, the theoretical framework will provide the basis for the hypothesis. The following part will explain the methodology of this research. The fourth section will present the results, after which the conclusions will be drawn in the fifth segment.

2. Theoretical Framework

Changes in the labour market nowadays are increasingly influenced by artificial intelligence, robotics, and adaptive automated learning (Koster and Brunori, 2021). The introduction of these technological advancements into the working environment will influence the skills and toolkits necessary for workers to possess (Crowley et al., 2021). In 1930, John Maynard Keynes argued that the new ways in which society can economize the use of labor will outpace the development of new jobs. The prediction he made could already be noticed in society, as simpler jobs have been replaced because of technological advancements. To give an example, cashiers have been largely replaced by self-scanning checkout machines. However, given that the pace of technological advancements is increasing faster than in previous three industrial revolutions, continuous developments in automation are now predicted to replace jobs that require more cognitive abilities and skills, as the pace of new job creation cannot keep up (Brynjolffson and McAfee, 2012). Therefore, the changes that the new fourth revolution will lead to could be extremely disruptive, as Audretsch (2018) pointed out that the previous three industrial revolutions have been known to completely change the geography of economies. This process, as referred to by Schumpeter (1942) as creative destruction, is anything but new to the literature. While the impacts of technological advancements on the labour market are well-documented in the academic world, most studies did not include a spatial contingent.

The extent to which workers are able to withstand the substitution of jobs and provide the subsequent newly required skills differs from region to region. To predict the impact that urbanization might have on the risk of people losing their jobs, theories of regional resilience, vulnerability and growth provide theories and arguments. According to Boschma (2015), the ability of regions to withstand shocks has everything to do with the industrial composition of those regions. Boschma (2015) explains that a diversified industrial structure is more resilient to shocks, since the variety of industry spreads the risks. Therefore, the strength of regions to absorb the impacts of automation is determined largely by the type of jobs present in that region. Muro et al. (2019) argue that regions with lower human capital and more specialization in low-end services and manufacturing jobs will feel bigger impacts of automation developments. Within the literature on regional resilience, it is agreed upon that if there is more variety of industrial structure and economic structure in a certain region that benefits from agglomeration effects, this region will be less susceptible to large shocks (Frenken et al., 2017). Furthermore, Boschma (2015) argues that regional variety in skill-related industries will speed up the process of recovery from certain shocks since employees will have an easier time finding a new suitable job. Therefore, the more diversified regions, as opposed to specialized regions, will have an easier time adapting to the changes that the continuous developments in automation will bring, and the more diversified regions are more likely to create new growth paths. One way in which regions can adapt and create new growth paths is by training and reskilling opportunities. According to Cilasun et al. (2018), the speed of technological advances requires workers to continuously update their skills, and participation in adult education can provide these skills that can make people adapt to a constantly developing labour market. However, the availability of these reskilling opportunities varies depending on the region a worker resides. Less urbanized areas tend to have worse access to these reskilling and retraining opportunities and are therefore less resilient.

One way to discover the spatially contingent feature of automation developments and the consequential risk of people losing their job is by looking at the city level. Nowadays, cities accommodate over half of the world's population, and urbanization is expected to grow even further in the future (Kraas et al., 2013). Therefore, cities are the world’s drivers in economic productivity, innovation, and opportunities. In their paper, Frank et al. (2018) discover how advancements in artificial intelligence will impact a variety of cities in the United States. Their results show that the impact of automation, or the risk of people losing their job, will be experienced less heavily in more urbanized, core regions, as opposed to less urbanized, non-core regions. While admitting that finding causality in this relationship is extremely difficult, Frank et al. (2018) divert special attention to the division of labour theory. The strong division of labour, and the variety of jobs available in more urbanized areas make them more resilient against automation developments, as opposed to the specialization of labour in less urbanized areas.

The findings from the paper of Frank et al. (2018) could be put into context with the work of Richard Florida. In his book, *The Rise of the creative class*, Florida (2005) discusses the role of the creative class in urban and regional growth. The creative class should be seen as a group of like-minded people that develop ideas and innovations, instead of physical products (LeGates and Stout, 2020). Florida (2005) makes a distinction between the “Super-Creative Core” and the “Creative Professionals”. The former group consists of occupations such as scientists, engineers, university professors, artists, actors, and entertainers, while the latter consists of employers working in knowledge-intensive industries such as legal and health professions (LeGates and Stout, 2020). According to Florida (2005), cities or regions that attract more creative professionals will be leading in development and innovation. Therefore, if regions or cities have more people doing creative jobs, these regions or cities will be impacted less by job automation. The work from Florida is opposed to the theories of Muro et al. (2019), who argue that regions with more human capital are more resilient to automation processes. Florida claims it is irrelevant how much human capital someone has if they do not apply it in a creative or economically smart way (Boschma and Fritsch, 2009).

Another framework to understand regional resilience against automation developments is the infamous MAR externalities, introduced by the scholars Marshall (1920), Arrow (1962), and Romer (1986). The MAR externalities create so-called knowledge spillovers that are beneficial to the overall area, since the knowledge created by one firm or industry can benefit another firm or industry, leading to innovation and productivity improvement. These MAR externalities provide a baseline to understand the differences in resilience between regions, as these externalities argue that a higher number of firms specializing in an industry, will lead to more innovation. Given that these externalities mainly occur in larger cities, this theory would further support the argument that more urbanized areas are more resilient to developments in automation and workers are less susceptible to job loss. These theories are opposed to the arguments by Florida (2005), who considers the knowledge spillovers of individuals, instead of focusing on firms and industries.

However, according to Frank et al. (2018), it is, *a priori*, still difficult to determine whether more urbanized regions will have a higher or lower risk of job loss. This is because the division of labour that is present in cities that result in occupational specialization is more prone to automation, as the division of labour encourages worker modularity (Frank et al., 2018). Following the fact that modular jobs, which are jobs that are easily replaceable, are exceedingly present in more agglomerated areas, workers in cities might be impacted more by developments in automation. This argument highlights the fact that this research is not about the absolute risk of job loss related to regions. Instead, this research focusses on the relative exposure of German regions to automation risk.

Nevertheless, building upon some of the earlier theories provided by Keynes and Schumpeter, the newer literature that discusses the role of regional resilience, and in particular the findings from Frank et al. (2018), Florida (2005), and Muro et al. (2019), the following hypothesis is formed: *The risk of job loss due to developments in automation in regions in Germany is lower in more urbanized, more creative, and higher educated areas.*

3. Methodology

To test the hypothesis, this research will apply a short explorative analysis followed by a quantitative analysis using statistical tests. The goal is to find out what impact the degree of urbanization, the creativity of jobs, and education have on the risk of people losing their job as a result of the constantly evolving automation technologies. Therefore, it is necessary to develop a method to quantify the risk of people losing their job. As mentioned before, there are several methods to quantify the risk of people losing their jobs, and these methods will lead to differentiating results. Hence, some studies find that 47% of the jobs are at risk for automation (Frey and Osborne, 2017), and other studies only come to 9% (Arntz et al, 2016).

3.1 Computing a Risk of Job Loss Statistic

This research will apply the frequently cited method by Frey and Osborne (2017) that developed a risk of job loss statistic for 702 occupations in the United States labour market. There are several reasons why this method will be applied in this research. Firstly, the method by Frey and Osborne (2017) has proven to be incredibly sound, as it finds statistics for 97% of the United States workforce. The statistics were developed together with machine-learning experts to find the impact of automation for 70 occupations at first. With the help of big data, algorithm applications, and data from the O*NET database, they discover the automatable and non-automatable tasks of these 70 occupations. The risk of job loss statistics of the other 632 occupations were calculated in the same way. The final statistic is a number between '0' and '1' where '0' is the lowest probability of an occupation being automized and '1' is the highest probability of a job being automized. Secondly, applying the method of Frey and Osborne (2017) is in line with other papers that use the risk of job loss statistics for regions in Europe (Crowley et al., 2021, Frank et al., 2018). By using the same method, this research can contribute to a standardized way of discovering the impacts of automation on the labour market, which enables studies to be compared to each other.

The statistics by Frey and Osborne (2017) are based on United States occupations using the US Standard Occupational Codes (SOC) at the six-digit level. To apply the statistics for European regions, the US SOCs must be translated into the International Standard Occupational Codes (ISCO). Converting the US SOCs into the three-digit European ISCO codes will be done using the official Bureau of Labour Statistics conversion table. It should be noted that the European ISCO codes are aggregated at a higher level. Instead of the 702 US SOCs, the European ISCO codes only include 122 occupations. Therefore, some of the US SOCs need to be combined into one ISCO code. When combining the multiple US SOCs into one ISCO code, this study will use the average of the US SOCs to come to one risk of job loss probability for a European ISCO code.

There are some examples where the translation of the US SOCs to the ISCO codes could result in issues of reliability. To provide an example, the three-digit ISCO code 324 represents the 'Veterinary Technicians and Assistants' occupation. This three-digit ISCO is made up of two occupations in the US SOCs, namely 'Veterinary Technologists and Technicians' and 'Veterinary Assistants and Laboratory Animal Caretakers'. The issue with reliability occurs since one job has a 0.86 probability of being automated, while the other occupation only has a 0.029 probability of being automated. When these two occupations are combined into one statistic, the number no longer accurately represents the difference in probability of being automated between the two occupations as the statistic is now somewhere in between the two extremes. After aggregating the probabilities of Frey and Osborne (2017) to the European occupation codes (ISCO, 3-digit) the average probability came to 0.50, with a minimum of 0.004 and a maximum of 0.97, and a standard deviation of 0.31. Compared to the US average of 0.53, with a minimum of 0.002, a maximum of 0.99 and a standard deviation of 0.36, the statistics remain quite similar. Furthermore, the study by Crowley et al. (2021) discovered that the same transition does not significantly impact the measure of automation. Therefore, this method does not lead to any reliability issues. All 122 occupations and their respective Risk of Job Loss probability statistics are included in Appendix A.

3.2 Methodology for Explorative Data Analysis

The new risk of job loss statistics based on the European ISCO codes will be matched to the respondents of the European Labour Force Survey, which is the database this research uses for the other explanatory and control variables. The total number of respondents in this survey is a little over 3 million. However, as this study is only interested in employed workers in Germany, the respondents are filtered based on country and employment status. After applying these filters, the number of respondents drops to just under 180.000. Before continuing with the statistical analysis, this research will first perform a short explorative data analysis of the risk of job loss probability statistics that have been calculated. This will mostly be done in the context of the theories by Florida (2005), who uses ISCO codes to distinguish jobs based on their creativity. This paper uses the occupations that Boschma (2015) specifies for the "creative core" and "creative professionals" based on the paper by Florida. While the occupations Boschma (2015) specifies are based on the ISCO-88 codes, the job descriptions were matched to the ISCO-08 code to find similar occupations.

3.3 Methodology for Statistical Analysis

The method of Frey and Osborne (2017) will be continued by calculating the proportion of jobs that are at high risk of automation for each of the 38 NUTS-2 regions in Germany. Occupations are assumed to be at high risk whenever the risk of job loss statistic > 0.7. This is in line with previous research that have used the same method (Frank et al. 2018, Crowley et al., 2019, Frey and Osborne, 2017, Arntz et al., 2016). The respondents of the European Labor Force Survey will be aggregated to the NUTS-2 level, and the total number of respondents at high risk of automation will be summed. Subsequently, the summed respondents will be divided by the total number of respondents in a NUTS-2 region to create a proportion of people at high risk of losing their job in all NUTS-2 region in Germany.

To create the explanatory variable, population density data at the NUTS-2 level was extracted from Eurostat in the year 2022. The use of population density to predict impacts on automation has been performed in previous studies (Frank et al. 2018, Crowley et al., 2019, Muro et al., 2019). These population density figures were then matched to the aggregated risk of job loss proportions from the EULFS. Before advancing to parametric tests, some issues with normality occurred. The NUTS-2 regions of Berlin, Hamburg and Bremen had population density figures that were much higher than those of other regions. Therefore, the population density data had issues with kurtosis and skewness. A logarithmic transformation was performed on the population density to overcome the lack of symmetry. To ensure there is a linear relation between the two variables, this research will first perform a Pearson's correlation. After the linear relation is established, a linear regression will be performed. Additionally, the impact of non-formal education on the proportion of jobs at high risk of automation will be assessed in line with the theories from Cilasun et al. (2019). To achieve this, data on participation in non-formal education in the last 4 weeks will be dummy coded and put into the regression analysis.

Furthermore, the explorative data analysis based on the rise of the creative class by Florida (2005) will be expanded upon with statistical tests. For this, the proportion of creative jobs in NUTS-2 regions in Germany will be tested in relation to the proportion of jobs at high risk of automation in NUTS-2 regions in Germany. The proportion of creative jobs will be calculated by summing the number of jobs that belong to either the "creative core" or "creative professionals", and dividing this number by the total number of jobs in a region. Lastly, the impact of education will be determined in relation to the proportion of jobs at high risk in German regions. The proportion of higher educated people are based on the International Standard Classification of Education (ISCED), where groups 1-4 are considered low educated and 5-8 are considered highly educated.

3.4 Ethical Considerations

The quantitative nature of this study means that objectivity and clarity in the data collection and interpretation process will be explained shortly, to ensure the ethical quality of this research. Research ethics in this paper are ensured by providing data accessibility. Data that was taken from other researchers and databases are explicitly mentioned, and data compiled by myself during this research is provided in tables and in the appendices. Furthermore, the methodology functions as a safeguard against unethical practice by describing the steps taken in the data collection and generation process. Lastly, analytical transparency is protected by explaining in detail how the conclusion evolved from the data processed and by referencing back to the theories and concepts included in the theoretical framework.

4. Results

4.1 Explorative Data Analysis

Table 1.1 represents similar professions as Florida (2005) classifies in his book as “creative core” professions together with the risk of job loss probability that has been translated from the method by Frey and Osborne (2017) into ISCO codes.

Table 1.1 – “Creative Core” Occupations and their Risk of Job Loss probability

“Creative Core” Occupations (ISCO Codes)	Risk of Job Loss Probability
Physical and Earth Science Professionals (211)	0.2251
Mathematicians, Actuaries, and Statisticians (212)	0.1484
Life Science Professionals (213)	0.0660
Medical Doctors (221)	0.0042
University and Higher Education Teachers (231)	0.0320
Secondary Education Teachers (233)	0.0078
Primary School and Early Childhood Teachers (234)	0.0830
Other Teaching Professionals (235)	0.0700
Librarians, Archivists, and Curators (262)	0.4517

From Table 1.1 it is noticeable that most of the “Creative Core” professions have a low Risk of Job Loss probability. Not one occupation is considered to be at high risk of automation, as no statistic is above the 0.7 threshold used in other research (Frank et al. 2018, Crowley et al., 2019, Frey and Osborne, 2017, Arntz et al., 2016). With an average Risk of Job Loss Probability of 0.1209, the “Creative Core” professions are at low risk of automation.

Table 1.2 represents similar professions as Florida (2005) classifies in his book as “creative professionals” together with the risk of job loss probability that has been translated from the method by Frey and Osborne (2017) into ISCO codes.

Table 1.2 – “Creative Professionals” occupations and their Risk of Job Loss probability

“Creative Professionals” Occupations (ISCO Codes)	Risk of Job Loss Probability
Legislators and Senior Officials (111)	0.0886
Nursing and Midwifery Professionals (222)	0.0090
Legal Professionals (261)	0.2836
Physical and Engineering Science Technicians (311)	0.4802
Traditional and Complementary Medicine Associate Professionals (323)	0.0550
Other Health Associate Professionals (325)	0.3397
Financial and Mathematical Associate Professionals (331)	0.7278

From Table 1.2 only the ‘Financial and Mathematical Associate Professionals’ are at high risk of being automated, as the Risk of Job Loss probability is larger than 0.7. However, the other occupations that belong to the “Creative Professionals” are not considered at high risk of being automated. The average Risk of Job Loss Probability for the “Creative Professionals” comes to 0.2834.

The “creative core” and “creative professionals” occupations from Florida that were covered in Table 1.1 and Table 1.2 are more prevalent in more densely populated, urban areas, since cities are the enablers of creative work. (Florida, 2005). Now that these have been covered, Table 1.3 displays the occupations that are part of the ISCO-08 major group ‘Skilled Agricultural, Forestry, and Fishery Labourers’ and their respective Risk of Job Loss probability. Logically, these occupations will be found in less densely populated areas, as the occupations specified in Table 1.3 are land-intensive.

Table 1.3 – Skilled Agricultural, Forestry and Fishery Labourers and their Risk of Job Loss Probability

‘Skilled Agricultural, Forestry and Fishery Labourers’ occupations (ISCO Codes)	Risk of Job Loss Probability
Market Gardeners and Crop Growers (611)	0.5920
Animal Producers (612)	0.7450
Mixed Crop and Animal Producers (613)	0.7450
Forestry and Related Workers (621)	0.7920
Fishery Workers, Hunters and Trappers (622)	0.7075

The occupations displayed in Table 1.3 show significantly higher Risk of Job Loss probability than those in Table 1.1 and Table 1.2. With the average Risk of Job Loss Probability being 0.7163 and four out of five occupations considered at high risk of automation, this line of work is in sharp contrast with the previous occupations. While the disparity between the Risk of Job Loss Probabilities therefore supports the hypothesis that the risk of job loss is experienced less in more urbanized, and densely populated areas, these statistics do not explain anything on the size of the workforces. This will be assessed in more detail with the statistical analysis.

4.2 Statistical Analysis

The proportion of jobs at high risk of occupation varies between 0.24 in the NUTS-2 region of Berlin and 0.38 in the NUTS-2 regions of Chemnitz, Koblenz and Niederbayern. Table 2 includes the minimum, maximum, mean, and standard deviation for this variable. All NUTS-2 regions in Germany and their respective proportion of jobs at high risk of automation are included in Appendix B. Glancing at the NUTS-2 proportions for jobs at high risk of automation would again support the hypothesis that the impacts of automation are experienced less heavily in more densely populated areas, since the NUTS-2 regions with lower probabilities are mostly densely populated regions, such as Berlin and Hamburg.

Table 2 – Descriptive Statistics for Proportion of Jobs at High Risk for NUTS-2 Regions in Germany

Minimum	Maximum	Mean	Std. Deviation
.24	.38	.3321	.02986

After normality was checked by the kurtosis and skewness values, and no apparent violation of the assumption was discovered, a Pearson’s correlation test was run to determine the correlation between the proportion of jobs at high risk of automation and population density for NUTS-2 regions in Germany. The null-hypothesis associated with this test is:

There is no linear relationship between population density and the proportion of jobs at high risk of automation in NUTS-2 regions in Germany.

The results of the Pearson's correlation test show a significant correlation with a p-value < 0.001. Furthermore, the Pearson correlation coefficient of -0.738 shows that the two variables are highly, and negatively, correlated (Table 3). Therefore, the null-hypothesis should be rejected, and this test concludes that there is a high correlation between population density and the proportion of jobs at high risk of automation in NUTS-2 regions in Germany. This determines that the population density could be used to predict the proportion of jobs at high risk of automation.

Table 3 – Pearson's Correlation Test

Correlations

		Proportion of Jobs at High Risk of Automation in Germany	Logarithmic Population Density NUTS-2 Regions Germany
Proportion of Jobs at High Risk of Automation in Germany	Pearson Correlation	1	-.738**
	Sig. (2-tailed)		<.001
	N	179954	178186
Logarithmic Population Density NUTS-2 Regions Germany	Pearson Correlation	-.738**	1
	Sig. (2-tailed)	<.001	
	N	178186	178186

**. Correlation is significant at the 0.01 level (2-tailed).

Following the establishment of a linear relationship, and with no other apparent violations of the assumptions of the test being discovered, the linear regression was performed on the relationship between population density and the proportion of jobs at high risk of substitution. The null hypothesis is the following:

There is no correlation between population density and the proportion of jobs at high risk of automation in NUTS-2 regions in Germany.

Table 4 displays the model summary statistics for the linear regression. The R value is the same value as was calculated before with the Pearson's correlation test. The R Square value of 0.544 indicates that 54.4% of the variance in the proportion of jobs at high risk of automation in NUTS-2 regions in Germany is explained by population density. Additionally, coefficients were further assessed to ascertain the influence of population density on the proportion of jobs at high risk of automation in NUTS-2 regions in Germany. The results shown in Table 4 reject the null-hypothesis, and reveal that population density has a significant, negative impact on the proportion of jobs at high risk of automation (B = -0.57, p = <0.001). Given that the independent variable was log transformed, the standardized coefficients should be interpreted in percentages. A 1% increase in population density will lead to a 5.7% decrease in risk of job loss probability.

Previous studies have used population density to measure the impact of agglomeration effects on the risk of people losing their job as a result of automation (Frank et al., 2018, Crowley et al., 2019, Muro et al., 2019). Frenken et al. (2017) argue that regions with a more varied workforce, that benefit from agglomeration effects, will be less susceptible to big shocks. The significant relationship in this study confirms the theory by Frenken et al. (2017), since more densely populated areas are less susceptible to automation developments, or big shocks.

Table 4 – Regression of Proportion of Jobs at High Risk of Automation

Variable	R Square	B (Std. Error)	Beta	P-value
Population Density	.544	-.057 (.000)	-.738	<.001
Constant = .475				
N= 38				

Now that the relationship between population density and the proportion of workers at risk of losing their job due to automation developments has been established, the next step in this research is to determine the impact of other variables. In line with the paper by Cilasun et al. (2019), which argues that participation in non-formal education (NFE) increases the resilience of regions to automation developments, this research used participation in non-formal education in the last 4 weeks to predict the impact on the proportion of jobs at high risk of automation. The dummy variable that was left out is “Participating in at least one job-related NFE or training activity”. Table 5 shows that people not participating in any NFE or training activity have a significantly higher risk of job loss compared to people participating in at least one job-related NFE or training activity. This confirms the theory by Cilasun et al. (2019) that participation in NFE makes people more resilient to automation.

Table 5 – Coefficients Regression of Proportion of Jobs at High Risk of Automation

Variable	B (Std. Error)	Beta	P-value
Population Density	-.57 (0.000)	-.737	<.001
Participating only in non-job-related/personal nonformal education or training activities	.000 (.001)		.819
Not participating in any non-formal education or training activity	.001 (.000)		<.001

The explorative data analysis results based on the job occupations by Florida (2005) will now be expanded upon. With no apparent violations of the assumptions of the test being discovered, a linear regression was performed on the relationship between the proportion of creative jobs and the proportion of jobs at high risk of automation, both aggregated at the NUTS-2 level. The null-hypothesis is the following:

There is no correlation between the proportion of creative jobs and the proportion of jobs at high risk of automation in NUTS-2 regions in Germany.

Table 6 shows a statistically significant relationship with a p-value of <.001. Therefore, the null-hypothesis must be rejected. The Beta value determines that the relationship is moderately negative. In other words, an increase in the proportion of creative jobs leads to a decrease in the proportion of jobs at high risk of automation. Additionally, the R square value of .383 explains that 38.3 % of the variance in the proportion of jobs at high risk of automation is explained by the proportion of creative jobs for NUTS-2 regions in Germany. These results further conclude the arguments created in the explorative data analysis based on the paper from Florida (2005). The creative class is namely more resilient to automation developments as opposed to people in other occupations. Thereby, the creativity of jobs is a significant factor in the resilience of regions to the continuous developments in automation.

Table 6 – Regression of Proportion of Jobs at High Risk of Automation

Variable	R Square	B (Std. Error)	Beta	P-value
Proportion of Creative Jobs	.383	-1.733 (.005)	-.619	<.001
Constant = .579 N = 38				

Now, the impact of education level will be assessed in relation to the proportion of jobs at high risk of automation. With no apparent violations of the assumptions of the test being discovered, a linear regression was performed on the relationship between the proportion of higher educated people and the proportion of jobs at high risk of automation in NUTS-2 regions in Germany with the following null hypothesis.

There is no correlation between the proportion of higher educated people and the proportion of jobs at high risk of automation in NUTS-2 regions in Germany.

Table 7 shows that the proportion of higher educated people has a significant impact on the proportion of jobs at high risk of automation for NUTS-2 Regions in Germany (p <.001). Furthermore, there is a strong negative correlation between the two variables, indicated by the Beta of -.901. This is further confirmed with the standardized coefficient, which explains that with an increase the proportion of higher educated people in a region, the proportion of jobs at high risk of automation lowers (B = -.490). Given that education is part of human capital, these findings confirm the theories by Muro et al. (2019) on the role of human capital to regional resilience.

Table 7 – Regression of Proportion of Jobs at High Risk of Automation

Variable	R Square	B (Std. Error)	Beta	P-value
Proportion of Higher Educated	.811	-.490 (.000)	-.901	<.001
Constant	.493			
N = 38				

5. Conclusions

The development of technological advancements has been a keen interest in literature for almost a century. Keynes (1930) and Schumpeter (1942) warned about the speed of technological advancements way before the development of artificial intelligence, the internet of things, machine learning and big data. Due to the developments in these aspects, it is nowadays not just the low-skill, labour-intensive jobs that are at high risk for automation. More cognitive medium and high-skill jobs that involve complex decision-making processes are at risk of substitution (Marengo et al., 2019). Therefore, the fourth industrial revolution that society is undergoing will change the dynamics of the labour market significantly. There is plenty of literature on this topic already, however as Leigh and Kraft (2018) point out, limited knowledge is available on the spatially contingent implications of Industry 4.0. Therefore, this research attempted to broaden the understanding of the spatial component of automation development, by which policy-makers are no longer having to operate in a knowledge vacuum. This paper used the automation probabilities created by Frey and Osborne (2017), and applied the method by Crowley et al. (2021) to discover the relationship between the risk of job loss, creativity of jobs, education, and population density for regions in Germany. The explorative data analysis finds that the creative core and creative professional occupations, categorized by Florida (2005), which are more prevalent in densely populated areas, are more resilient towards automation impacts opposed to jobs that are situated in less densely populated areas. This finding is in line with previous studies by Frank et al. (2018), Crowley et al., (2019), who discover that areas with higher density and more creative workers are less susceptible to job loss as a consequence of automation developments, and the results from the explorative data analysis are confirmed in the statistical analysis. The statistical analysis finds a highly correlated relationship between the proportion of jobs at risk of automation and the population density for NUTS-2 regions in Germany. According to Frenken et al. (2018), regions that benefit from agglomeration effects have a more varied workforce. Therefore, in line with previous studies that used population density to capture agglomeration effects (Frank et al., 2018, Crowley et al., 2019, Muro et al., 2019), this findings from this research further conclude that regions with a more varied workforce are less susceptible to job loss as a result of automation developments. The statistical analysis, in accordance with Florida (2005) and Muro et al. (2019), further confirmed a significant relation between the proportion of creative jobs and higher educated people to the resilience of regions to automation.

Although, this study was performed at the regional level in Germany, it is likely that in many other European countries, the proportion of jobs at high risk of substitution due to automation will be more prevalent in less urban and less densely populated areas. Besides. this generalization has been confirmed with previous studies (Frank et al., 2018, Crowley et al., 2019, Muro et al., 2019). Taking into account the findings from this research, policymakers should consider the indifferences that will occur in the labour market between densely populated and less densely populated areas. Since the speed of technological advancement is only expected to grow even faster, policy should focus on preventing the increase of disparity between the urban and the rural by stimulating the local labour markets and investing in reeducation and retraining skills for the people in less densely populated regions. In line with the limitations that will be discussed in the following section, future research could analyse the relationship between risk of job loss and population density at a lower scale to allow policymakers to work in more detail.

5.1 Limitations

The methodology used in this research to capture the risk of people losing their jobs is based on a method developed by Frey and Osborne (2017). However, there is not one agreed upon methodology to capture the risk of workers losing their job. Several other methodologies exist that could create different outcomes. Therefore, the results of this research should always be interpreted with the methodology in mind. Originally, this study aimed to analyse the relationship between population density and risk of job loss at the NUTS-3 level for regions in Germany. However, issues with incomplete data shifted the scale of measure to NUTS-2 instead. Thereby, the n value dropped from over 300 to 38. While the minimum requirement of respondents for parametric tests is met, the power of the analysis drops, since the results describe the relationship in less detail.

References

Arntz, M., Gregory, T., Zierahn, U. (2016). *The risk of automation for jobs in OECD countries: A comparative analysis.*

Arrow, K. J. (1962). The economic implications of learning by doing. *The review of economic studies, 29*(3), 155-173.

Audretsch, D. (2018, October). Developing strategies for industrial transition. *Background paper for an OECD/EC Workshop on*, 15., 5-5.

Boschma, R. A., & Fritsch, M. (2009). Creative class and regional growth: Empirical evidence from seven European countries. *Economic geography*, *85*(4), 391-423.

Boschma, R. (2015). Towards an evolutionary perspective on regional resilience. *Regional studies*, *49*(5), 733-751.

Brynjolfsson, E., & McAfee, A. (2012). *Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy*. Brynjolfsson and McAfee.

Cilasun, S. M., Demir-Şeker, S., Dincer, N. N., & Tekin-Koru, A. (2018). Adult education as a stepping-stone to better jobs: an analysis of the adult education survey in Turkey. *Adult Education Quarterly*, 68(4), 316–346

Crowley, F., Doran, J., McCann, P. (2021). The vulnerability of European regional labour markets to job automation: the role of agglomeration externalities. *Regional Studies*, 55(3), 1-13.

Dijkstra, L., Poelman, H., & Rodríguez-Pose, A. (2020). The geography of EU discontent. *Regional Studies*, *54*(6), 737-753.

Florida, R., 2005. *Cities and the creative class*. Routledge.

Frank, M. R., Sun, L., Cebrian, M., Youn, H., & Rahwan, I. (2018). Small cities face greater impact from automation. *Journal of the Royal Society Interface*, *15*(139)

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional studies*, *41*(5), 685-697.

Frey, C. B. & Osborne, M. A. (2017). The future of jobs: How susceptible are jobs to computerisation. *Technological Forecasting and Social Change*, 114, 254-280.

Gates, B., Myhrvold, N., Rinearson, P., & Domonkos, D. (1995). The road ahead.

Keynes, J. M. (1930). *Economic possibilities for our grandchildren* (pp. 321-332). Palgrave Macmillan UK.

Koster, S. & Brunori, C. (2021). What to do when robots come? Non-formal education in jobs affected by automation. *International Journal of Manpower*, 42(8), 1397-1419.

Kraas F., Aggarwal S., Coy M., Mertins G. (2013) Megacities: our global urban future. Berlin, Germany: Springer Science & Business Media.

Marengo, L. (2019). Is this time different? A note on automation and labour in the fourth industrial revolution. *Journal of Industrial and Business Economics*, *46*(3), 323-331.

Marshall, A. (1920*). Principles of economics* (8th Ed.). Macmillan

LeGates, R. T., & Stout, F. (Eds.). (2020). *The city reader*. London: Routledge.

Leigh, N. G., & Kraft, B. R. (2018). Emerging robotic regions in the United States: insights for regional economic evolution. *Regional Studies*, *52*(6), 804-815.

Romer, P. M. (1986). Increasing returns and long-run growth. *Journal of political economy*, *94*(5), 1002-1037.

Rodríguez-Pose, A. (2018). The revenge of the places that don’t matter (and what to do about it). *Cambridge journal of regions, economy and society*, *11*(1), 189-209.

Schmidt, E., & Cohen, J. (2013). *The new digital age: Reshaping the future of people, nations and business*. Hachette UK.

Schumpeter, J.A. (1942). Capitalism, Socialism and Democracy

Appendix A – Risk of Job Loss Statistic Matched to ISCO 3-digit codes

ISCO 3 Digit Code	Occupation Description (ISCO8_3d)	Risk of Job Loss Probability Statistic
111	Legislators and Senior Officials	0.0886
112	Managing Directors and Chief Executives	0.0875
121	Business Services and Administration Managers	0.3066
122	Sales, Marketing and Development Managers	0.0193
131	Production Managers in Agriculture, Forestry and Fisheries	0.0470
132	Manufacturing, Mining, Construction and Distribution Managers	0.2353
133	Information and Communication Technology Services Managers	0.0350
134	Professional Services Managers	0.0690
141	Hotel and Restaurant Managers	0.0435
142	Retail and Wholesale Trade Managers	0.1600
143	Other Services Managers	0.1970
211	Physical and Earth Science Professionals	0.2251
212	Mathematicians, Actuaries, and Statisticians	0.1484
213	Life Science Professionals	0.0660
214	Engineering Professionals (excluding Electrotechnology)	0.0702
215	Electrotechnology Engineers	0.0988
216	Architects, Planners, Surveyors, and Designers	0.1787
221	Medical Doctors	0.0042
222	Nursing and Midwifery Professionals	0.0090
223	Traditional and Complementary Medicine Professionals	0.0200
224	Paramedical Practitioners	0.1400
225	Veterinarians	0.0380
226	Other Health Professionals	0.0288
231	University and Higher Education Teachers	0.0320
232	Vocational Education Teachers	0.1344
233	Secondary Education Teachers	0.0078
234	Primary School and Early Childhood Teachers	0.0830
235	Other Teaching Professionals	0.0700
241	Finance Professionals	0.7229
242	Administration Professionals	0.1729
243	Sales, Marketing, and Public Relations Professionals	0.1928
251	Software and Applications Developers and Analysts	0.1347
252	Database and Network Professionals	0.0300
261	Legal Professionals	0.2836
262	Librarians, Archivists, and Curators	0.4517
263	Social and Religious Professionals	0.0714
264	Authors, Journalists, and Linguists	0.2240
265	Creative and Performing Artists	0.1481
311	Physical and Engineering Science Technicians	0.4802
312	Mining, Manufacturing and Construction Supervisors	0.1187
313	Process Control Technicians	0.6821
314	Life Science Technicians and Related Associate Professionals	0.6150
315	Ship and Aircraft Controllers and Technicians	0.2561

321	Medical and Pharmaceutical Technicians	0.5037
322	Nursing and Midwifery Associate Professionals	0.0565
323	Traditional and Complementary Medicine Associate Professionals	0.0550
324	Veterinary Technicians and Assistants	0.4445
325	Other Health Associate Professionals	0.3397
331	Financial and Mathematical Associate Professionals	0.7278
332	Sales and Purchasing Agents and Brokers	0.5176
333	Business Services Agents	0.5184
334	Administrative and Specialized Secretaries	0.6757
335	Government Regulatory Associate Professionals	0.3379
341	Legal, Social, and Religious Associate Professionals	0.5843
342	Sports and Fitness Workers	0.2126
343	Artistic, Cultural, and Culinary Associate Professionals	0.4925
351	Information and Communications Technology Operations and User Support Technicians	0.5725
352	Telecommunications and Broadcasting Technicians	0.6400
411	General Office Clerks	0.9700
412	Secretaries (General)	0.9600
413	Keyboard Operators	0.9000
421	Tellers, Money Collectors, and Related Clerks	0.7450
422	Client Information Workers	0.6996
431	Numerical Clerks	0.9686
432	Material Recording and Transport Clerks	0.8820
441	Other Clerical Support Workers	0.8997
511	Travel Attendants, Conductors, and Guides	0.3689
512	Cooks	0.7320
513	Waiters and Bartenders	0.8567
514	Hairdressers, Beauticians and Related Workers	0.3569
515	Building and Housekeeping Supervisors	0.8467
516	Other Personal Services Workers	0.3714
521	Street and Market Salespersons	0.9133
522	Shop Salespersons	0.5850
523	Cashiers and Ticket Clerks	0.9000
524	Other Sales Workers	0.8039
531	Child Care Workers and Teachers’ Aides	0.2400
532	Personal Care Workers in Health Services	0.5073
541	Protective Services Workers	0.4027
611	Market Gardeners and Crop Growers	0.5920
612	Animal Producers	0.7450
613	Mixed Crop and Animal Producers	0.7450
621	Forestry and Related Workers	0.7920
622	Fishery Workers, Hunters and Trappers	0.7075
711	Building Frame and Related Trades Workers	0.7809
712	Building Finishers and Related Trades Workers	0.7324
713	Painters, Building Structure Cleaners and Related Trades Workers	0.8050
721	Sheet and Structural Metal Workers, Moulders and Welders, and Related Workers	0.7764
722	Blacksmiths, Toolmakers and Related Trades Workers	0.8500
723	Machinery Mechanics and Repairers	0.5946
731	Handicraft Worker	0.5901
732	Printing Trades Workers	0.7275
741	Electrical Equipment Installers and Repairers	0.5389
742	Electronics and Telecommunications Installers and Repairers	0.5597

751	Food Processing and Related Trades Workers	0.7731
752	Wood Treaters, Cabinet-makers and Related Trades Workers	0.8500
753	Garment and Related Trades Workers	0.6224
754	Other Craft and Related Workers	0.6071
811	Mining and Mineral Processing Plant Operators	0.7789
812	Metal Processing and Finishing Plant Operators	0.8800
813	Chemical and Photographic Products Plant and Machine Operators	0.8825
814	Rubber, Plastic and Paper Products Machine Operators	0.8737
815	Textile, Fur and Leather Products Machine Operators	0.8680
816	Food and Related Products Machine Operators	0.8160
817	Wood Processing and Papermaking Plant Operators	0.7800
818	Other Stationary Plant and Machine Operators	0.8700
821	Assemblers	0.8988
831	Locomotive Engine Drivers and Related Workers	0.6387
832	Car, Van and Motorcycle Drivers	0.5440
833	Heavy Truck and Bus Drivers	0.5447
834	Mobile Plant Operators	0.7313
835	Ships' Deck Crews and Related Workers	0.7250
911	Domestic, Hotel and Office Cleaners and Helpers	0.6025
912	Vehicle, Window, Laundry and Other Hand Cleaning Workers	0.6675
921	Agricultural, Forestry and Fishery Labourers	0.8900
931	Mining and Construction Labourers	0.7730
932	Manufacturing Labourers	0.7050
933	Transport and Storage Labourers	0.7272
941	Food Preparation Assistants	0.8600
952	Street Vendors (excluding Food)	0.9400
961	Refuse Workers	0.6297
962	Other Elementary Workers	0.8158

Appendix B: Proportion of Jobs at High Risk of Automation for NUTS-2 German Regions

Region Code	Name of Region (NUTS-2)	Proportion of Jobs at High Risk of Automation
DE11	Stuttgart	0.32
DE12	Karlsruhe	0.34
DE13	Freiburg	0.35
DE14	Tübingen	0.32
DE21	Oberbayern	0.29
DE22	Niederbayern	0.38
DE23	Oberpfalz	0.36
DE24	Oberfranken	0.34
DE25	Mittelfranken	0.33
DE26	Unterfranken	0.34
DE27	Schwaben	0.37
DE30	Berlin	0.24
DE40	Brandenburg	0.35
DE50	Bremen	0.33
DE60	Hamburg	0.26
DE71	Darmstadt	0.31
DE72	Gießen	0.33
DE73	Kassel	0.35
DE80	Mecklenburg-Vorpommern	0.33
DE91	Braunschweig	0.34
DE92	Hannover	0.32
DE93	Lüneburg	0.35
DE94	Weser-Ems	0.37
DEA1	Düsseldorf	0.32
DEA2	Köln	0.31
DEA3	Münster	0.34
DEA4	Detmold	0.36
DEA5	Arnsberg	0.36
DEB1	Koblenz	0.37
DEB2	Trier	0.38
DEB3	Rheinhessen-Pfalz	0.33
DEC0	Saarland	0.35
DED2	Dresden	0.33
DED4	Chemnitz	0.38
DED5	Leipzig	0.31
DEE0	Sachsen-Anhalt	0.37
DEF0	Schleswig-Holstein	0.34
DEG0	Thüringen	0.35