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AUTOMATION RISK OF JOBS FOR NUTS II AND NUTS III REGIONS IN TÜRKİYE*

TÜRKİYE'DE DÜZEY 2 VE DÜZEY 3 BÖLGELERİ İÇİN İŞLERİN OTOMASYON RİSKİ

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Abstract

The impact of digitalization varies across countries, while subregions within countries are also affected by this process at different levels. Especially for countries aiming to reduce regional disparities, it's essential to assess the regional consequences of digitalization. Despite a growing body of literature on digitalization and its impact on the labour market, there is limited consideration of automation risk at the local level. This paper contributes to the field of regional studies by examining spatial variations in the effects of automation in Türkiye. It potentially offers insights for crafting localized interventions that can address the unique needs of different regions. By deploying the automation risk methodology developed by Frey and Osborne, automation risks are calculated for NUTS II and NUTS III regions and to determine the impact of digital technologies on the regional labour market. The primary finding reveals that 54 percent of employees in Türkiye are at high risk of job displacement due to digital transformation. Additionally, regions and cities with a strong focus on the manufacturing sector face above-average automation risks. This underscores the need for tailored, localized national policies instead of one-size-fits-all approach, emphasizing a bottom-up, place-based strategy.

Keywords: Automation of Jobs, Digitization, Automation Risk in Regions, Digital Transformation

Öz

Dijitalleşmenin etkisi ülkeler arasında farklılaşmakta, diğer yandan ülkelerin kendi sınırları dahilinde olan bölgeler de bu süreçten farklı düzeyde etkilenmektedir. Özellikle bölgesel eşitsizlikleri azaltmayı hedefleyen ülkeler için dijitalleşmenin bölgesel sonuçlarının değerlendirilmesi çok önemlidir. Dijitalleşme ve bunun iş gücü piyasası üzerindeki etkisi konusunda giderek gelişen bir literatür olmasına rağmen, yerel düzeyde otomasyon riskine ilişkin değerlendirmeler sınırlıdır. Bu makale, Türkiye'de otomasyon etkisinin mekansal farklılıklarını inceleyerek bölgesel çalışmalar alanına katkıda bulunmaktadır. Farklı bölgelerin kendine özgü ihtiyaçlarına cevap verebilecek mekana özgü müdahalelerin hazırlanmasına yönelik iç görüler sunmaktadır. Frey ve Osborne tarafından geliştirilen otomasyon riski metodolojisi kullanılarak, İBBS Düzey 2 ve Düzey 3 bölgeleri için otomasyon riskleri hesaplanmış ve dijital teknolojilerin bölgesel iş gücü piyasasına etkisi belirlenmiştir. Temel bulgu, Türkiye'deki çalışanların yüzde 54'ünün dijital dönüşüm nedeniyle işlerinden olma riskinin yüksek olduğunu ortaya koymaktadır. Buna ek olarak, imalat sektörünün baskın olduğu bölge ve şehirlerin otomasyon riskinin, Türkiye ortalamasının üstünde olduğu görülmektedir. Bu durum, tüm bölgelere uyan tek bir yaklaşım yerine, aşağıdan yukarıya, mekan bazlı bir stratejiyi vurgulayan; özel, yerelleştirilmiş ulusal politikalara duyulan ihtiyacın altını çizmektedir.

Anahtar kelimeler: İşlerin Otomasyonu, Dijitalleşme, Bölgesel Otomasyon Riski, Dijital Dönüşüm

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Introduction

Since the Industrial Revolution, increases in productivity have been driven by scientific and technological developments. Widely well-known economics theorists such as Schumpeter (1942) and Romer (1990) have shown that technological improvements are almost the primary driver of economic growth. Therefore, there is a broad consideration that technological improvements are key to productivity growth which, in turn, increase incomes and well-being.

Actually, technology so far has been recognized as the primary source of economic wealth; however, it has also caused anxiety throughout history (Mokyr et al., 2015). The effect of technological change on the labour market, in particular, is a controversial issue. Concerns about the adverse impact of new technologies on jobs and labour market are not a recent phenomenon, dating back at least to the Luddites movement at the advent of the Industrial Revolution. Nevertheless, technological progress in the late 20th century and today differs significantly from those experienced in the 19th and early 20th centuries. In the 19th century, because the newly created tasks required no skill, emerging industrial production provided vast employment opportunities for large numbers of people. At the beginning of 20th century, often referred as Fordist era, adaptation of the assembly line allowed work to be divided into parts, each of which could be done by massive low-skilled workers in a few hours. Fordist era created rapid growth and vast employment opportunities, accompanied by increasing real wages in entirely new occupations and industries. In fact, technological developments had no effect on reducing the labour share in total valued-added in the 1970s; on the contrary, real wages increased faster than in the following decades. However, the reverse effect of technological development on the labour share increased in the 1980s and 1990s (Autor and Salomons, 2018). During the 1980s, technological advancements resulted in a reduction in the costs of physical capital goods, making it easier for firms to substitute labour with physical capital. This led to a decrease in the labour share of national income (Karabarbounis and Neiman, 2014).

Literature in this area shows that, in the late 20th century, the reduction in the cost of physical capital and growing prevalence of technology-driven production processes have resulted in an increased demand for highly skilled labour. This phenomenon is often described as polarization, characterized by increased concentration of employment in high paying and high-skilled occupations and in lower paying low-skilled jobs (Acemoglu and Autor, 2010: 1071; Autor and Dorn, 2013; Goos et al., 2014; Michaelset al., 2014; Graetz and Michaels, 2018). This phenomenon, during the 2000s, has become even more visible in many countries. Over the past three decades, there has been a notable and pronounced decrease in labour shares, primarily attributed to technological advancements and global integration. This decline has been particularly sharp for middle-skilled labour which in turn, contributed to a polarization of jobs, with an increasing concentration in high-skilled and low-skilled occupations. (Dao et al., 2017: 36-38).

As Keynes noted very long ago, the increase of technical efficiency takes place faster than we can deal with the problem of labour absorption (Keynes, 1933). The skill requirements of jobs eliminated by digitalization do not perfectly align with the skill requirements of the newly created positions. Hence, automation has the potential to cause short-term rises in unemployment, with the possibility of these effects lasting for an extended period. According to a report by the Organisation for Economic Cooperation and Development (OECD), 14 percent of jobs are at high risk of automation due to the digital transformation (OECD, 2018a: 47). World Development Report indicates that around two-thirds of all jobs in the developing world are at risk of automation (WB, 2016: 126-129).

Technological progress also has a place-based dimension. It causes permanent gains or losses for some groups of workers and regional economies. Within the same country, disparities across local labour markets are increasing because of uneven impact of these trends on places. Certain regions can harness the benefits of new technologies and enhanced integration into global markets, thereby these regions are attracting both firms and workers. However other regions may encounter difficulties in achieving growth in the digital age (OECD, 2018b: 26-29).

Due to the differentiation of the regions' economic and social structure, digital infrastructure, and human capital, space becomes an important factor of difference in impact of digitalization. While technological advances reveal economic and social opportunities, they may also cause a digital divide for some regions (OECD, 2018b: 40).

Therefore, it is crucial to measure the regional effect of the digitalization on the labour market for the countries struggling with regional disparities. Conceiving policies and practices to make regional and local economies resilient and prepared against the destructive effects of the digitalization process can enable regions to turn the tools offered by digitalization into regional development opportunities.

Having this approach, this paper aims to make contribution to the field of regional studies. The first section of this paper starts with a literature review on the possible effects of automation on labour and countries. The following section explains the methodology based on study of Carl Benedikt Frey and Michael A. Osborne (2013: 40), *"The Future of Employment: How Susceptible Are Jobs to Computerization?"*. Deploying their methodology, share of employees in high risk occupations are determined by national and regional level. Finally, conclusion section summarizes findings, and then, emphasizes the importance of policies making regions adapt to digital transformation inclusively and having the approach leaving no region behind.

1. Literature Review

Automation risk generally refers to the possibility that existing jobs can be performed by technologies when conditions are suitable. These conditions include the presence of necessary data for these technologies, affordability and accessibility of the technology, and a cultural and political climate that supports such changes. Automation risk is a term applicable to both occupations and jobs. It refers to the likelihood of an occupation being performed by technology. The automation risk of occupations refers to how likely they are to be affected by technological advancements, while the automation risk for jobs indicates the proportion of workers employed in high-risk occupations compared to the total workforce.

There is a large body of literature on the impact of technological change on labour, such as employment, wages or productivity. However, this section presents literature on how technological change has an impact on tasks or occupations.

Indeed, the prevailing consensus in the existing literature was that technology primarily had a more substantial impact on manual labour tasks than the cognitive tasks. Because manual tasks are done by low-skilled labour and do not need high level of education. In contrast, cognitive tasks are more knowledge-intensive and require higher educational levels and sophisticated competencies.

However, technological transformation has impact on both high-skilled and low-skilled jobs. Technologies tend to play a complementary role in high-skilled jobs, whereas they have a substitution feature in low-skilled jobs. This phenomenon is called *Skill-Biased Technological Change* (SBTC). But later, in their work Autor, Levy, and Murnane (2003) suggested *Routine Biased Technological Change* (RBTC) which slightly differs than SBTC. The idea of RBTC is that technological developments replace labour performing routine, repetitive tasks.

The most commonly referenced initial source regarding the impact of technology on tasks is the work of Autor, Levy, and Murnane. They analysed how computerization changes job skill demands in their work which is later referred as ALM model (Autor et al., 2003). They argued that many manual human tasks can be expressed by computer codes or done by machines. However, they faced some problem with this approach. For example, picking an apple from a bowl of fruit or moving across an uneven surface is also manual tasks. But it is difficult to develop machines carrying out these tasks. To address this issue, they employed a two-by-two matrix to categorize workplace tasks. One axis distinguished between routine and non-routine tasks, while the other axis distinguished between manual and cognitive tasks (see Figure 1). Routine tasks are those that follow explicit rules and can be executed by machines. Non-routine tasks, on the other hand, are not fully understood sufficiently to be programmed into computer code. Furthermore, each of these task categories can be either manual or cognitive in nature (Autor et al., 2003). Manual tasks involve physical labour while cognitive tasks involve knowledge-intensive work.

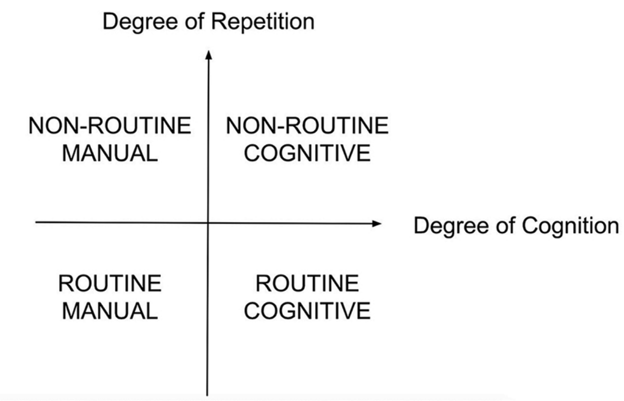


Figure 1: Categorization of Labour Based on Degree of Cognition and Repetition (Source: Autor et al., 2003)

Using data on task input for the years from 1960 to 1998, they concluded that computerization reduces labour input of routine manual and routine cognitive tasks and increases labour input of non-routine cognitive tasks (Autor et al., 2003). This finding indicates that non-routine tasks cannot be substituted by machines; rather, they can be complemented by machines or computers, regardless of whether they are manual or cognitive. According to their study, computers performs tasks that can be expressed rule-based logic: if-then-do statements. As a result, computers have substitutive features for workers in performing routine cognitive and routine manual tasks, but it is complementary for workers in performing non-routine problem solving, creative and complex communication tasks. Therefore, ALM introduced the *Routine Biased Technological Change* (RBTC) approach for the first time (Autor et al., 2003).

However, ALM's categorization of tasks is not completely valid in today new economic circumstances. Historically, computerization has primarily been limited to manual and cognitive routine tasks. However, as Brynjolfsson and McAfee (2011: 19-20) pointed out in their book that recent technological progress and accessibility of big data have enabled computers to execute tasks traditionally classified as non-routine (Brynjolfsson and McAfee, 2011: 19-20).

In a similar approach, Carl Benedikt Frey and Michael A. Osborne (2013: 22) explained in their widely cited study in this field, that computerization is no longer confined to routine manufacturing tasks (Frey and Osborne, 2013: 22). Because, recent progress in Machine Learning (ML) and Mobile Robotics (MR), driven by the availability of big data, has broadened the applicability of computerization to include a wide range of non-routine cognitive tasks. This expansion covers any non-routine task that is not constrained by engineering obstacles (Frey and Osborne, 2013: 18).

In order to assess the potential effects of future computerization on the United States (US) labour market, they employed a methodology that involved estimating the probability of computerization for 702 occupations using ML techniques. Their key assumption is that, due to current engineering bottlenecks, some occupations will not be easy to be computerized (Frey and Osborne, 2013: 26). Firstly, jobs that involve tasks related to perception and manipulation, especially when they require working in unstructured environments or confined spaces, are often considered less prone to automation. Secondly, occupations that require creativity, such as artistic activities or the generation of original ideas, are typically less susceptible to automation. Finally, tasks that depend on social intelligence, including roles that involve persuasion, negotiation, project management, or providing care for others, are generally less automatable (Frey and Osborne, 2013: 27-30). Then, they proceeded to assess the likelihood of jobs being susceptible to computerization by considering the task characteristics described above that are not prone to automation. Frey and Osborne identified that 47 percent of jobs in the US are susceptible to automation (Frey and Osborne, 2013: 41).

In 2016, Arntz, Zierahn, and Gregory (2016: 21-15) highlight that not entire jobs but certain tasks within jobs can be displaced by machines. According to the study, even if an occupation undergoes to automation, it still includes tasks that cannot be automated. According to the study, if there are many tasks in an occupation that can be automated, the likelihood of that occupation's automation is high; if there are few tasks that can be automated, the likelihood of automation is low. Arntz, Zierahn, and Gregory, using a task-based approach and building upon Frey and Osborne's method, re-evaluated the automation risk of occupations by considering the relationship between tasks and automation. In the prediction made by Arntz, Zierahn, and Gregory for 21 OECD member countries, the share of workers in occupations with a high probability of automation is calculated as 9 percent of the total workforce (Arntz et al., 2016: 8). Their research indicates that jobs requiring high education, collaboration with other workers, and spending time to influence others, or involving face-to-face interactions are less likely to be automated (Arntz et al., 2016: 19).

According to the study for European Union (EU) countries by Konstantinos Pouliakas (2018: 24), occupations with a low-skill level, such as machine operators, have a very high risk of automation, whereas professions in social and personal services, education, health services, and the cultural sector show a low risk of automation (Pouliakas, 2018: 24). Jobs with precarious conditions, temporary characteristics, and low wage levels are found to have a higher risk of automation. Study estimates that 14 percent of the total workforce in EU countries is employed in jobs with a high risk of automation. Additionally, 40 percent of jobs fall into the probability range of 50-70 percent for automation (Pouliakas, 2018: 18).

In 2018, another OECD study utilizing data for 32 countries, was conducted by Nedelkoska and Quintini (2018: 47-49). According to their predictions on the likelihood of jobs being automated by artificial intelligence and robots, the overall employment rate for occupations classified in the high-risk category was estimated to be 14 percent for the OECD average (Nedelkoska and Quintini, 2018: 47). According to their prediction, occupations in the low-skill category with the highest risk of automation include food preparation assistants, assemblers, cleaners, and assistants. Another occupational group with a high risk of automation includes those who have received at least some education but are required to work with machines, especially in the manufacturing sector. This group encompasses occupations such as fixed plant and machine operators, drivers, and mobile machine operators (Nedelkoska and Quintini, 2018: 49).

Some studies argue that regardless of whether automation risk is task-based or job-based, there are regional differences in any case. The OECD study stands out as a significant example in this context. According to its findings, the influence of automation on employment will differ significantly across OECD regions and localities. The geographical dispersion of occupations facing high automation risk exhibits a nine-fold difference across regions in 21 OECD countries (OECD, 2018b: 26).

Another example of regional approach is adopted by Crowley and Doran from the Spatial and Regional Economics Research Centre, University College Cork. By deploying Frey and Osborne automation risks to towns of Ireland, Crowley and Doran analyse the percentage of jobs susceptible to automation across 200 towns in Ireland. They aimed to uncover regional disparities in the spatial distribution of job automation risk. Their findings indicate that variations in automation risk are primarily influenced by differences in population, education levels, age demographics, the proportion of creative occupations within each town, town size, and variations in industry types across towns (Crowley and Doran, 2019: 25).

2. Automation Risk of Jobs for NUTS II and NUTS III Regions in Türkiye

In order to reveal the spatial variations in the effects of automation across regions, this study employs the automation risk methodology developed by Frey and Osborne. Automation risks are calculated for

Türkiye's NUTS II and NUTS III regions[2] to estimate the impact of digital technologies on the labour market.

First of all, the automation risk of jobs is determined at the national level. Then, the automation risk is determined in 26 NUTS II regions and 81 NUTS III regions (provinces). Next, the study evaluates what types of features are most associated with the job's automation to see if the regions have spatial characteristics.

2.1. Data and Methodology

The automation risk of occupations refers to their susceptibility to technological transformations, while the automation risk for jobs reveals the percentage of employees working in high-risk occupations relative to the overall employment. For example, if a job market employs 10 million people and 2 million of them are in occupations deemed highly susceptible to automation, the automation risk for jobs in that market would be 20 percent.

Automation risks of occupations are calculated for NUTS II and NUTS III regions by deploying the automation risk methodology developed by Frey and Osborne from Oxford University. They estimated 702 occupations in Standard Occupational Classification (SOC) 2010. SOC 2010 is an occupational classification system in the USA. The automation risk of each of 702 occupations in the SOC 2010 occupational classification was calculated by using the Machine Learning by them (Frey and Osborne, 2013: 30-39). Then, the number of employees under these occupations are calculated. Figure 2 illustrates Frey and Osborne's model's estimates predicting the probability of automation for occupations, categorizing them into low, medium, and high-risk levels, and infers that around 47 percent of all jobs in the USA are potentially automatable over the years (Frey and Osborne, 2013: 41).

2 Türkiye is statistically divided into 12 NUTS I; 26 NUTS II and 81 NUTS III levels, NUTS is abbreviation of *Nomenclature des Unités Territoriales Statistiques* in French. In this paper, regions and provinces correspond to NUTS II and NUTS III level, respectively. NUTS III Regions are 81 provinces of Türkiye.

NUTS II Regions are listed as follows:

TR10 NUTS II Region (İstanbul)
TR21 NUTS II Region (Tekirdağ, Edirne, Kırklareli)
TR22 NUTS II Region (Balıkesir, Çanakkale)
TR31 NUTS II Region (İzmir)
TR32 NUTS II Region (Aydın, Denizli, Muğla)
TR33 NUTS II Region (Manisa, Afyonkarahisar, Kütahya, Uşak)
TR41 NUTS II Region (Bursa, Eskişehir, Bilecik)
TR42 NUTS II Region (Kocaeli, Sakarya, Düzce, Bolu, Yalova)
TR51 NUTS II Region (Ankara)
TR52 NUTS II Region (Konya, Karaman)
TR61 NUTS II Region (Antalya, Isparta, Burdur)
TR62 NUTS II Region (Adana, Mersin)
TR63 NUTS II Region (Hatay, Kahramanmaraş, Osmaniye)
TR71 NUTS II Region (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir)
TR72 NUTS II Region (Kayseri, Sivas, Yozgat)
TR81 NUTS II Region (Zonguldak, Karabük, Bartın)
TR82 NUTS II Region (Kastamonu, Çankırı, Sinop)
TR83 NUTS II Region (Samsun, Tokat, Çorum, Amasya)
TR90 NUTS II Region (Trabzon, Ordu, Giresun, Rize, Artvin, Gümüşhane)
TRA1 NUTS II Region (Erzurum, Erzincan, Bayburt)
TRA2 NUTS II Region (Ağrı, Kars, Iğdır, Ardahan)
TRB1 NUTS II Region (Malatya, Elazığ, Bingöl, Tunceli)
TRB2 NUTS II Region (Van, Muş, Bitlis, Hakkari)
TRC1 NUTS II Region (Gaziantep, Adıyaman, Kilis)
TRC2 NUTS II Region (Şanlıurfa, Diyarbakır)
TRC3 NUTS II Region (Mardin, Batman, Şırnak, Siirt)

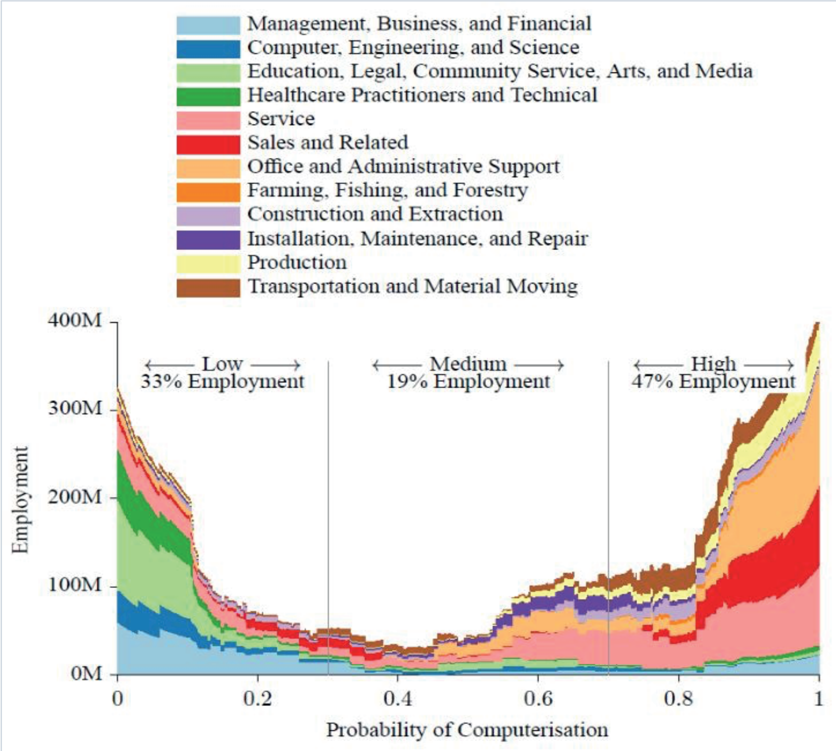


Figure 2: US Employment by Risk Category
(Source: Frey and Osborne, 2013: 40)

With a similar method, the automation risk of occupations and the employment share in these occupations are calculated for Türkiye. Additionally, these calculations are done for NUTS II and NUTS III levels. Spatial analysis of Türkiye's automation risk is carried out with the help of labour data received from the Entrepreneur Information System Database (EIS) at Republic of Türkiye, Ministry of Industry and Technology.

For this purpose, firstly, automation risk of occupations should be determined. After that, share of employee in these occupations can be calculated easily. Automation risk of occupations is determined by using the calculations made by Frey and Osborne in their essay. They determined the automation risk for occupations in SOC system. However, in Türkiye, the International Standard Classification of Occupations 2008 (ISCO-08) system is officially adopted for defining, categorizing, and providing information on the structure of occupations. To determine the automation risks for 433 different occupations according to ISCO-08, the 6-digit SOC 2010 codes must be matched with the 4-digit occupation codes in the ISCO-08 classification. This matching process is necessary because automation risk of occupations calculated by Frey Osborne are only available in SOC system. Therefore, correspondence tables published by the US Bureau of Labour Statistics are used for conversion (US Bureau of Labor Statistics, 2024).

However, in the conversion from SOC 2010 to ISCO-08, some occupations do not match exactly, or there may be more than one occupation code in the same group in the SOC 2010 for an occupation in ISCO-08. For example, 2120 Mathematicians, Actuaries and Statisticians coded in ISCO-08 match five different professions in the SOC 2010. Mathematicians, Actuaries and Statisticians occupations in ISCO-08 match with 19-3022 Survey Researchers, 15-2041 Statisticians, 15-2011 Actuaries, 15-2021 Mathematicians, 15-2031 Operations Research Analysts. Therefore, the automation risk for 2120 Mathematicians, Actuaries and Statisticians coded in ISCO-08 is determined as the average of the automation risks of these five SOC 2010 occupations. A sample calculation of this conversion is given in Table 1.

Table 1: Sample Calculation for ISCO-08 Occupations Conversion (Source: Compiled by the author using microdata obtained from the EIS.)

SOC 2010 Code	SOC 2010 Title	F&O Automation Risk	ISCO Code	ISCO-08 Title	Calculated Automation Risk
19-3022	Survey Researchers	0.23	2120	Mathematicians, actuaries and statisticians	0.15
15-2041	Statisticians	0.22	2120	Mathematicians, actuaries and statisticians	
15-2011	Actuaries	0.21	2120	Mathematicians, actuaries and statisticians	
15-2021	Mathematicians	0.047	2120	Mathematicians, actuaries and statisticians	
15-2031	Operations Research Analysts	0.035	2120	Mathematicians, actuaries and statisticians	

Another limitation of the study is the lack of automation risk for 15 occupations in SOC 2010. To overcome this limitation, the following approach has been taken: In occupational classifications, according to ISCO-08, occupations are classified based on the required skills, level of expertise, and tasks involved in performing a job. A group of jobs with largely similar duties and responsibilities form an occupational group. Accordingly, ISCO-08 consists of 10 occupational groups coded with numbers from 0 to 9. These 10 occupational groups are main categories and they are further divided into subgroups and 433 occupational units (ILO, 2012).

So, if the automation risk of occupation in the 4th digit is not available, the average automation risk value of the occupational group in the 3rd digit is taken. In another saying, average value of the occupation risk in 3rd digit is assigned as the value. For instance, from the Frey and Osborne calculation, the automation risk for occupational codes 1112, 1113, and 1114 can be determined with the help of corresponding tables. But automation risk value is not available for code 1111 Legislators in their work. Since these four codes belong to the same occupational group, the automation risk for code 1111 was determined by averaging the risks of the other three codes. Another 15 occupations in ISCO-08 having same situation with 1111 Legislators have not automation risk value. Using this method, the automation risk for another 15 occupational codes[3] is calculated. A sample calculation for those the automation risk value is not given is provided in Table 2.

3 Other professions for which automation risk value is not given and whose value is determined by average of same occupational groups are:

2222 Midwifery professionals
2513 Web and multimedia developers
2523 Computer network professionals
2659 Creative and performing artists not elsewhere classified
3253 Community health workers
3413 Religious associate professionals
4213 Pawnbrokers and money-lenders
5161 Astrologers, fortune-tellers and related workers
7133 Building structure cleaners
8155 Fur and leather preparing machine operators
8159 Textile, fur and leather products machine operators not elsewhere classified
9332 Drivers of animal-drawn vehicles and machinery
9510 Street and related service workers
9613 Sweepers and related labourers

Table 2: Assigning Automation Risk Values for Empty Fields (Source: Compiled by the author using microdata obtained from the EIS.)

111	Legislators and Senior Government Officials	Calculated Automation Risk
1111	Legislators*	0.07
1112	Senior government officials	0.06
1113	Traditional chiefs and heads of villages	0.02
1114	Senior officials of special-interest organizations	0.14

*The "Legislators" occupation (1111 in ISCO) is highlighted in red to indicate that its the calculation by the author, based on the other occupations' risks.

Thus, the automation risk of 433 occupation in the ISCO-08 has been identified. Occupations that have 70 percent or higher probability of being done by machines are considered as high risk. This means that the jobs performing these occupations can be substituted by technologies. Occupations that have between 70 percent and 30 percent probability are considered medium, and occupations having 30 percent or lower probability are considered as low risk.

After finding the probability of automation in occupations, the next step is to determine the number of employees working in these occupations. Once the probability of automation in various occupations has been determined, the next step is to ascertain the number of employees within those occupations. And finally, the distribution of jobs at risk of automation across the 26 regions and 81 provinces are calculated. Microdata from the EIS database at Ministry of Industry and Technology is used to reveal the distribution of jobs impacted by automation. The Turkish labour force's microdata ISCO-08 system for the year 2019 is obtained from the EIS database (Ministry of Industry and Technology, 2019). The data include only contract workers with a 4a status, excluding public officials or self-employees. These data are sourced from administrative records provided by the Social Security Institution and the Turkish Revenue Administration. The reason selecting the year of 2019 is that exploring the distortions data in the periods after the COVID 19.

2.2. Results

It is found that 39.7 percent of the 433 occupations have an automation probability of 70 percent or higher. Another saying, 39.7 percent of the 433 occupations are easily substituted by technologies, while 33.7 percentage of occupations fall into the safe area. Left graph in the Figure 3 demonstrates the distribution of risk by occupations.

When analysing the employment numbers in these occupations, as depicted in the right graph of Figure 3, it is concluded that 54 percent of jobs in Türkiye are easily substitutable by technologies. In other words, 54 percent of total employment is in occupations with high automation risk. Jobs in the moderate risk category account for 30 percent, while those in the low-risk category make up 16 percent. Figure 3 illustrates the distribution of highly automatable occupations and their corresponding share of employment.

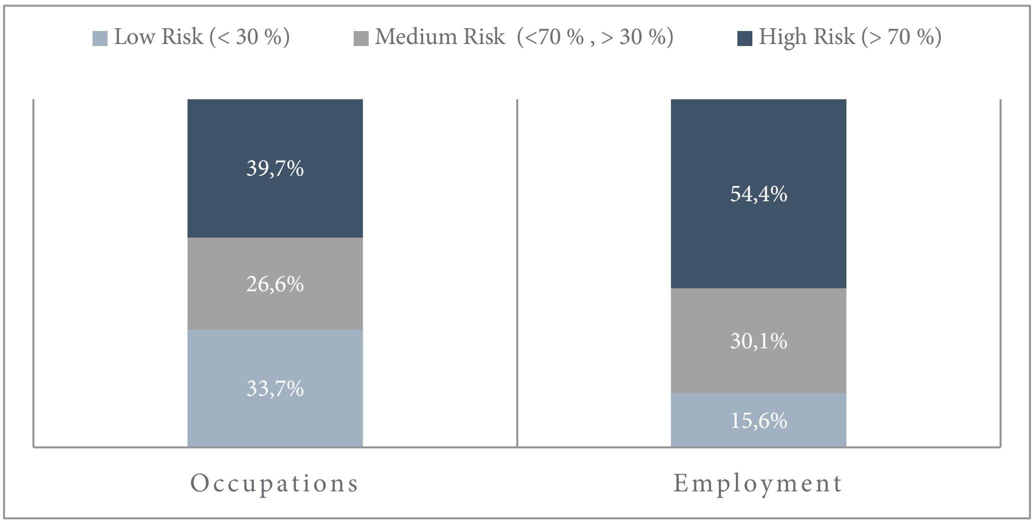


Figure 3: Distribution of Automation Risk by Occupation and Employment
(Source: Calculated by the author using microdata obtained from the EIS.)

Data entry clerks, accountants, assemblers, machine operators, those working in agriculture, forestry, fishing and construction sectors, office clerks, receptionists, cashiers, and ticket agents have high automation risks. The automation risks of these occupations can be found in Annex 1.

The occupational groups coded 1, 2, and 3 are considered high-skill by the ILO; groups coded 4, 5, 6, 7, and 8 are considered middle-skill, while group 9 is considered low-skill (ILO, 2012). When we examining automation risk based on skill levels, it is observed that occupations with high skill levels do not face high automation risk. On the other hand, the highest automation risk is observed in occupations with middle-skilled levels. Figure 4 is presenting automation risk according to skill level. It can be concluded from Figure 4 that middle-skilled jobs are more susceptible to automation.

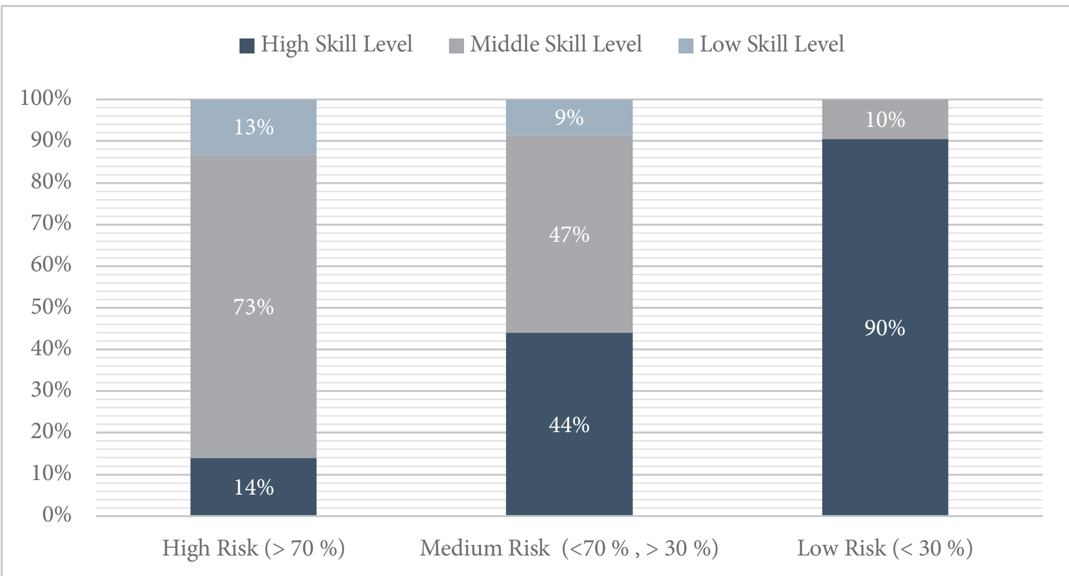


Figure 4: Automations Risk by Skill Level in Türkiye
(Source: Calculated by the author using microdata obtained from the EIS.)

The high risk of automation in middle-skilled occupations can have serious consequences due to the majority of the workforce being employed in these occupations. According to Turkish Statistical Institute's labour force statistics, for the third quarter of 2023, the employment rate in middle-skilled occupations stands at 60 percent. This number corresponds 65 percent in 2014, indicating a declining trend in middle-skilled occupations between 2014-2023 (TURKSTAT, 2019). Therefore, the issue of polarization in the labour market may intensify in the near future due to ongoing technological advancements. Further studies are needed to clarify and understand the full impact of this trend.

However, it is important to note here that the most significant feature of digital transformation is not only its impact on low-skilled jobs. Figure 5 below provides the share of employees in occupation by their risk in one digit. As can be seen from the Figure 5, except 1 coded and 9 coded occupations, all occupations have high, medium and low automation risk. According to the ILO, as classified before, 1, 2, 3 coded occupations are high skill level, 4, 5, 6, 7, and 8 coded occupations are middle-skill level, and 9 is lower skill. There are no high-risk jobs in 1-Managerial Occupations, and there are no low-risk occupations in 7-Craft and Related Trades Workers, 8-Plant and Machine Operators, and Assemblers, and 9-Elementary Occupations. Additionally, there are no medium risk occupations in 6-Skilled Agricultural, Forestry and Fishery Workers. Figure 5 presents that almost 30 percent of employees working in 9-Elementary Occupations are in the high-risk group, 70 percent of employees are in medium risk.

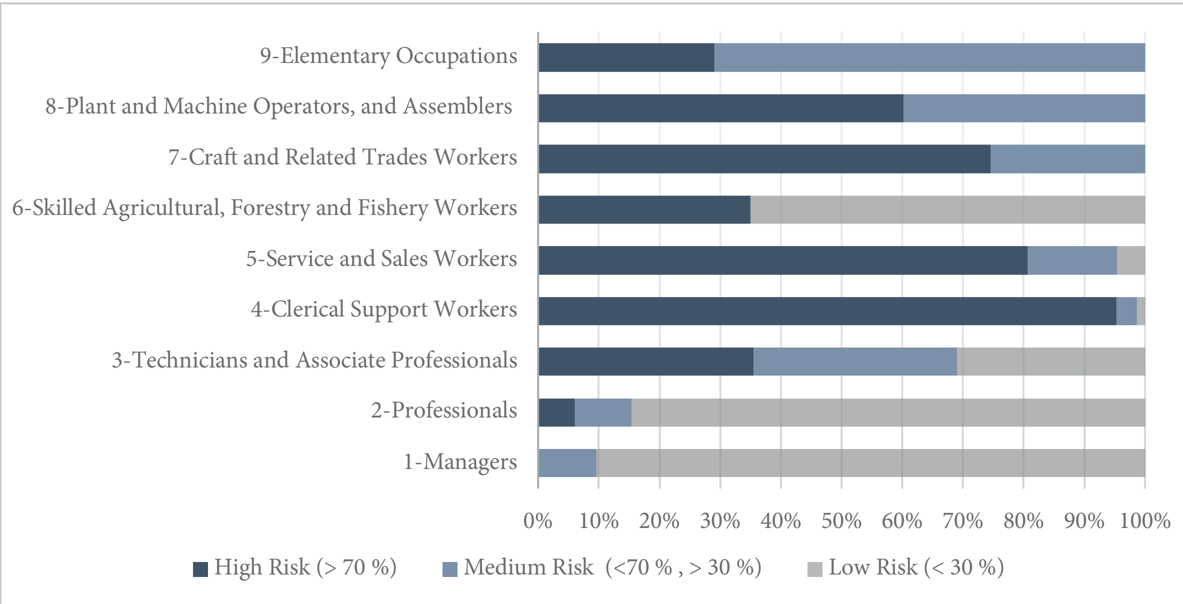


Figure 5: Share of Employees in Occupation by Automation Risk in Türkiye
(Source: Calculated by the author using microdata obtained from the EIS.)

According to the analysis based on the NUTS II region, the region with the highest proportion of employees doing jobs likely to be replaced by digital technologies is TR41 NUTS II Region (Bursa, Eskişehir, Bilecik) with 62 percent. The other five regions where automation risk is highest, respectively, are TRC1 NUTS II Region (Gaziantep, Adıyaman, Kilis) with 58 percent, TR21 NUTS II Region (Tekirdağ, Edirne, Kırklareli) with 58 percent, TR32 NUTS II Region (Aydın, Muğla, Denizli) with 58 percent, TR82 NUTS II Region (Kastamonu, Sinop, Çankırı) with 57 percent and TR52 NUTS II Region (Konya, Karaman) with 56 percent. Figure 6 provides the regional results of automation impact by NUTS II.

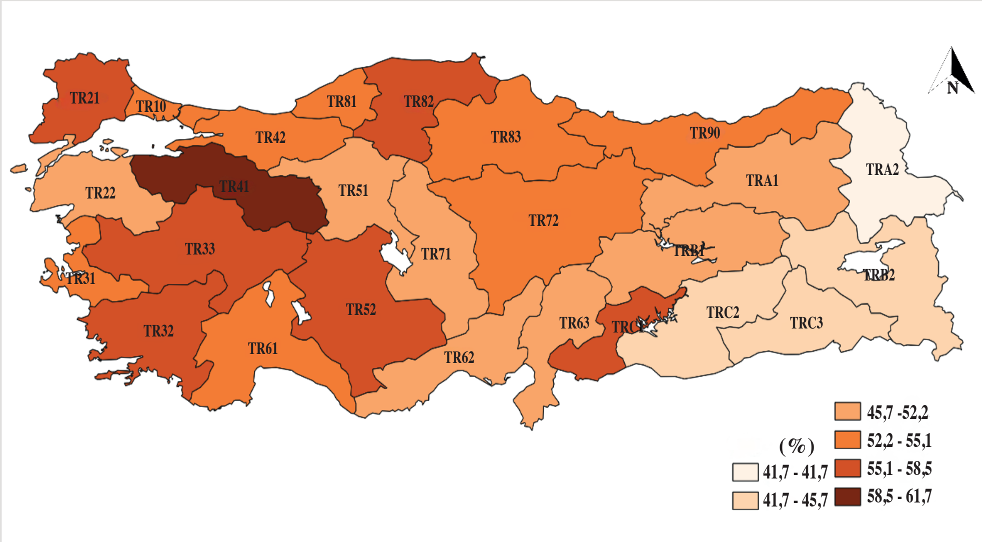


Figure 6: Distribution of High-Risk Jobs by NUTS II
(Source: Calculated by the author using microdata obtained from the EIS.)

Furthermore, Figure 7 provides a detailed breakdown of the automation impact on labour by provinces. According to Figure 7, the top five provinces with high automation risk are Karaman with 65 percent, Bursa with 63 percent, Uşak with 62 percent, Denizli with 62 percent, and Bolu with 61 percent. The automation risks of jobs by NUTS III and NUTS II regions can be found in Annex 2 and Annex 3, respectively.

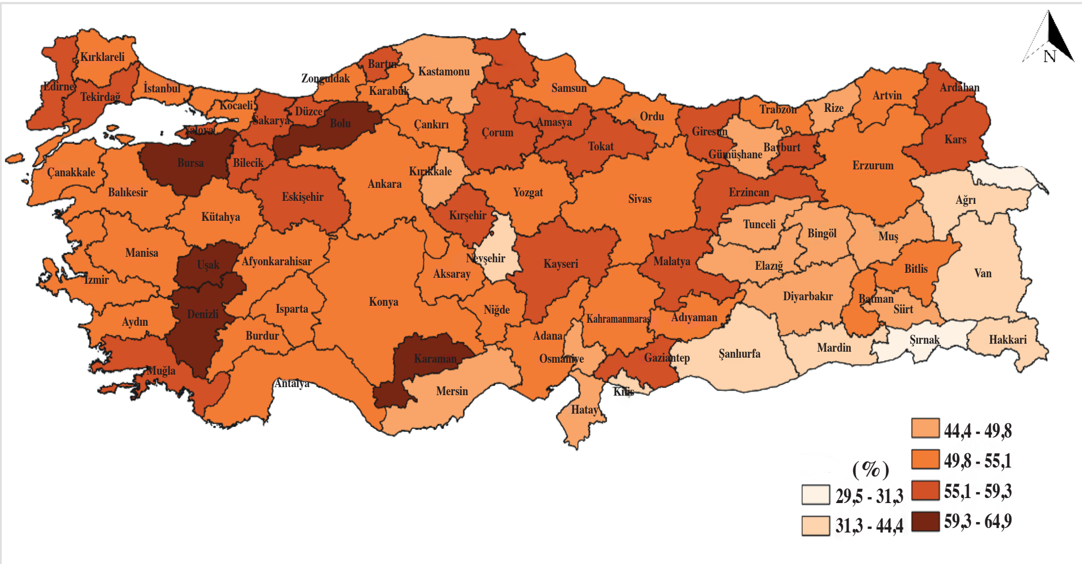
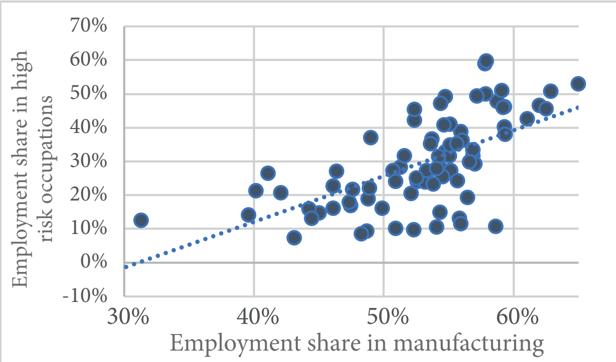


Figure 7: Distribution of High-Risk Jobs by NUTS III
(Source: Calculated by the author using microdata obtained from the EIS.)

It is observed that the economic activities of regions characterized by a strong presence of manufacturing employment have a high proportion of employees who are likely to be replaced by technology. In Figure 8, correlation coefficient of 65 percent between the number of employees in the manufacturing sector and automation risk at the provincial level indicates a moderate positive correlation. Similarly, a correlation coefficient of 69 percent at the regional level indicates a strong positive correlation. The blue dots on the graph represent NUTS II and NUTS III regions. This suggests that as the number of employees in the manufacturing sector increases, there is a tendency for automation risk to increase as well. On the other hand, Table 3 presents data on regional distribution of employees in high-risk occupations and the share of manufacturing employees in the top five and bottom five provinces and regions.



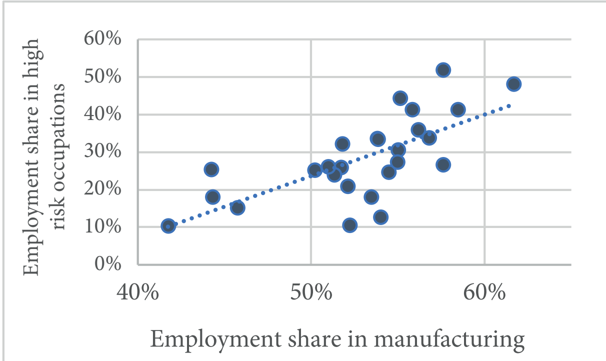


Figure 8: Correlation Between Automation Risk and Manufacturing Employment in NUTS III (left) and in NUTS II (right)
(Source: Calculated by the author using microdata obtained from the EIS.)

Table 3: Regional Distribution of Employees in High-Risk Occupations and the Share of Manufacturing Employees (in the top five and bottom five by automation risk) (Source: Compiled by the author using microdata obtained from the EIS.)

NUTS III Region	**Employment in High Risk Occupations**	**Employment in Manufacture**	**NUTS II Regions**	**Employment in High Risk Occupations**	**Employment in Manufacture**
Karaman	0.65	0.53	TR41 NUTS II (Bursa, Eskişehir, Bilecik)	0.62	0.48
Bursa	0.63	0.51	TRC1 NUTS II (Gaziantep, Adıyaman, Kilis)	0.58	0.41
Uşak	0.62	0.46	TR21 NUTS II (Tekirdağ, Edirne, Kırklareli)	0.58	0.52
Denizli	0.62	0.47	TR32 NUTS II (Aydın, Denizli, Muğla)	0.58	0.27
Bolu	0.61	0.43	TR82 NUTS II (Kastamonu, Çankırı, Sinop)	0.57	0.34
…					
Mardin	0.41	0.27	TR71 NUTS II (Kırıkkale, Aksaray, Niğde, Nevşehir, Kırşehir)	0.50	0.25
Şanlıurfa	0.40	0.21	TRB2 NUTS II (Van, Muş, Bitlis, Hakkari)	0.46	0.15
Ağrı	0.40	0.14	TRC2 NUTS II (Şanlıurfa, Diyarbakır)	0.44	0.18
Iğdır	0.31	0.13	TRC3 NUTS II (Mardin, Batman, Şırnak, Siirt)	0.44	0.25
Şırnak	0.30	0.07	TRA2 NUTS II (Ağrı, Kars, Iğdır, Ardahan)	0.42	0.10

Additionally, the correlation coefficient between automation risk of occupations and employment in services sectors in NUTS III regions is negative with the coefficient 70 percent. Correlation coefficient is 72 percent for NUTS II regions. Similarly, there is a negative relation between share of employment in high risk occupations and service employment in NUTS II regions. This could be attributed to the inherent characteristics of the service sector. Service sectors like healthcare, education, and justice, as well as managerial services and artistic, scientific or intellectual activities involve creative and critical thinking, require human interaction, negotiation and problem-solving skills. Tasks in this area are generally non-repetitive and unpredictable, making them difficult to automate for machines. Therefore, these sectors are more likely to experience engineering bottlenecks compared to manufacturing. Figure 9 demonstrates the correlation for NUTS II and NUTS III regions respectively, and blue dots represent regions and provinces.

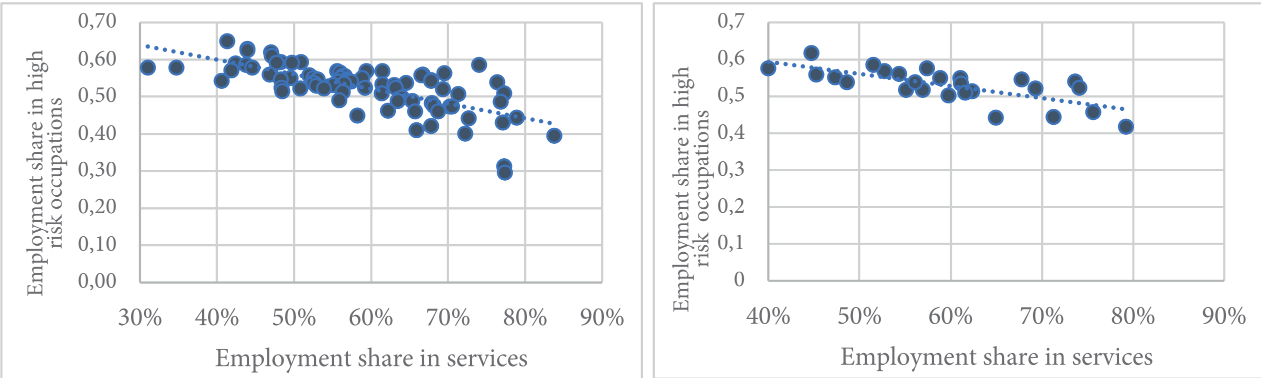


Figure 9: Correlation Between Automation Risk and Services Employment in NUTS III (left) and in NUTS II (right)
(Source: Calculated by the author using microdata obtained from the EIS.)

Lastly, the correlation between employees in the agriculture sector and a high automation risk of job has been observed to be weak (26 percent). This may stem from a lack of comprehensive data on registered workers within the agriculture sector.

Considering that new generation technologies like robots and artificial intelligence are highly capable of executing predictable and repeatable tasks, it is anticipated that provinces and regions with a robust manufacturing sector will likely experience significant impacts. However, it's important to note that correlation does not imply causation. One reason for the high proportion of jobs susceptible to automation is the presence of low technology level production in manufacturing. These high-risk regions stand out for their manufacturing sectors with low levels of technology, including food, textiles, clothing, leather, wood, and paper production. This phenomenon can be attributed to the predominance of small and medium-sized enterprises (SMEs) in the manufacturing sector in Türkiye, which typically operate with medium to low technology levels and do not require highly skilled labour contributing significantly to spatial differentiation. Furthermore, according to Turkish Statistical Institute's labour force statistics, as of 2023, still 43 percent of those currently employed have less than a high school education, 26 percent have a high school degree, and 30 percent have a bachelor's degree (TURKSTAT, 2023). These regions, categorized as relatively developed regions[4], are distinguished by their significant contributions to the manufacturing industry. For instance, Bursa NUTS III Region is in the highest development category. NUTS III Regions such as Bilecik, Bolu, Uşak, and Denizli rank second in development, while Karaman NUTS III Region is in third place. These regions need to embrace digital transformations to enhance their added value in the manufacturing

4 According to the Socio-Economic Development Index (SEDI) 2017 result. The Socio-Economic Development Index Studies (SEGE) analytically and objectively measure and compare the socio-economic development of NUTS II regions, NUTS III regions (provinces), and districts in Türkiye. These studies are carried out periodically by the General Directorate of Development Agencies (STB, 2017).

sector and boost their competitiveness in social and economic development. However, the workforce could be negatively impacted by these transformations. Unless the workforce is adequately prepared for the digitalization, they may face redundancy due to the technological changes, which could lead to potential job losses, particularly in these specific areas.

3. Conclusion and Discussion

Digital technologies are changing jobs, work practices, and social life. Additionally, cutting-edge technologies are creating new occupations or making some jobs redundant. Regardless of whether new technologies are complementing the skills of workers or substituting for them, it is most certain that its effect in all part of social and work life. For every individual to continue doing their job and actively participate in social life, they need to have digital skills. Equipping individuals with the skills required by the new era is essential for integrating them into the workforce and daily life. Mitigating the disruptive effects of new technologies, and ensuring the workforce's employability is obligation to sustain social well-being.

This article identifies the proportion of workers at risk of being replaced by digital technologies in both national and regional breakdowns. It has been identified that the spatial impact of transformation may vary across Türkiye. Digital transformation is inevitable to sustain international competitiveness and promote productivity-driven production. However, it is found that workforce is susceptible to the disruptive effects of transformation. Within this context, if the skills of the current workforce are not developed to align with the qualifications required by new technologies, 54 percent of jobs in Türkiye may face the possible displacement due to the technological transformation. Additionally, it is important to note that 30 percent of employees are employed in medium-risk occupations. This situation may increase polarization in the labour market in future. Because while some jobs may be completely displaced by technology, many others are transformed by it. Adapting the workforce to the skills needed for both transforming and emerging professions should be a key priority in public policy. Without this adaptation, there is a significant risk of facing the detrimental impacts of digital transformation on welfare. Considering all, policymakers are thus confronted with challenging dilemmas finding the balance between encouraging automation to boost productivity in regions and handling job losses resulting from it. Policies should consider both the skills of workers and the adaptation of businesses (particularly SMEs) for digital age.

The unequal effects of automation among different regions may exacerbate disparities in employment conditions. Deteriorating labour welfare may further increase this difference in Türkiye, which has already a high regional disparity. This persistent inequality among regions underscores the need for a spatially-focused approach in policy design and implementation. Hence, to ensure that digital transformation is inclusive for both individuals and regions, it is imperative to design regional digital transformation programmes that consider socio-economic disparities and factors such as infrastructure, businesses, and workforce.

Disclosure

Declaration of Conflict
No potential conflict of interest has been declared by the author.

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No funding was received from any official, commercial, or non-profit organization for this Study.

Compliance with Ethical Standards
It has been declared by the author that the tools and methods used in the Study do not require Ethics Committee Permission.

Ethics Statement
It has been declared by the author that all the studies used are stated in the bibliography.

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Annex 1: Automation Risk of Occupation in ISCO-08 (Source: Calculated by the author.)

ISCO-08	Automation Risk
1111 Legislators	0.07
1112 Senior government officials	0.06
1113 Traditional chiefs and heads of villages	0.02
1114 Senior officials of special-interest organizations	0.14
1120 Managing directors and chief executives	0.09
1211 Finance managers	0.07
1212 Human resource managers	0.32
1213 Policy and planning managers	0.25
1219 Business services and administration managers not elsewhere classified	0.36
1221 Sales and marketing managers	0.01
1222 Advertising and public relations managers	0.03
1223 Research and development managers	0.02
1311 Agricultural and forestry production managers	0.05
1312 Aquaculture and fisheries production managers	0.05
1321 Manufacturing managers	0.03
1322 Mining managers	0.25
1323 Construction managers	0.07
1324 Supply, distribution and related managers	0.59
1330 Information and communications technology service managers	0.04
1341 Child care services managers	0.02
1342 Health services managers	0.01
1343 Aged care services managers	0.08
1344 Social welfare managers	0.01
1345 Education managers	0.01
1346 Financial and insurance services branch managers	0.11
1349 Professional services managers not elsewhere classified	0.25
1411 Hotel managers	0.00
1412 Restaurant managers	0.08
1420 Retail and wholesale trade managers	0.16
1431 Sports, recreation and cultural centre managers	0.17
1439 Services managers not elsewhere classified	0.25
2111 Physicists and astronomers	0.07
2112 Meteorologists	0.67
2113 Chemists	0.06
2114 Geologists and geophysicists	0.32
2120 Mathematicians, actuaries and statisticians	0.15
2131 Biologists, botanists, zoologists and related professionals	0.08
2132 Farming, forestry and fisheries advisers	0.01
2133 Environmental protection professionals	0.02
2141 Industrial and production engineers	0.03
2142 Civil engineers	0.02
2143 Environmental engineers	0.02
2144 Mechanical engineers	0.13

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
2145 Chemical engineers	0.02
2146 Mining engineers, metallurgists and related professionals	0.09
2149 Engineering professionals not elsewhere classified	0.03
2151 Electrical engineers	0.10
2152 Electronics engineers	0.12
2153 Telecommunications engineers	0.03
2161 Building architects	0.02
2162 Landscape architects	0.05
2163 Product and garment designers	0.03
2164 Town and traffic planners	0.13
2165 Cartographers and surveyors	0.63
2166 Graphic and multimedia designers	0.05
2211 Generalist medical practitioners	0.00
2212 Specialist medical practitioners	0.00
2221 Nursing professionals	0.01
2222 Midwifery professionals	0.01
2230 Traditional and complementary medicine professionals	0.02
2240 Paramedical practitioners	0.14
2250 Veterinarians	0.04
2261 Dentists	0.02
2262 Pharmacists	0.01
2263 Environmental and occupational health and hygiene professionals	0.11
2264 Physiotherapists	0.02
2265 Dieticians and nutritionists	0.00
2266 Audiologists and speech therapists	0.00
2267 Optometrists and ophthalmic opticians	0.14
2269 Health professionals not elsewhere classified	0.01
2310 University and higher education teachers	0.03
2320 Vocational education teachers	0.10
2330 Secondary education teachers	0.01
2341 Primary school teachers	0.09
2342 Early childhood educators	0.08
2351 Education methods specialists	0.00
2352 Special needs teachers	0.01
2353 Other language teachers	0.11
2354 Other music teachers	0.13
2355 Other arts teachers	0.07
2356 Information technology trainers	0.01
2359 Teaching professionals not elsewhere classified	0.01
2411 Accountants	0.96
2412 Financial and investment advisers	0.41
2413 Financial analysts	0.46
2421 Management and organization analysts	0.07
2422 Policy administration professionals	0.23

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
2423 Personnel and careers professionals	0.24
2424 Training and staff development professionals	0.01
2431 Advertising and marketing professionals	0.32
2432 Public relations professionals	0.18
2433 Technical and medical sales professionals (excluding ICT)	0.16
2434 Information and communications technology sales professionals	0.11
2511 Systems analysts	0.01
2512 Software developers	0.09
2513 Web and multimedia developers	0.20
2514 Applications programmers	0.48
2519 Software and applications developers and analysts not elsewhere classified	0.22
2521 Database designers and administrators	0.03
2522 Systems administrators	0.03
2523 Computer network professionals	0.09
2529 Database and network professionals not elsewhere classified	0.22
2611 Lawyers	0.04
2612 Judges	0.52
2619 Legal professionals not elsewhere classified	0.06
2621 Archivists and curators	0.38
2622 Librarians and related information professionals	0.52
2631 Economists	0.43
2632 Sociologists, anthropologists and related professionals	0.11
2633 Philosophers, historians and political scientists	0.17
2634 Psychologists	0.01
2635 Social work and counselling professionals	0.04
2636 Religious professionals	0.02
2641 Authors and related writers	0.33
2642 Journalists	0.08
2643 Translators, interpreters and other linguists	0.21
2651 Visual artists	0.04
2652 Musicians, singers and composers	0.04
2653 Dancers and choreographers	0.07
2654 Film, stage and related directors and producers	0.12
2655 Actors	0.37
2656 Announcers on radio, television and other media	0.30
2659 Creative and performing artists not elsewhere classified	0.15
3111 Chemical and physical science technicians	0.70
3112 Civil engineering technicians	0.56
3113 Electrical engineering technicians	0.83
3114 Electronics engineering technicians	0.84
3115 Mechanical engineering technicians	0.48
3116 Chemical engineering technicians	0.24
3117 Mining and metallurgical technicians	0.58
3118 Draughtspersons	0.51

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
3119 Physical and engineering science technicians not elsewhere classified	0.34
3121 Mining supervisors	0.17
3122 Manufacturing supervisors	0.02
3123 Construction supervisors	0.17
3131 Power production plant operators	0.61
3132 Incinerator and water treatment plant operators	0.60
3133 Chemical processing plant controllers	0.85
3134 Petroleum and natural gas refining plant operators	0.83
3135 Metal production process controllers	0.88
3139 Process control technicians not elsewhere classified	0.36
3141 Life science technicians (excluding medical)	0.54
3142 Agricultural technicians	0.97
3143 Forestry technicians	0.42
3151 Ships' engineers	0.04
3152 Ships' deck officers and pilots	0.15
3153 Aircraft pilots and related associate professionals	0.25
3154 Air traffic controllers	0.07
3155 Air traffic safety electronics technicians	0.84
3211 Medical imaging and therapeutic equipment technicians	0.26
3212 Medical and pathology laboratory technicians	0.69
3213 Pharmaceutical technicians and assistants	0.92
3214 Medical and dental prosthetic technicians	0.47
3221 Nursing associate professionals	0.06
3222 Midwifery associate professionals	0.06
3230 Traditional and complementary medicine associate professionals	0.06
3240 Veterinary technicians and assistants	0.44
3251 Dental assistants and therapists	0.60
3252 Medical records and health information technicians	0.91
3253 Community health workers*	0.44
3254 Dispensing opticians	0.71
3255 Physiotherapy technicians and assistants	0.19
3256 Medical assistants	0.30
3257 Environmental and occupational health inspectors and associates	0.53
3258 Ambulance workers	0.05
3259 Health associate professionals not elsewhere classified	0.20
3311 Securities and finance dealers and brokers	0.05
3312 Credit and loans officers	0.51
3313 Accounting associate professionals	0.98
3314 Statistical, mathematical and related associate professionals	0.77
3315 Valuers and loss assessors	0.95
3321 Insurance representatives	0.66
3322 Commercial sales representatives	0.85
3323 Buyers	0.64

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
3324 Trade brokers	0.36
3331 Clearing and forwarding agents	0.99
3332 Conference and event planners	0.04
3333 Employment agents and contractors	0.97
3334 Real estate agents and property managers	0.68
3339 Business services agents not elsewhere classified	0.30
3341 Office supervisors	0.01
3342 Legal secretaries	0.98
3343 Administrative and executive secretaries	0.68
3344 Medical secretaries	0.85
3351 Customs and border inspectors	0.06
3352 Government tax and excise officials	0.93
3353 Government social benefits officials	0.39
3354 Government licensing officials	0.27
3355 Police inspectors and detectives	0.17
3359 Regulatory government associate professionals not elsewhere classified	0.94
3411 Legal and related associate professionals	0.66
3412 Social work associate professionals	0.13
3413 Religious associate professionals	0.40
3421 Athletes and sports players	0.28
3422 Sports coaches, instructors and officials	0.37
3423 Fitness and recreation instructors and programme leaders	0.07
3431 Photographers	0.02
3432 Interior designers and decorators	0.17
3433 Gallery, museum and library technicians	0.54
3434 Chefs	0.37
3435 Other artistic and cultural associate professionals	0.61
3511 Information and communications technology operations technicians	0.78
3512 Information and communications technology user support technicians	0.65
3513 Computer network and systems technicians	0.65
3514 Web technicians	0.03
3521 Broadcasting and audio-visual technicians	0.60
3522 Telecommunications engineering technicians	0.84
4110 General office clerks	0.97
4120 Secretaries (general)	0.96
4131 Typists and word processing operators	0.81
4132 Data entry clerks	0.99
4211 Bank tellers and related clerks	0.97
4212 Bookmakers, croupiers and related gaming workers	0.62
4213 Pawnbrokers and money-lenders	0.84
4214 Debt-collectors and related workers	0.95
4221 Travel consultants and clerks	0.26
4222 Contact centre information clerks	0.76
4223 Telephone switchboard operators	0.97

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
4224 Hotel receptionists	0.58
4225 Enquiry clerks	0.91
4226 Receptionists (general)	0.96
4227 Survey and market research interviewers	0.94
4229 Client information workers not elsewhere classified	0.70
4311 Accounting and bookkeeping clerks	0.97
4312 Statistical, finance and insurance clerks	0.97
4313 Payroll clerks	0.97
4321 Stock clerks	0.86
4322 Production clerks	0.88
4323 Transport clerks	0.96
4411 Library clerks	0.97
4412 Mail carriers and sorting clerks	0.86
4413 Coding, proof-reading and related clerks	0.84
4414 Scribes and related workers	0.41
4415 Filing and copying clerks	0.95
4416 Personnel clerks	0.90
4419 Clerical support workers not elsewhere classified	0.92
5111 Travel attendants and travel stewards	0.38
5112 Transport conductors	0.39
5113 Travel guides	0.35
5120 Cooks	0.73
5131 Waiters	0.90
5132 Bartenders	0.77
5141 Hairdressers	0.33
5142 Beauticians and related workers	0.37
5151 Cleaning and housekeeping supervisors in offices, hotels and other establishments	0.94
5152 Domestic housekeepers	0.94
5153 Building caretakers	0.66
5161 Astrologers, fortune-tellers and related workers	0.40
5162 Companions and valets	0.41
5163 Undertakers and embalmers	0.37
5164 Pet groomers and animal care workers	0.46
5165 Driving instructors	0.13
5169 Personal services workers not elsewhere classified	0.97
5211 Stall and market salespersons	0.94
5212 Street food salespersons	0.90
5221 Shopkeepers	0.16
5222 Shop supervisors	0.28
5223 Shop sales assistants	0.95
5230 Cashiers and ticket clerks	0.90
5241 Fashion and other models	0.98
5242 Sales demonstrators	0.51
5243 Door to door salespersons	0.94

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
5244 Contact centre salespersons	0.99
5245 Service station attendants	0.43
5246 Food service counter attendants	0.93
5249 Sales workers not elsewhere classified	0.97
5311 Child care workers	0.08
5312 Teachers' aides	0.56
5321 Health care assistants	0.47
5322 Home-based personal care workers	0.40
5329 Personal care workers in health services not elsewhere classified	0.59
5411 Fire-fighters	0.09
5412 Police officers	0.22
5413 Prison guards	0.31
5414 Security guards	0.83
5419 Protective services workers not elsewhere classified	0.46
6111 Field crop and vegetable growers	0.72
6112 Tree and shrub crop growers	0.72
6113 Gardeners, horticultural and nursery growers	0.74
6114 Mixed crop growers	0.72
6121 Livestock and dairy producers	0.76
6122 Poultry producers	0.76
6123 Apiarists and sericulturists	0.76
6129 Animal producers not elsewhere classified	0.76
6130 Mixed crop and animal producers	0.80
6210 Forestry and related workers	0.79
6221 Aquaculture workers	0.76
6222 Inland and coastal waters fishery workers	0.70
6223 Deep-sea fishery workers	0.70
6224 Hunters and trappers	0.67
6310 Subsistence crop farmers	0.87
6320 Subsistence livestock farmers	0.87
6330 Subsistence mixed crop and livestock farmers	0.87
6340 Subsistence fishers, hunters, trappers and gatherers	0.80
7111 House builders	0.07
7112 Bricklayers and related workers	0.82
7113 Stonemasons, stone cutters, splitters and carvers	0.86
7114 Concrete placers, concrete finishers and related workers	0.88
7115 Carpenters and joiners	0.72
7119 Building frame and related trades workers not elsewhere classified	0.59
7121 Roofers	0.90
7122 Floor layers and tile setters	0.82
7123 Plasterers	0.75
7124 Insulation workers	0.74
7125 Glaziers	0.73
7126 Plumbers and pipe fitters	0.49

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
7127 Air conditioning and refrigeration mechanics	0.33
7131 Painters and related workers	0.81
7132 Spray painters and varnishers	0.80
7133 Building structure cleaners	0.81
7211 Metal moulders and coremakers	0.81
7212 Welders and flamecutters	0.78
7213 Sheet-metal workers	0.78
7214 Structural-metal preparers and erectors	0.71
7215 Riggers and cable splicers	0.89
7221 Blacksmiths, hammersmiths and forging press workers	0.93
7222 Toolmakers and related workers	0.77
7223 Metal working machine tool setters and operators	0.87
7224 Metal polishers, wheel grinders and tool sharpeners	0.93
7231 Motor vehicle mechanics and repairers	0.65
7232 Aircraft engine mechanics and repairers	0.36
7233 Agricultural and industrial machinery mechanics and repairers	0.62
7234 Bicycle and related repairers	0.47
7311 Precision-instrument makers and repairers	0.56
7312 Musical instrument makers and tuners	0.46
7313 Jewellery and precious-metal workers	0.95
7314 Potters and related workers	0.47
7315 Glass makers, cutters, grinders and finishers	0.84
7316 Sign writers, decorative painters, engravers and etchers	0.95
7317 Handicraft workers in wood, basketry and related materials	0.04
7318 Handicraft workers in textile, leather and related materials	0.52
7319 Handicraft workers not elsewhere classified	0.04
7321 Pre-press technicians	0.57
7322 Printers	0.83
7323 Print finishing and binding workers	0.95
7411 Building and related electricians	0.15
7412 Electrical mechanics and fitters	0.64
7413 Electrical line installers and repairers	0.05
7421 Electronics mechanics and servicers	0.54
7422 Information and communications technology installers and servicers	0.58
7511 Butchers, fishmongers and related food preparers	0.85
7512 Bakers, pastry-cooks and confectionery makers	0.89
7513 Dairy-products makers	0.79
7514 Fruit, vegetable and related preservers	0.61
7515 Food and beverage tasters and graders	0.68
7516 Tobacco preparers and tobacco products makers	0.75
7521 Wood treaters	0.66
7522 Cabinet-makers and related workers	0.92
7523 Woodworking-machine tool setters and operators	0.97
7531 Tailors, dressmakers, furriers and hatters	0.84

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
7532 Garment and related pattern-makers and cutters	0.53
7533 Sewing, embroidery and related workers	0.82
7534 Upholsterers and related workers	0.39
7535 Pelt dressers, tanners and fellmongers	0.41
7536 Shoemakers and related workers	0.52
7541 Underwater divers	0.18
7542 Shotfirers and blasters	0.48
7543 Product graders and testers (excluding foods and beverages)	0.98
7544 Fumigators and other pest and weed controllers	0.73
7549 Craft and related workers not elsewhere classified	0.51
8111 Miners and quarriers	0.70
8112 Mineral and stone processing plant operators	0.89
8113 Well drillers and borers and related workers	0.77
8114 Cement, stone and other mineral products machine operators	0.88
8121 Metal processing plant operators	0.88
8122 Metal finishing, plating and coating machine operators	0.88
8131 Chemical products plant and machine operators	0.85
8132 Photographic products machine operators	0.99
8141 Rubber products machine operators	0.82
8142 Plastic products machine operators	0.91
8143 Paper products machine operators	0.81
8151 Fibre preparing, spinning and winding machine operators	0.96
8152 Weaving and knitting machine operators	0.73
8153 Sewing machine operators	0.89
8154 Bleaching, dyeing and fabric cleaning machine operators	0.97
8155 Fur and leather preparing machine operators	0.87
8156 Shoemaking and related machine operators	0.97
8157 Laundry machine operators	0.71
8159 Textile, fur and leather products machine operators not elsewhere classified	0.87
8160 Food and related products machine operators	0.82
8171 Pulp and papermaking plant operators	0.74
8172 Wood processing plant operators	0.86
8181 Glass and ceramics plant operators	0.81
8182 Steam engine and boiler operators	0.89
8183 Packing, bottling and labelling machine operators	0.98
8189 Stationary plant and machine operators not elsewhere classified	0.92
8211 Mechanical machinery assemblers	0.81
8212 Electrical and electronic equipment assemblers	0.92
8219 Assemblers not elsewhere classified	0.97
8311 Locomotive engine drivers	0.68
8312 Railway brake, signal and switch operators	0.56
8321 Motorcycle drivers	0.48
8322 Car, taxi and van drivers	0.57
8331 Bus and tram drivers	0.61

Annex 1: Automation Risk of Occupation in ISCO-08 (Cont'd)

ISCO-08	Automation Risk
8332 Heavy truck and lorry drivers	0.41
8341 Mobile farm and forestry plant operators	0.83
8342 Earthmoving and related plant operators	0.89
8343 Crane, hoist and related plant operators	0.65
8344 Lifting truck operators	0.48
8350 Ships' deck crews and related workers	0.73
9111 Domestic cleaners and helpers	0.69
9112 Cleaners and helpers in offices, hotels and other establishments	0.57
9121 Hand launderers and pressers	0.81
9122 Vehicle cleaners	0.37
9123 Window cleaners	0.66
9129 Other cleaning workers	0.83
9211 Crop farm labourers	0.87
9212 Livestock farm labourers	0.87
9213 Mixed crop and livestock farm labourers	0.87
9214 Garden and horticultural labourers	0.91
9215 Forestry labourers	0.87
9216 Fishery and aquaculture labourers	0.85
9311 Mining and quarrying labourers	0.37
9312 Civil engineering labourers	0.88
9313 Building construction labourers	0.80
9321 Hand packers	0.38
9329 Manufacturing labourers not elsewhere classified	0.84
9331 Hand and pedal vehicle drivers	0.94
9332 Drivers of animal-drawn vehicles and machinery	0.70
9333 Freight handlers	0.51
9334 Shelf fillers	0.64
9411 Fast food preparers	0.88
9412 Kitchen helpers	0.85
9510 Street and related service workers	0.94
9520 Street vendors (excluding food)	0.94
9611 Garbage and recycling collectors	0.48
9612 Refuse sorters	0.93
9613 Sweepers and related labourers	0.70
9621 Messengers, package deliverers and luggage porters	0.89
9622 Odd job persons	0.64
9623 Meter readers and vending-machine collectors	0.90
9624 Water and firewood collectors	0.85
9629 Elementary workers not elsewhere classified	0.79

Annex 2: Employment Share in High-risk Occupation in NUTS III Regions (Source: Calculated by the author using microdata obtained from the EIS.)

Province Name	High Risk	Medium Risk	Low Risk
Karaman	0.649252311555877	0.258209352764354	0.0925383356797687
Bursa	0.628518229367113	0.232306682940597	0.139175087692291
Uşak	0.624793686816588	0.281823808541366	0.0933825046420466
Denizli	0.619385061235832	0.250626914653592	0.129988024110575
Bolu	0.609950052576236	0.296694269190326	0.0933556782334385
Sinop	0.593330622204148	0.323220821472143	0.0834485563237088
Bartın	0.592694122147138	0.301606528114242	0.10569934973862
Gaziantep	0.592411148724517	0.283305192590806	0.124283658684677
Sakarya	0.591593401075475	0.265591191695653	0.142815407228872
Yalova	0.590644153346954	0.28043504386492	0.128920802788126
Kahramanmaraş	0.586829723529183	0.300112765874713	0.113057510596104
Ardahan	0.586091328026812	0.312107247591119	0.10180142438207
Tekirdağ	0.578601324852519	0.289185314570082	0.132213360577398
Düzce	0.578183271177411	0.314970697922216	0.106846030900373
Bilecik	0.577743902439024	0.317868504772004	0.104387592788971
Kırklareli	0.571494042163153	0.310227619920562	0.118278337916285
Edirne	0.56980198019802	0.297220106626047	0.132977913175933
Çorum	0.568492162013915	0.304310170616935	0.12719766736915
Amasya	0.568281335522715	0.324712643678161	0.107006020799124
Kastamonu	0.565966536133856	0.33186187255251	0.102171591313635
Bayburt	0.56391997287216	0.326212275347575	0.109867751780264
Kütahya	0.559798050443677	0.324933339161603	0.11526861039472
Muğla	0.558917197452229	0.306533373534843	0.134549429012927
Eskişehir	0.55875323250529	0.297997805814591	0.143248961680119
Erzincan	0.557978108035953	0.311382041470143	0.130639850493904
Giresun	0.556197087158195	0.330013947906192	0.113788964935613
Tokat	0.556057955708109	0.334070431367372	0.109871612924519
Burdur	0.550969322539412	0.353376651043886	0.0956540264167022
Konya	0.550960334220077	0.317019992869484	0.132019672910439
Karabük	0.550620931628272	0.303817921610267	0.145561146761461
İzmir	0.550159170679944	0.302960691255524	0.146880138064531
Çankırı	0.547016426416359	0.334227287965136	0.118756285618505
Adıyaman	0.546844281743611	0.351603281133482	0.101552437122907
Kayseri	0.54605393369619	0.321882731321128	0.132063334982682
İstanbul	0.544777334964765	0.279503401895572	0.175719263139663
Manisa	0.543563306922086	0.323851720798286	0.132584972279629
Afyonkarahisar	0.543545791384408	0.347075115086642	0.109379093528949
Trabzon	0.543203786414239	0.335324311712553	0.121471901873208
Kırşehir	0.541820599970445	0.355992315649475	0.10218708438008
Ordu	0.540500437018517	0.32703213610586	0.132467426875622
Antalya	0.540119883642347	0.300420180413128	0.159459935944524

Annex 2: Employment Share in High-risk Occupation in NUTS III Regions (Cont'd)

Province Name	High Risk	Medium Risk	Low Risk
Samsun	0.537738867397691	0.323289025915477	0.138972106686833
Aksaray	0.536944294629787	0.339317358810386	0.123738346559827
Malatya	0.535881306508702	0.325160012470886	0.138958681020412
Adana	0.533320524378889	0.326091347551273	0.140588128069838
Niğde	0.532507089591429	0.358103140426426	0.109389769982145
Isparta	0.531583914274407	0.334287192913026	0.134128892812567
Çanakkale	0.529489135581628	0.350239385489556	0.120271478928816
Aydın	0.525191433292653	0.351999654394056	0.122808912313292
Yozgat	0.52502994011976	0.367065868263473	0.107904191616766
Kocaeli	0.523491712421344	0.328977746735735	0.147530540842921
Batman	0.523269758984874	0.344520097489265	0.132210143525862
Artvin	0.522901969042856	0.390228493208382	0.0868695377487628
Ankara	0.520832263720048	0.29444980043393	0.184717935846021
Zonguldak	0.515538014125467	0.348608226007478	0.135853759867054
Balıkesir	0.512434421203243	0.360671215409922	0.126894363386835
Erzurum	0.508982187011152	0.337387091890801	0.153630721098047
Sivas	0.508941196040922	0.355762566192575	0.135296237766503
Bitlis	0.506951259404645	0.368089630356559	0.124959110238796
Rize	0.498491162523351	0.382562149734157	0.118946687742492
Osmaniye	0.489860535243121	0.351488880512627	0.158650584244252
Mersin	0.488605592964463	0.381778533943591	0.129615873091946
Elazığ	0.487862753654811	0.385555313113681	0.126581933231508
Kars	0.486677407361507	0.39732308836287	0.115999504275623
Siirt	0.482306343743913	0.361794688656581	0.155898967599507
Muş	0.47561517278138	0.384827218619526	0.139557608599094
Bingöl	0.474051737819394	0.40850658625615	0.117441675924456
Diyarbakır	0.473337304338486	0.383911570272144	0.14275112538937
Kırıkkale	0.463176064441887	0.387719875061647	0.149104060496466
Hatay	0.460899808266821	0.390110135105007	0.148990056628171
Tunceli	0.460600907029478	0.42687074829932	0.112528344671202
Gümüşhane	0.449699054170249	0.442992261392949	0.107308684436801
Van	0.443908059677772	0.42050579096887	0.135586149353358
Nevşehir	0.442003719200372	0.447078878041221	0.110917402758407
Hakkari	0.430501174628034	0.447729052466719	0.121769772905247
Kilis	0.420611646418098	0.47863426895685	0.100754084625052
Mardin	0.410315925209542	0.492806484295846	0.0968775904946118
Şanlıurfa	0.401269584008644	0.478768233387358	0.119962182603998
Ağrı	0.395365292764904	0.466566424907129	0.138068282327967
Iğdır	0.312545962641565	0.576996617149581	0.110457420208854
Şırnak	0.295399980793239	0.60650148852396	0.0980985306828003

Annex 3: Employment Share in High Risk Occupation in NUTS II Regions (Source: Calculated by the autor using microdata obtained from the EIS.)

Region Name	High Risk	Medium Risk	Low Risk
TR10 NUTS II Region (İstanbul)	0.544777334964765	0.279503401895572	0.175719263139663
TR21 NUTS II Region (Tekirdağ Edirne Kırklareli)	0.576201270308832	0.293569061536337	0.13022966815483
TR22 NUTS II Region (Balıkesir Çanakkale)	0.5170404893679	0.357853829048049	0.125105681584051
TR31 NUTS II Region (İzmir)	0.550159170679944	0.302960691255524	0.146880138064531
TR32 NUTS II Region (Aydın Denizli Muğla)	0.576113302463843	0.294414908820671	0.129471788715486
TR33 NUTS II Region (Manisa Afyonkarahisar Kütahya Uşak)	0.558025113434089	0.322591313977384	0.119383572588527
TR41 NUTS II Region (Bursa Eskişehir Bilecik)	0.616617433625915	0.244371894018714	0.139010672355371
TR42 NUTS II Region (Kocaeli Sakarya Düzce Bolu Yalova)	0.551140569986943	0.309620092030143	0.139239337982913
TR51 NUTS II Region (Ankara)	0.520832263720048	0.29444980043393	0.184717935846021
TR52 NUTS II Region (Konya Karaman)	0.561501515961462	0.310712930355547	0.127785553682991
TR61 NUTS II Region (Antalya Isparta Burdur)	0.539924225995331	0.305795308134862	0.154280465869806
TR62 NUTS II Region (Adana Mersin)	0.513142492572457	0.351220712233075	0.135636795194468
TR63 NUTS II Region (Hatay Kahramanmaraş Osmaniye)	0.517713935569881	0.347538431601479	0.13474763282864
TR71 NUTS II Region (Kırıkkale Aksaray Niğde Nevşehir Kırşehir)	0.502061919761273	0.380284316976127	0.117653763262599
TR72 NUTS II Region (Kayseri Sivas Yozgat)	0.538174577638506	0.331099702027055	0.130725720334438
TR81 NUTS II Region (Zonguldak Karabük Bartın)	0.538584814065296	0.328634763180367	0.132780422754337
TR82 NUTS II Region (Kastamonu Sinop Çankırı)	0.568075386585622	0.330370625226982	0.101553988187396
TR83 NUTS II Region (Samsun Tokat Çorum Amasya)	0.549790794979079	0.321712586510881	0.128496618510039
TR90 NUTS II Region (Trabzon Ordu Giresun Rize Atvin Gümüşhane)	0.534557142785058	0.344864995786637	0.120577861428305
TRA1 NUTS II Region (Erzurum Erzincan Bayburt)	0.522222222222222	0.331345224823486	0.146432552954292
TRA2 NUTS II Region (Ağrı Kars Iğdır Ardahan)	0.417387346381429	0.46038303980953	0.12222961380904
TRB1 NUTS II Region (Malatya Elazığ Bingöl Tunceli)	0.509741802629495	0.358923230309073	0.131334967061433
TRB2 NUTS II Region (Van Muş Bitlis Hakkari)	0.45732927910807	0.409058659571772	0.133612061320157
TRC1 NUTS II Region (Gaziantep Adıyaman Kilis)	0.584532675242234	0.294033501495992	0.121433823261773
TRC2 NUTS II Region (Şanlıurfa Diyarbakır)	0.44309687218403	0.423714501073965	0.133188626742005
TRC3 NUTS II Region (Mardin Batman Şırnak Siirt)	0.442345826594473	0.441361366992476	0.116292806413051