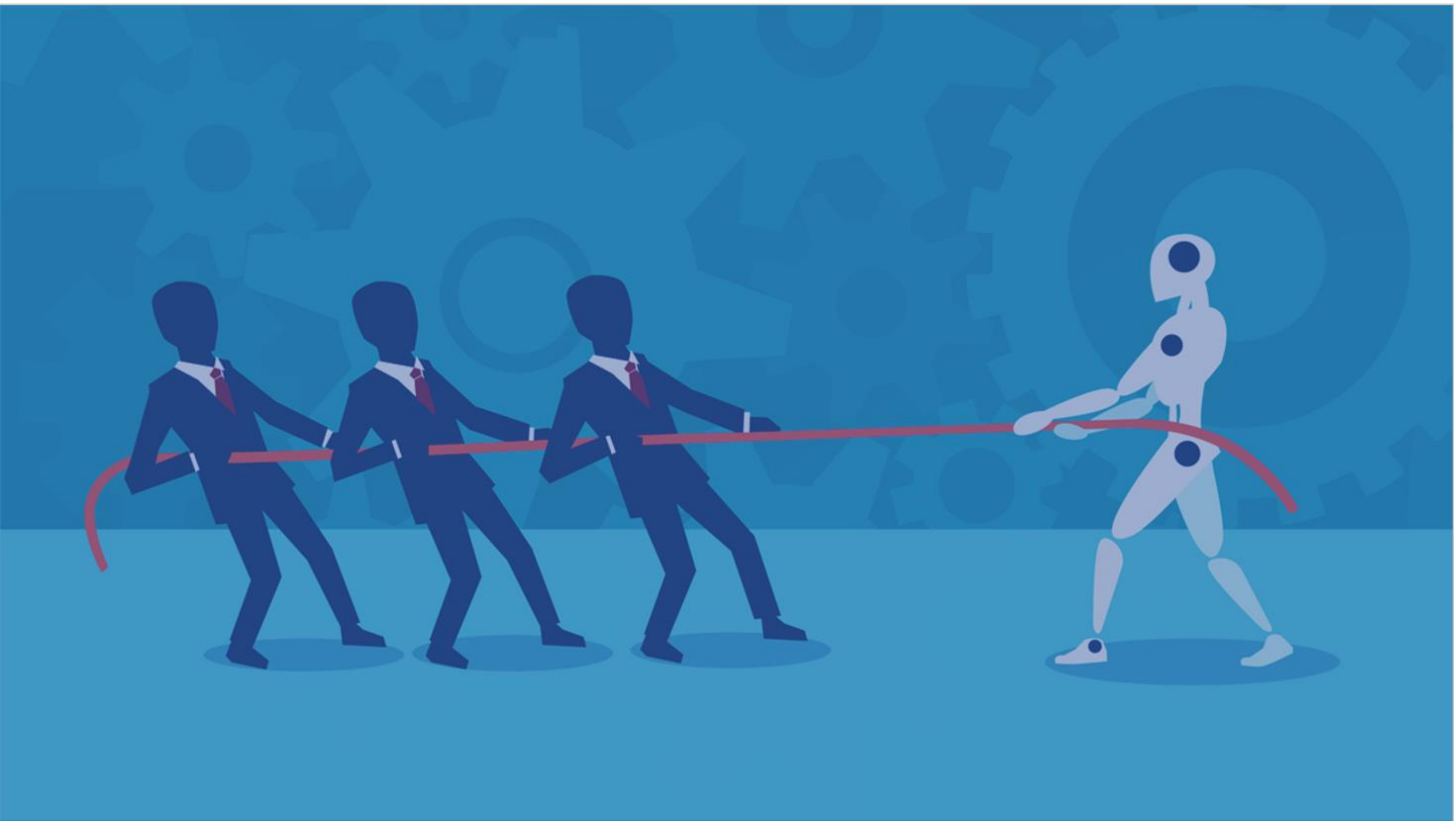
Climbing down the ladder?

With a special focus on mid-level workers at risk of job automation in European labour markets



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Title:	*Climbing down the ladder?*
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Abstract

Ongoing automation processes may render a fair share of existing mid-level jobs redundant. Mid-level workers are put in a difficult position, as laid-off workers might find it difficult to get appropriate new jobs again for lack of new skills or jobs having been made scarce by new technologies. This can create scenarios where mid-level workers, when laid-off, are forced to take on jobs at lower levels i.e. moving down the career ladder. As a result, these workers suffer decreased employability due to job automation. The extent of this phenomenon and how individual-demographic and regional contextual factors influence it are studied in this thesis. The results, however, somewhat contradict the polarization effect automation is expected to have as low-level jobs are found to be most at risk of suffering decreased employability due to automation. For all low-level workers, 9.48 percent are found to be at risk of climbing down the ladder, while for the mid-level workers this is 5.46 percent. Indicating that jobs which were previously perceived as being low at risk of automation may have started to gain more automation potential and have been subjected to labour displacements as automation ingenuity improved. In this study, the evidence is found that education and training play a crucial role in protecting oneself from experiencing decreased employability. Demographically, the evidence is found that females and young workers are more at risk compared to males and other age groups. The regional context also plays an important role in the extent of workers experiencing decreased employability due to automation. Where for instance, strict employment protection legislation is found to have a lower likelihood of the phenomenon compared to lenient employment protection. Moreover, governments that intervene in labour markets to help workers in disadvantageous positions seem to substantially lower the likelihood of these workers experiencing decreased employability due to job automation.

Keywords: automation, employability, polarization, individual-demographic, regional context

Table of contents

1. Introduction

Job automation, due to digitalization and robotization, has been identified as one of the major trends changing society in the short and long term. Some authors even speak of a new industrial revolution, i.e. a technological revolution (Degryse, 2016; Schwab, 2015; Thinen, et al., 2016). Perhaps they are right. Perhaps the digital computer was one of the greatest, if not the greatest invention ever made. It transformed how we conduct our daily lives, led to an increase in productivity, enabled us to let machines handle chores with incredible speed and with great accuracy and reliability. Moreover, machines will increasingly be able to perform intellectual tasks and decision-making (Neumeier, et al., 2017). The positive effects are well identified. Yet, not all changes are positive. Strong concerns arise that as technology will develop further, it will become possible that machines will perform tasks at least as efficiently as humans who are currently carrying them out. Consequently, it is feared that automation will lead to a massive wipe-out of jobs (Sorgner, 2017). Though, the extent of the expected job losses is heavily debated in the literature. According to researchers from the University of Oxford, about 47 percent of the US labour force are in jobs highly at risk of job automation (Frey & Osborne, 2017). However, the OECD studies by Arntz et al. (2017) and Nedelkoska and Quintini (2018) showed more modest results of 9 percent and 14 percent of all jobs in OECD countries to be at risk of automation, although there are high variations between countries. Moreover, a study on 5 ASEAN countries, Cambodia, Indonesia, the Philippines, Thailand and Vietnam, predicts 56 percent of employment at high risk of displacement (Chang & Huynh, 2016). Regardless of the exact scope of the effect, it is safe to say that a large portion of employees will see their jobs changed or lost to automation. Take Germany for example, with a relatively modest prediction of 15 percent in 2013, and a working population of 42,2 million, would suggest 6,3 million workers active in soon-to-be redundant jobs (Dengler & Matthes, 2018).

Who are at risk of job automation?

In order to understand which jobs and workers are at high risk of being automated, it is necessary to analyse what type of tasks can be efficiently performed by computers and in which tasks computers merely supplement human labour. According to Autor, Levy and Murnane (2003), a differentiation can be made between two broad sets of tasks according to the extent of their vulnerability to automation, namely, routine and non-routine tasks. The latter group of non-routine tasks can furthermore be split up in manual and abstract tasks. Because of the nature of routine tasks that may be both cognitive (e.g. performing calculations) and physical (e.g. repetitive operations in a non-changing environment) they can be fully codified and, thus, jobs that mainly comprise routine tasks are highly susceptible to automation (Autor, et al., 2003). Although machines outperform humans in many of the routine tasks, they do not achieve high-performance levels yet when executing non-routine tasks, that is, manual and abstract tasks. Manual tasks are those activities that can be easily performed by humans but which require enormous computing power from machines. An example of this are tasks such as manual operations in unstable changing environments that require high adaptability and manual dexterity, as well as visual and language recognition. However, one should note, that the current progress in artificial intelligence is quite impressive and it can be expected that machines will learn to perform those tasks even better in the near future (Brynjolfsson & McAfee, 2014). Still, humans currently perform these tasks at a much lower cost, which is the reason for a relatively low risk of automation for jobs that comprise manual tasks. On the other hand, abstract tasks require creativity, persuasion and problem-solving abilities, in which computers rather complement high-educated workers (Autor, et al., 2003).

Polarization of labour markets

Generally, the tasks of mid-level jobs comprise routine tasks, and therefore, are more susceptible to being high at risk of automation (Acemoglu & Autor, 2011). On the other hand, low- and high-level jobs experience a much lower risk of automation. Given this trend, observed in many developed countries, labour markets are becoming increasingly polarized (Goos, et al., 2014). Job polarization is a phenomenon which refers to the growth of employment at opposite ends of the occupational skill distribution, but low to negative growth for mid-level employment of the distribution. Figure 1 shows this polarization of labour markets, where the red bars are the mid-level jobs that are changing or disappearing completely.

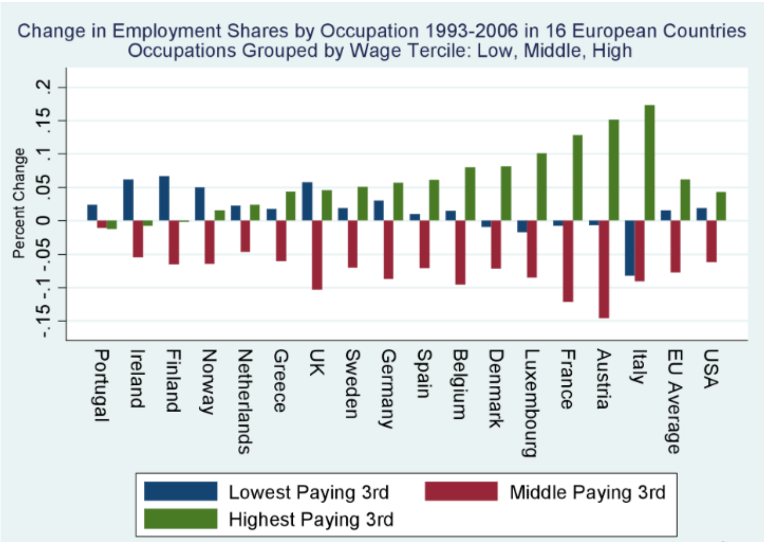


Figure 1

These trends of decreasing mid-level jobs put mid-level workers in a difficult position because automation not only make many jobs at the middle level redundant, but the laid-off workers might find it difficult to get appropriate new jobs again for lack of new skills or jobs having been made scarce by new technologies. This can create scenarios where mid-level workers, when laid-off, are forced to take on jobs at lower levels i.e. moving down the career ladder.

Relevance

The changes of employment across jobs are seen as a driver of regional disparity with increasing inequality of wages and earnings across regions (Acemoglu & Autor, 2011) (Böhm, et al., 2019). Regional disparity has been a prominent issue in the policy agenda of the EU, which resulted in the launch and implementation of the European Regional Development Fund (ERDF). The program aims to strengthen economic and social cohesion in the European Union by correcting imbalances between its regions. Since the launch in 1970, many academics were stimulated to research imbalances between European regions. Many studies found and emphasized the issue of increasingly larger polarized labour markets. Some show indications of decreased employability of mid-level workers in the vulnerable labour markets. However, the actual extent where mid-level workers, in European regions, suffer decreased employability and drop to lower-level jobs has not been studied. This thesis will study this extent and it will explain how certain factors influence the extent the 'CDTL (climbing down the ladder) phenomenon' occurs. Besides the job automation risk factor, there are external factors that need to be taken into account. These external factors can be factors that influence the chance of finding a new job and factors that influence the chance of losing one's job. These include demographic, individual, policy, legislation and regional specific factors. For now, the importance of these external factors will be mentioned shortly, the next chapter will discuss them in much greater length.

Individual, demographic factors

The demographic factors include age, gender, level of mobility, level of education and level of training. The correlation between age and the job automation risk is of importance, as age is a defining factor for the flexibility of a person in the labour market (Kanfer, et al., 2016). This flexibility is also of importance for the factor of the mobility of people. This is because when people are younger, they are faster inclined to move when opportunities arise than older people are. According

to Leana (1991) people with higher mobility generally tend to find better and new jobs quicker, this could mean that the CDTL phenomenon can be smaller for higher mobile persons.
Gender is also an important factor, as males tend to find new and better jobs quicker than females (Leana & Feldman, 1991).
The importance of educational level and training are also widely discussed in the literature. How higher the educational attainment and training the higher the skills someone has and the easier it is for someone to find a new job and to stay active in the labour market (Nedelkoska & Quintini, 2018).

Regional contextual factors

Employment Protection Legislation is an important contextual factor to consider. EPL is a set of rules that imposes additional firing costs on employers, making them less inclined to both fire and hire workers, as employers consider potential future firing costs already when making hiring decisions. EPL, therefore, results in less personnel turnover with stringent EPL. According to Samaniego (2006), the EPL also affects the implementation of automation in the labour market, as having to consider potential firing costs could make adopting new technologies less attractive. On the other hand, a country that has a stringent EPL might also encourage faster automation by making hiring more expensive (Samaniego, 2006).

Active labour market policies can include, upskilling and training in the form of public training programs. Furthermore, ALMP's can include direct job creation in the public sector, special youth measures and job-search assistance. According to the International Labour Office (2017), ALMP's are necessary to ensure that job changes and losses deriving from technological advances are offset by other employment opportunities.

Due to the heterogeneity of regions, where regions have their unique demographic, economic and political compositions, the effects of job automation on workers at risk can have varying impacts. Where some regions could be left unscathed and others hit tremendously and in different ways. Therefore, it is of importance to highlight the extent of the problem per region and take into account the differences in external factors and its influences on the phenomenon so that it can be made easier for governments to make region-specific solutions. To further highlight these regional differences, urban and rural differences and region-specific exposure rates to automation are taken into account. This study will try to find new insights and will try to discover potential patterns in the problem of the deterioration of employability of the mid-level workers in labour markets at risk of job automation. In doing so, the following research questions need answering.

Main research question:

To what extent are mid-level workers, at risk of job automation, susceptible to climbing down the career ladder in increasing polarized labour markets in Europe.

Sub-questions needed to answer this question:

- What are the characteristics and efforts of the workers at risk of automation?
- To what extent are mid-level workers at risk of climbing down the ladder?
- What are the regional differences across Europe where this phenomenon is experienced?
- To what extent do individual-demographic and regional contextual factors influence the phenomenon across European regions?

2. Theoretical Framework

So, job automation is a key driver of economic change. Automation of tasks implies their reallocation between workers and machines. Workers now need to focus more on complex tasks, with basic tasks becoming increasingly performed by machines. This process is an ongoing one, which is constantly influencing labour markets, leading to productivity enhancements, better services for customers, but also increasingly polarizes labour markets, and creates job changes. These two latter points are certainly not positive for the mid-level workers, as many mid-level jobs are changing or disappearing completely. These developments can severely weaken the positions of mid-level workers in labour markets since automation not only make jobs at the middle level redundant, but the laid-off workers might find it difficult to get appropriate new jobs again for lack of new skills or jobs having been made scarce by new technologies. Moreover, for this group of workers, regaining the competitive advantage over machines through upskilling and training may be difficult to achieve, especially taking into account the speed technological developments can make. This can create scenarios where mid-level workers, when laid-off, are forced to take on jobs at lower levels, i.e. moving down the career ladder. This phenomenon of climbing down the ladder will from now on be abbreviated to 'CDTL'. This chapter is made to explore which factors may influence the extent of this phenomenon. This chapter includes a discussion of the existing academic literature on the subject. And in doing so, it tries to explore which factors may influence the extent of this phenomenon. This framework is not only needed to create a clear theoretical overview and basis for the study but also so comprehensive decisions and justifications can be made in the statistical department.

This chapter will start by further discussing the concept of job automation and its influences on labour markets, mid-level workers and their employability. Afterwards, factors that may influence the extent of the CDTL phenomenon are explored. Lastly, a summary is made and conclusions are drawn regarding the relevant relationships in the form of hypotheses. These expectations are made based on the surrounding academic literature, which is later tested by the statistical analysis using logistic regressions.

2.1. Job automation

In this study job automation is defined as the practice of substituting human labour with technology to perform jobs or specific tasks. Job automation involves mechanization but also uses technology to replace jobs and people in performing tasks. Since concepts such as digitalization and robotization do the same, they fall under the definition of job automation in this study.

Increasing adaptation of automatable technologies

The actual extent of the risk of job automation and its impacts on labour markets will depend on how fast technology develops, is adopted, and how people and places react to it. For instance, as automation ingenuity improves, jobs currently perceived as being low at risk may start to gain more automation potential and undergo labour displacements. A report by Servoz (2019) showed that in some regions, automation technologies have already surpassed human capabilities. For example, error rates for image labelling have fallen from 28,5 percent to below 2,5 percent from 2010 to 2018. However, despite these improvements, humans are still needed to supervise robots. The company Amazon showed this, where along with adding robots to its US operations to perform heavy lifting tasks, they also added 80.000 warehouse employees overseeing these machines (Servoz, 2019). So, a key factor determining the impact of automation on jobs depends on the uptake of technologies, which in turn is affected by the relative cost of replacing workers with technology. According to Servoz (2019) the estimated payback period in China was 5,3 years in 2010. This dropped to 1,5 years in 2016, influenced by falling prices of automated technologies and rising labour costs. A graph from the ESDE 2018 report shows that this is also happening in the US, where labour costs keep increasing and automated technologies become ever cheaper (ESDE, 2018).

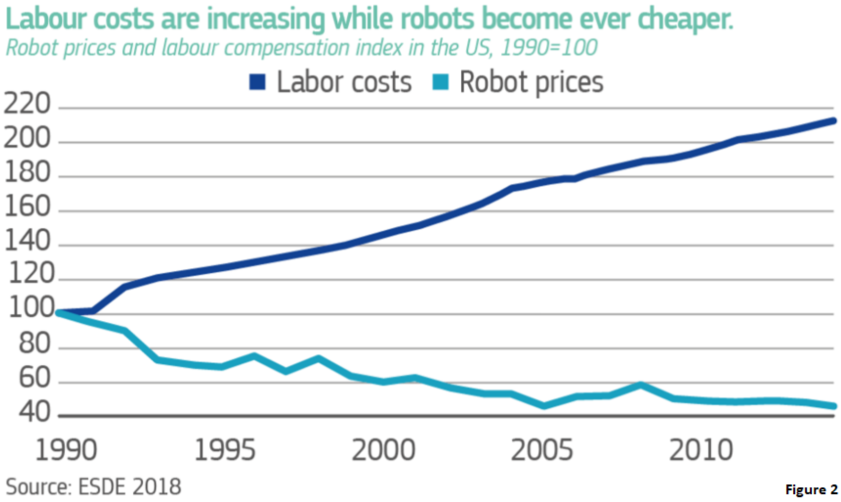


Figure 2

Thus, with these developments firms get strong economic incentives to substitute relatively expensive human labour with ever cheaper computing power. What are the effects?

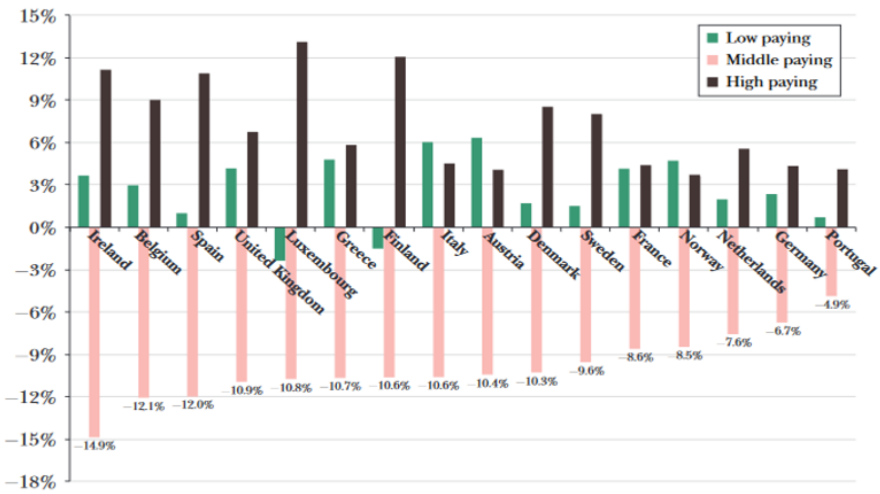
What are automated technologies substituting?

The main effect is, indeed, substitution. As the price of computing power has fallen, automated technologies have increasingly displaced workers in accomplishing explicit, codifiable tasks (Autor, 2015). These explicit codifiable tasks are oftentimes labelled as routine tasks, not because they are mundane, but because they can be fully codified and hence automated (Autor, et al., 2003). Routine tasks are typical features of many middle-skilled manual and cognitive activities: for instance, the retrieving, storing and sorting of structured information typical of clerical work; the mathematical calculations involved in simple bookkeeping and the precise performance of a repetitive physical task in an unchanging environment. Because these tasks follow specific well-understood procedures, they are increasingly codified in computer software and performed by machines (Acemoglu & Autor, 2011). As a result, a considerable decrease in employment in clerical, administrative support, and to a lesser degree in production and operative employment (Servoz, 2019). However, the opportunity for this kind of substitution is, to a certain extent, limited as there are many tasks that people understand tacitly and accomplish effortlessly but for which computer programmers cannot articulate the explicit procedures (Autor, 2015). Autor (2015) refers this constraint to Polanyi's paradox, named after the Austro-Hungarian economist, sociologist and philosopher Polanyi who observed that "We know more than we can tell" when studying tacit knowledge (Polanyi, 1966). Polanyi stated that there are tasks that we only tacitly understand how to perform. Following his thoughts, the tasks that have proved most difficult to automate are those including, judgement, flexibility and common sense (these being skills that we only understand tacitly). Furthermore, according to Autor (2015), Polanyi's paradox hints why high-level reasoning is straightforward to automate and particular sensorimotor skills are not. Autor goes on to explain that, high-level reasoning adopts a set of formal logical mechanisms that are used to specifically undertake formal problems. For instance, using calculations or making logical deductions, which are all quite easily automated. But on the other hand, humans also possess capabilities that were evolved. Examples of these capabilities include intuition, persuasion, judgement, creativity, and common sense. Coding these skills requires reverse-engineering a set of tasks that we normally carry out using only tacit knowledge. This, of course, is far more difficult and inefficient to automate. These abstract skills are often involved in problem-solving jobs, where intuition, persuasion and creativity are needed. These occupations generally include professional, technical and managerial aspects with workers having high levels of education, strong inductive reasoning, communication abilities and analytical capabilities. Contrary to these jobs with abstract tasks, there are also other relatively safe jobs from being automated. These occupations often include manual tasks, where situational adaptability, visual and language recognition and in-person interactions are required. Examples of jobs including these manual tasks are occupations in food preparation, cleaning, maintenance, and in other services etc. These workers are often physically skilled and capable to communicate fluently in spoken language. Although the tasks are not considered highly skilled, they show daunting challenges for automation (Autor, 2015). Moreover, something noteworthy, is that many of these jobs have to be performed mainly on-site or in person, and thus these jobs are not subject to outsourcing. Plus, the supply of workers who can perform these tasks are very large, which means wages are low. Resulting in automating these occupations not being as beneficial as automating routine and (formal) high-level reasoning jobs are. Though, one should note, that the current progress in artificial intelligence is quite impressive and it can be expected that machines will learn to perform those tasks as well or even better in the future (Brynjolfsson & McAfee, 2014).

2.2. Polarization

So, many low- and high-skilled occupations are not close to being at risk of job automation, as these include many of the manual and abstract tasks which are difficult to automate. Not only are they relatively safe from job automation, but employment in these occupations and sectors are also increasing. For example, in the EU between 1993 and 2010, nearly every country saw low- and high-skilled jobs increase employment (Deutsche Bank, 2018). The large employment growth in low- and high-skilled occupations has considerably reduced the amount of employment in middle-skilled occupations. Moreover, mid-level jobs often include the above-mentioned routine and/or high-level reasoning tasks, which are easily automated. Autor (2015) tracked four mid-level occupations, office and administrative workers; production workers; operatives; and sales. These accounted for 60 percent of employment in 1979. In 2012, after a constant decrease, the percentage was 46 percent. As the employment shares of the mid-level occupations keep decreasing and the employment shares on the opposite ends of the occupational skill spectrum keep increasing, labour markets have become increasingly polarized. Goos et al. (2014) showed this job polarization for sixteen EU countries from 1993 to 2010, see below. It reveals that polarization is present in all countries, albeit to a different degree.

Change in Occupational Employment Shares in Low, Middle, and High-Wage Occupations in 16 EU Countries, 1993–2010



Source: Goos, Manning, and Salomons (2014, table 2).

Figure 3

The similar relationships of these shifts across many developed countries make it expected that a common set of forces is responsible for these shared labour market developments. At the same time, the considerable variations among the countries emphasize that no single factor explains the diversity of experiences across the European countries. Thus, the heterogeneity of regions and their distinct individual and demographic factors need to be taken into account when assessing the extent where mid-level workers suffer decreased employability and drop down to lower-level jobs.

2.3. Individual-demographic influences

This section will discuss the relevant individual and demographic factors that may influence the extent of the CDTL phenomenon. It will start by discussing demographic factors such as age, mobility and gender. Afterwards, the two individual factors of education and training are discussed.

Age and mobility

The age of mid-level workers is one of the factors that could influence the extent where mid-level workers have to climb down the ladder to lower-level jobs. According to Nedelkoska & Quintini (2018), the relationship between automation and age is U-shaped. Though, the main peak of automation risk is found for youth jobs. As a result, young people might be more exposed to automation risks (Nedelkoska & Quintini, 2018). Yet, younger people may also be better equipped to deal with the risks of automation compared to older people. This could be because younger people hold skills which allow them to easier adapt to new technologies (Nedelkoska & Quintini, 2018). Additionally, it could be because younger people are more flexible in labour markets, which makes it easier for them to quickly find other jobs (Leana & Feldman, 1991). One of the reasons for this is because younger people have higher mobility. For example, younger people are faster inclined to move when opportunities arise than older people are (Leana & Feldman, 1991).

Another reason is that, older workers have lower levels of participation in education and job skills training, which could help strengthen one's position in the labour market (Hamil-Luker & Uhlenberg, 2002). One could argue though, that the longer someone has worked the more skills that person has attained throughout his life, however, the actual skills attained are often very firm-specific capital (Becker, 1993). This being, a form of knowledge that is valued more by the current organization than it is by the external market (Maestas & Li, 2006). The process of these skills becoming more outdated can contribute to mismatches between the human capital of older job seekers and the type of skills desired by future employers (Hirsh, et al., 2000). According to Daniel & Heywood (2007), when older workers are trying to find a new job, they are frequently segregated into a cramped range of industries and jobs compared to younger workers. Since, these industries and occupations are also frequently in decline, the amount of other laid-off workers is large and thus more will be competing for fewer job openings, which leads to reduced reemployment speed and quality (Daniel & Heywood, 2007). Training could serve as an effective method for alleviating these problems, though the literature suggests that there are age-related variations in the motivation and effectiveness of such training for older workers (Kanfer, et al., 2016). According to Kanfer et al. (2016), older workers are less likely to participate in career development and training to keep their skills up to date. On the other hand, employers might also be less inclined to provide training to older workers compared to younger workers. This is simply because older workers are nearer to retirement and the benefits of training are thus believed to be smaller (Maurer, et al., 2003).

All in all, younger people may be more exposed to automation risks, which could make them more at risk of experiencing decreased employability when laid-off due to automation. Yet, it might be counterbalanced by their advantage of being better equipped to deal with it. As a result, younger people may be less at risk of experiencing climbing down the ladder than older workers.

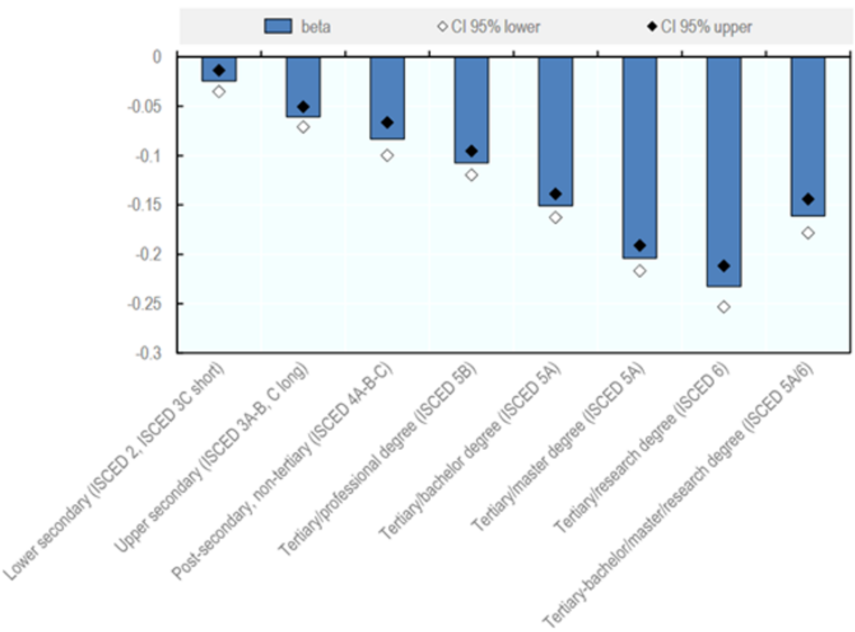
Gender

According to Hawksworth & Berriman (2018), males may face greater risks of job automation in the future, as they are more frequently found in routine-task-focused occupations and sectors such as manufacturing, storage and transportation. In contrast, females tend to be more concentrated in occupations and sectors surrounding education and health, which require more personal and social skills that tend to be less automatable. However, in the shorter term, females might be more at risk of automation. This is primarily driven by a greater proportion of women employed in occupations containing clerical tasks, which are considered highly automatable.
Males, generally, also tend to find new jobs quicker and of higher quality and are considered to have stronger labour market positions compared to females (Leana & Feldman, 1991).

Education & Training

These two individual factors are expected to have a large influence on the extent of the CDTL phenomenon. This is because the level of educational attainment displays a notably clear pattern in relation to the risk of job automation: the higher the educational attainment the lower the risk of automation. The figure below, from an OECD analysis on 32 OECD countries, show this unmistakably clear pattern. Where the higher the educational attainment the lower the risk of automation becomes. In the long term, highly educated workers could maintain these lower automation risks. Since, workers with higher educations are, generally, more represented in professional, scientific, technical and educational sectors (Hawksworth & Berriman, 2018). The tasks in these sectors oftentimes comprise skills of intellectual reasoning and of supervision that will still be needed alongside computers and other AI-based systems, hence the consistently low automation risks for higher educated persons. Moreover, the flexibility of a worker increases with higher educational attainment, as it becomes easier to move around various occupations and industries and thus potentially avoid automation risks (Hawksworth & Berriman, 2018).

Partial correlations – automatability and educational attainment



Source: Survey of Adult Skills (PIAAC) 2012, 2015.

Figure 4

As of these reasons, it is not strange to assume that the level of educational attainment could affect the extent of the CDTL phenomenon to a large amount. It can be expected that higher educated persons, when laid-off, will drop less to lower-level jobs. Like Nedelkoska & Quintini (2018) stated, the higher the education the higher the skills someone has and the easier it is to find a new suitable job and to stay active in the labour market.

The same goes for training, as following training is another way to boost skills and prevent, when laid-off, to be forced to take on jobs at lower levels. Moreover, attaining relevant and current skills through training will, generally, improve the capabilities of workers to adjust to new technologies and increase their employability (Groot & Van den Brink, 2000). However, regaining the competitive advantage over machines through upskilling and training is no easy task, especially taking into account the speed technological developments can make. Therefore, the importance of consistent and relevant training, also known as lifelong learning, is oftentimes emphasized (Arntz, et al., 2016).

Taking into account the speed technological developments can and have made, one would expect that participation in lifelong learning would have increased in tandem with these developments, as to avoid further skill mismatches. Though, the actual extent of lifelong learning has not picked up, which is most evident for low and medium-skilled workers as shown in the ESDE graph below (ESDE, 2018).

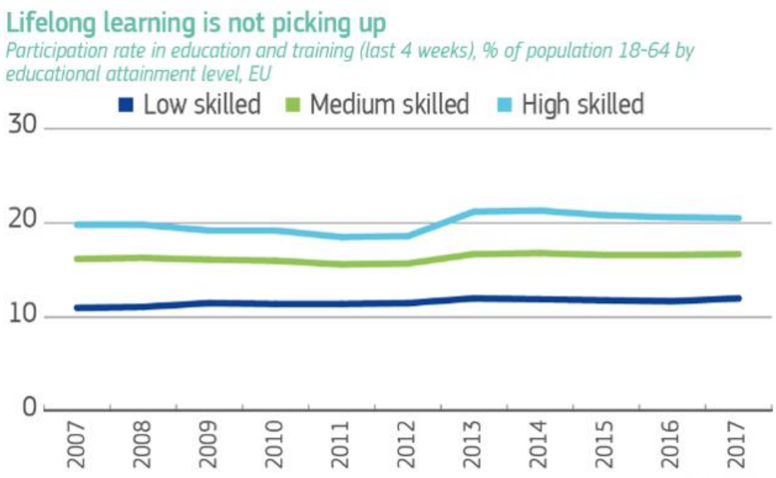


Figure 5

Moreover, looking at the relevance of lifelong learning systems, Nedelkoska & Quintini (2018) found that the odds of engaging in any type of training, either at work or in free time, are significantly lower among workers with jobs at risk of automation. So, even though the risk of automation exacerbates an urgency of developing stronger employability for these workers, they likely stand a lower chance of actually receiving it. This could to some extent be the result of firms not being interested in investing in employees that already hold jobs that may become expendable in the near future. Furthermore, the willingness of workers to follow training differs substantially between the different groups, where low and medium-skilled workers generally tend to be less willing to follow training (Servoz, 2019). Thus, it could be expected that low and medium-skilled workers tend to follow less training not only due to the provision of training but also due to their own willingness. This could result in these workers being at an even greater risk of losing their jobs and having to drop to lower levels as for example skills are not up to par anymore. For these reasons, the expectation that low and medium-skilled workers drop to lower levels of jobs is even larger now. In addition, it will be interesting to see what the effect of training is on the occurrence of the CDTL phenomenon. For instance, will workers who do actually follow training experience the phenomenon to a lesser extent than workers who do not follow training?

2.4. Regional contextual influences

This section will discuss the relevant regional factors that might affect the extent of the CDTL phenomenon. Two institutional factors which may affect it are active labour market policies and employment protection legislation. These factors are on the national level, yet the effects of automation are also unevenly distributed among regions. As heterogeneities can be found between regions, it is also important to assess these regional levels. This is done by looking at urban-rural differences and by investigating automation risk exposure on the regional level.

Active Labour Market Policies

Active labour market policies are government programmes that intervene in the labour market to help the unemployed find work or help workers at risk to strengthen their labour market positions. Another goal of ALMPs is to increase the employment opportunities for job seekers and to improve matching between jobs and workers. Some examples that ALMPs can include are upskilling and training in the form of public training programs. Additionally, it can include direct job creation in the public sector, special youth measures and job-search assistance. Training usually accounts for the largest share of spending of ALMPs, though this is not surprising as these programs also tend to be among the most expensive measures (Martin & Grubb, 2001). According to the OECD (2019), ALMPs need adequate and sustainable financing to operate well. While guaranteeing sufficient funding for ALMPs is a key challenge today, arguably it will become even more urgent in the future. As the demand for training and stronger labour market positions is likely to increase in the context of automation, the financial resources dedicated to ALMPs might increase as well.

ALMPs are considered to be highly valuable in the context of job automation. According to the International Labour Office (2017), ALMPs are necessary to ensure that job changes and losses deriving from technological advances are offset by other employment opportunities. These employment opportunities can arise from boosting one’s skills from the abovementioned training programs, job creation and job-search assistance. Besides this ALMPs are also effective for lowering barriers to training, increasing the quality of training and encouraging employers to train groups at risk so that the provision of training can be boosted (OECD, 2020).

Moreover, ALMPs want to incentivize employers to train their lowest skilled workers or their workers at risk of automation. ALMPs want to achieve this by lowering to costs for these employers, again by means of targeted financial incentives. Moreover, policies are made to provide better information to firms about the benefits of training and the availability of training opportunities (OECD, 2019). The focus on improving the quality of training is done because existing training programs are not always relevant and useful. Often times there exists a disconnect between the content of training and labour market needs (Servoz, 2019). Making training programs more aligned to current skill needs is a way how ALMPs want to improve this. As a result, the skill mismatch due to current developments could decrease. This could enable the adaptability and skills, which are deemed critical for the groups at risk, to share in the gains from new technologies and work more effectively with them (Servoz, 2019). Spending on Active Labour Market Policy will for these reasons be used as a proxy of the extent governments intervene in the labour market to help workers in disadvantageous positions.

Employment Protection Legislation

The OECD (2004) defines employment protection legislation as rules governing the hiring and firing process. Employment protection concerns to regulations regarding firing, where for example mandated prenotification periods and severance payments are included. Furthermore, it also concerns regulations having to do with hiring, which can include rules favouring groups at risk and certain conditions for various contracts. The whole set of rules regarding Employment protection legislation (EPL) can differ from country to country, where the strictness is often times the measurement of comparison. According to Bennet (2016) the strictness of EPL is measured by the costs that are associated with lay-offs of employees. All in all, the primary focus and ideas behind employment protection legislation are to improve protection for employees when the market is volatile and to weaken incentives for employers to discharge employees (Skedinger, 2011). For these reasons, EPL is especially relevant in the context of job automation. Skedinger (2011) also stated that it is often claimed that the driving factors of countries to develop and strengthen employment protection is because of the constant technological change that labour markets face. Though, what are the effects of EPL on labour markets in this context?

The most immediate effect of regulated EPL is that the cost for employers to alter the size and structure of their workforce increases. Increasing the lay-off costs does not only lower the predisposition towards firing workers, it additionally results in a decreasing willingness of employers to hire new workers in the first place (Samaniego, 2006). This is because employers can include future lay-off costs with current hiring decisions. High firing costs can, as a result, become an employment obstacle for job searchers by reducing the incentives of firms to recruit new workers. This can specifically occur for occupations that are at risk of automation due to technological advancements (Bennett, 2016).

Furthermore, employment protection legislation may have effects on the adaptation of new automation processes. Where more stringent EPL should make firms less willing to adopt automation processes since firings costs are higher than otherwise (Samaniego, 2006). So, due to more stringent EPL automation becomes costlier to implement. Naturally, in countries were the EPL is more lenient this could result in quicker adaptations of automation processes. Moreover, with fewer barriers to firing and hiring workers, this could result in quicker turnovers in these labour markets. For these reasons, the level of employment protection legislation and its geographical differences are important in relation to the climbing down the ladder phenomenon. As the abovementioned effects of either stringent or lenient EPL might differ the extent of the CDTL phenomenon across different European countries.

Urban-rural differences

According to Frank et al. (2018) cities could be more exposed to the risks of job automation compared to rural areas. This is because innovation in cities and the scale benefits of implementing automation are much greater. On the other hand, cities do tend to have more workers who are willing to both use and improve automatable technologies (Frank, et al., 2018). These workers hold more skills and are more specialized in their respective fields, which makes them less likely to be replaced by automatable technologies (Frank, et al., 2018). Yet, specialization can become dangerous when it goes towards overspecialization. As for example happened with Detroit, which suffered large economic declines with many worker displacements because of its overspecialization in the automotive industry.

Besides that cities hold more workers with higher skills, cities also provide much wider employment opportunities compared to rural areas (Bagchi, 1973). As a result, if a worker in a city does get laid-off by automation it may find a new job quicker compared to workers in rural areas. So, the exposure to automation may be higher in cities but as skills and employment opportunities are also higher, cities might be better equipped to deal with this higher exposure compared to rural areas.
The researchers Devaraj et al. (2020) agree with the notion that cities hold more employment opportunities compared to rural areas, however they are more pessimistic for the rural regions in the

context of automation risk. According to Devaraj et al. (2020), rural areas can have substantial exposure to automation risk as well, as these areas can include specific occupations that hold very high risks of automation. An example could be the agricultural and fishery labourers. Moreover, Devaraj et al. (2020) state that rural areas have more vulnerable populations in terms of lower levels of socioeconomic status and educational attainment. This might make workers in rural areas worse equipped to deal with potential lay-offs from job automation. This could render rural workers more at risk of suffering decreased employability due to job automation

Automation risk exposure among regions

Vermeulen et al. (2018), studied how structural change may come about in different regional labour markets due to automation. Certain labour market structures might have to undergo changes as they hold many occupations that are considered high at risk, while others are less exposed to the risks or even create new jobs (Vermeulen, et al., 2018). For example regions that have their labour market structure focused on technological occupations may be the ones to experience job creation, as these occupations are low at risk of automation and have workers that have the skills to adapt to new technologies (Autor, 2015). Yet, regions that experience a high exposure to automation risks, may be far less resilient to automation risks and have to undergo structural changes (Vermeulen, et al., 2018). These regions can be less resilient, as they hold more vulnerable workers. This is due the fact that primarily low and medium educated workers are at risk of automation, which may be less equipped to deal with automation changes (Autor, et al., 2016). Moreover, these regions, with higher exposure, may hold less employment opportunities (Böhm, et al., 2019). One of the reasons that employment opportunities may be scarce in these regions is that competition for these opportunities is higher. This is a result of more laid-off workers, due to automation, having to compete for the same kind of jobs. This scenario could result in these workers being forced to take on jobs at lower levels and thus climb down the ladder. For these reasons, the exposure rate per region can be seen as an indication of how resilient labour market structures in regions are in relation to automation risks.

Summary

The amount of automatable job keeps increasing due to fast technological developments, which puts certain workers in a difficult position. Not only are more jobs becoming redundant, it might also become more difficult to get appropriate new jobs again for lack of new skills or jobs having been made scarce by new technologies. This creates scenarios where workers, when laid-off, are forced to take on jobs at lower levels i.e. the Climbing Down the Ladder phenomenon (CDTL). This chapter has discussed the relevant concepts related to this phenomenon. Concepts that help explain how this phenomenon can occur and concepts that explain what influences it and/or could alleviate the extent of it.

Firstly, the concept of job automation is thoroughly discussed, which is defined as the practice of substituting human labour with technology to perform jobs or specific tasks.
The strong developments in the adaptation of automatable technologies are shown to result in strong economic incentives to substitute relatively expensive human labour with ever-cheaper computing power. Showing that automation is something that will only keep increasing in the near future. After this, the actual tasks that are automated are discussed so that the occupations and groups at risk can be identified. Discussing the polarization of labour markets driven by this automation complements this and again shows that the mid-level jobs are most at risk.

Secondly, the heterogeneity of regions and their distinct individual and demographic factors are discussed as these can influence and/or alleviate the extent of the CDTL phenomenon. The individual factors education and training show a notably clear pattern in relation to the risk of job automation:

the higher the educational attainment and training the lower the risk of automation. Though, the uptake of training is not increasing in tandem with the increasing technological developments, which could further increase skill mismatches. Moreover, the odds of engaging in any type of training are significantly lower among workers with jobs at risk of automation. This is not only due to their own willingness that is lacking, it is also due to the lacking provision of training. So, even though the risk of automation increases the need of developing stronger employability for these workers, they likely stand a lower chance of actually receiving it.
In addition to education and training, the demographic factors age, mobility and gender are discussed. Here, the surrounding academic literature generally believes that females and older people are found to be more at risk of suffering decreased employability when laid-off due to automation.

Lastly, the main concepts that can influence the phenomenon on the regional level are discussed. The institutional factors are ALMP (Active Labour Market Policies) and EPL (Employment Protection Legislation). ALMPs are government programmes that intervene in the labour market to help the unemployed find work or help workers at risk to strengthen their labour market positions. ALMPs are considered to be highly valuable in the context of job automation and alleviating the extent of the CDTL phenomenon. EPLs concerns to regulations regarding firing and hiring. The main effect of regulated EPL is that the cost for employers to alter the structure of their workforce increases. The effect EPL could have on the CDTL phenomenon could go both ways. This is because, increasing lay-off costs do not only lower the predisposition towards firing workers, it additionally results in a decreasing willingness of employers to hire new workers in the first place. EPL can therefore on the one hand become an employment obstacle but on the other hand, a protective governmental institution that strengthens the positions of people at risk of automation. Still, academics lean towards the latter effect. Additionally, heterogeneities between regions are discussed. This is done by looking at urban-rural differences and by investigating the effects of high exposure to job automation in regions. In general, researchers agree with one another that there exist more employment opportunities in cities and that therefore they may be better equipped to deal with the negative effects of job automation. Yet, the academics are divided over what area is more exposed to automation risks. Some researchers believe that urban areas are more exposed, as innovation and scale benefits are much greater in cities. Others believe rural areas might be more exposed, as rural areas could hold more vulnerable populations and occupations at risk.
The last factor is the exposure rate of regions to automation risk. This exposure rate can indicate how well certain regions are performing in the context of job automation. If a region has a high exposure rate, then employment opportunities are fewer and the chance of suffering decreased employability might be higher for the workers in that region.

Hypotheses

On the basis of the academic literature discussed in this chapter, the following expectations are made.

- The level of education has a positive significant relationship with a lower occurrence of the CDTL phenomenon.
- Following training has a positive significant relationship with a lower occurrence of the CDTL phenomenon
- Being male/young has a positive significant relationship with a lower occurrence of the CDTL phenomenon
- Higher active labour market policy investments have a positive significant relationship with a lower occurrence of the CDTL phenomenon
- Stricter employment protection legislation has a positive significant relationship with a lower occurrence of the CDTL phenomenon
- Living in an urban area has a positive significant relationship with a lower occurrence of the CDTL phenomenon
- Living in a region that has a labour market structure that is not highly exposed to job automation has a positive significant relationship with a lower occurrence of the CDTL phenomenon

Conceptual model

Figure 6 shows an overview of all the relevant variables in relation to the CDTL phenomenon.

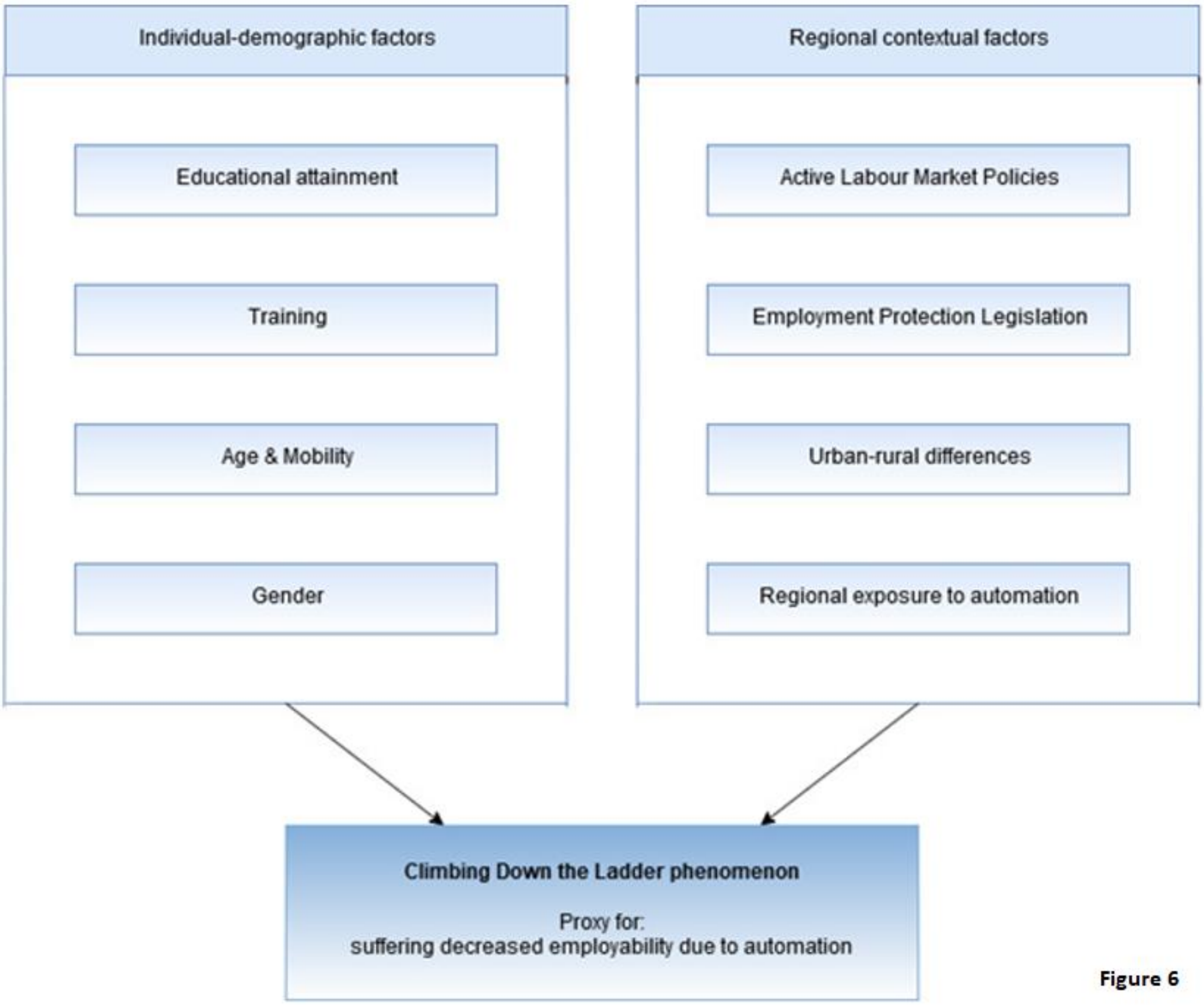


Figure 6

3. Methodology

The goal of this research is to try to find new insights and discover potential patterns in the problem of the deterioration of employability of the mid-level workers at risk of job automation. The phenomenon of 'climbing down the ladder' is used as a proxy to showcase these developments. To be able to show this extent and to answer the accompanying research questions, a database on these workers, including relevant individual and regional factors, is necessary. Occupational data is important, as each occupation can be scored on its automation risk, based on the measures created by Frey and Osborne (2017). As a result, each worker in the dataset will include a data point which assesses the level of risk of automation this worker has. This data on occupations and the risk of automation will be crucial to be able to create the dependent variable which will measure the phenomenon of 'climbing down the ladder'. How this is done, will be discussed in detail later on.

When the dataset is finalized for analysis the incidence of the CDTL phenomenon is compared between the different skill-level workers (low/mid/high-level workers). The distinction between different workers is made with the help of the International Labour Office's mapping of occupations based on their skill levels (International Labour Office, 2012). After this, the regional differences across Europe of this phenomenon are mapped. And finally, logistic regression models are estimated to explore the relationship between the phenomenon and the underlying individual and regional characteristics. The individual factors of workers primarily include the level of education and the attendance of training. The demographic factors will include age, gender, and mobility. The regional factors that are tested in relation to the CDTL phenomenon include country levels of Active Labour Market Policy spending and the level of Employment Protection Legislation and regional levels of urban-rural differences and regional exposure rates of automation. To showcase these regional differences and to potentially discover regional patterns, data on regions (on Nuts 2 level) is included. This means that besides country-level differences, regional differences can be analyzed as well. All in all, this chapter will discuss the methodology used in creating the necessary dataset for studying this research. It will do so by discussing how the data is collected, edited and finally analyzed.

3.1 Data collection

The necessary data, as described above, has to be put together into a dataset, where individual data is needed for the workers. This study is done on a large scale, across Europe, therefore the study will make use of secondary microdata from the European Labour Force Survey. This is a survey that is conducted yearly where a large household sample is taken, which provides results on labour participation of people aged 15 and over as well as persons outside the labour force. The large household sample is taken for all the member states of the European Union, four candidate countries and three countries of the European Free Trade Association (Eurostat, 2019). The survey includes harmonized country data on individuals on occupations, education, training, age, gender, region of residence and more. So, this dataset provides numerous relevant variables which will be a good basis for this study. A complete overview of the EU-LFS variables used can be seen in appendix 1. However, to answer all the research questions information on other relevant variables are needed as well. The EU-LFS for instance does not include data on the necessary institutional variables. These being, the strictness of Employment Protection Legislation (EPL) and the Active Labour Market Policy (ALMP) spending per country. The OECD documents data on these factors and can thus be included in the dataset (OECD, 2019) (OECD, 2020). Both factors show in a way how labour markets are regulated. EPL will show the strictness in which countries regulate their labour markets, which for instance has effects on both the hiring and firing process, as discussed in detail in chapter two. Additionally, ALMP spending will be used as a proxy of the extent governments intervene in the labour market to help workers in disadvantageous positions. Besides the regional contextual factors, automation risk data has to be added to the dataset as well. This includes the individual levels of automation risk per worker and levels of automation risk experienced by regions as a whole.

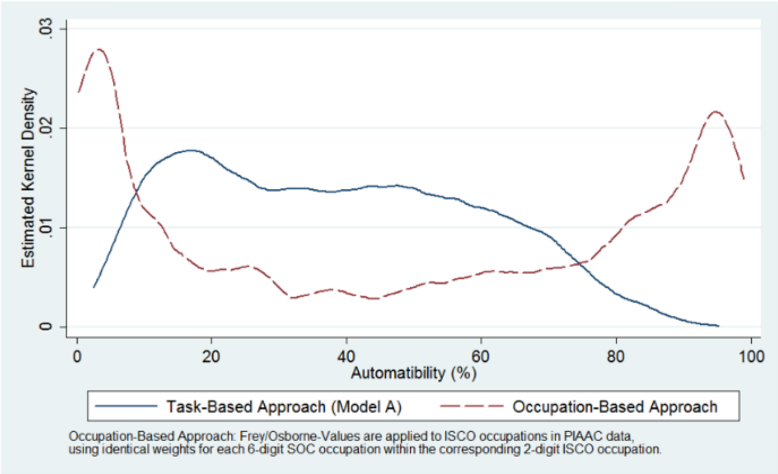
Automation risk data

As the introduction showed, the extent of the risk of job automation is heavily debated among researchers. The estimation of the percentages of jobs high at risk of automation differs substantially. Frey and Osborne (2017) state a pessimistic 47 percent of jobs high at risk of job automation, high at risk meaning being above 70 percent chance of being automated in the near future. However, the OECD studies by Arntz et al. (2017) and Nedelkoska and Quintini (2018) show a more 'optimistic' view with percentages being respectively 9 percent and 14 percent of all jobs in OECD countries to be at high risk of automation, with high variations between countries though.

The differences between these studies depend on the different methodologies used. Frey and Osborne (2017) focused on the occupations, where each occupation can be described with a combination of eight task groups. Arntz et al. (2017), alternately, chose to focus on the tasks specifically, since they suggest that the actual tasks performed in occupations could vary considerably by firm, industry, skill level and geography. Therefore, each labelled occupation could hide a considerable amount of variation in the actual task profile. So, one could definitely argue that assessing the susceptibility to automation is best done at the level of the task, using the information on the specific tasks performed rather than on an assumed mean task-profile per occupation. Others claim that the occupational-approach is easier used for how datasets are often set-up (Frey & Osborne, 2017).

As the data available for this research only has occupational data, this makes adopting the task-based approach of Arntz et al. impossible. Thus, this study has to rely on the occupational-based approach, which is the index developed by Frey and Osborne (2017). In this approach, each occupational code is couple to a likelihood of automation. Frey and Osborne developed the index based on estimations by experts on the risk of automation on 70 common occupations. They used these estimations in combination with their own prediction model, which allowed it to be extrapolated to cover the entirety of 702 SOC-occupations, which is the Standard Occupational Classification used in the USA. This resulted in an index between zero and one, where a number of one is an occupation with a hundred percent chance of being automated in the near future. The EU-LFS dataset that this research will be using does not classify occupations to the SOC standards though. Instead, the EU-LFS used the ISCO-08 standards from 2008, therefore the SOC occupations scores from Frey & Osborne will be translated to the ISCO-08 scores. This makes it possible to couple the automation risk data directly to each occupation. The translation to ISCO-08 occupation codes is made possible with the use of crosswalks available at the US Bureau of Labour Statistics (U.S. Bureau of labor statistics, 2012).

One should note that these ratios are estimations and conclusions have to be drawn carefully. Moreover, with using the occupational-approach index of Frey and Osborne (2017), the analysis could assume a relatively higher risk profile for all occupations compared to other methods. As can be seen in the graph in figure 7. The graph shows the abstract results of the two different approaches. The occupational-based approach is the red line, which shows relatively many jobs with a low and high risk of automaton. Taking this in regard, this study will only use the absolute risk levels to order occupations on a relative scale. This is done to somewhat protect against the possible upward bias of this automation risk method. The occupations will be ordered to low-, medium- and high-risk occupations. All occupations scoring below 0,3 on the index are deemed low at risk, all occupations above 0.7 will be labelled high at risk, and all occupations in-between are labelled at medium risk. Especially, the distinction of workers high at risk will be important in assessing the dependent variable on the climbing down the ladder phenomenon.



Source: Arntz et al. (2017)

Figure 7

Creating the dependent variable: 'Climbing Down the Ladder'

This section will explain how the dependent variable: Climbing Down the Ladder is created, and why it is used as a proxy to measure the deterioration of employability of the mid-level workers at risk of job automation.

The dependent variable CDTL will be a binary measurement that will test if workers suffered decreased employability due to automation. The basis of this variable is checking if a person has become recently unemployed and if this person has an automation risk exposure higher than 70 percent, which is considered high at risk. This leaves the counterfactual group, so all the zero's in this binary variable, to be persons who are employed (with any automation risk) and unemployed persons (with automation risks lower than 70 percent).

So, the assumption made is that workers who were confirmed to be (recently) unemployed are considered at risk of climbing down the ladder if the individual's risk of automation also exceeds 70 percent. The following paragraph is made to serve as an argument to back this assumption up. It includes a quick summary of important points that were made in both chapter 1 and 2 on the basis of academic literature.

Automation often happens suddenly and on a large scale, as a result, workers can be put in a difficult position. The laid-off workers not only have the problem of finding a new job, but they also have to compete for it with the other laid-off workers. This is especially the case if these workers are not able to get jobs in other regions than their own. Workers that are laid-off because of automation often hold skill sets that are useful for explicit and codifiable tasks, which are highly automatable. These type of skill sets make it difficult to attain jobs at higher levels, which typically include more complex and abstract tasks. Thus, these workers often have to compete for the same type of jobs they had before. These jobs with their explicit and codifiable tasks are becoming more and more redundant due to automation. So, it could become increasingly difficult to get appropriate new jobs again for lack of new skills or these jobs having been made scarce by new technologies. As a result, these persons either have to be lucky to win the competition between the workers and gain, once again, a job at the same level, which is again likely to be high at risk of automation and does not hold a stable prospect for the future. Another possibility could be to make concessions or be forced to take on a job at a lower level. And lastly, one could remain unemployed, which could only make the skill mismatch larger with time (unless training or education is followed). All options could be regarded as a deterioration of the (future) employability of the worker and that is why this assumption is made regarding the dependent variable: Climbing Down the Ladder.

How was dealt with implications

Deterioration of employability is probably most accurately measured comparing the current and previous occupation per individual. For instance, if an individual would have dropped from a higher-skilled/paid occupation ('previous occupation') to a lower-skilled/paid occupation ('current occupation') and if that person holds an automation risk of higher than 0,7 (thus classified as high at risk) then this individual could have been confirmed to have climbed down the ladder due to automation. However, there are implications hindering this approach. The biggest implication is the fact that for all respondents in the EU-LFS dataset either only previous occupation or current occupation is filled in. After checking with the respective employment factors per individual, a conclusion could be drawn that individuals who had filled in 'previous occupation' (and thus not 'current occupation') were persons being unemployed. In turn, the assumption could be made that individuals who filled in 'current occupation' (and thus not 'previous occupation') either were unemployed before or simply did not fill in this question. Another implication is the fact that the EU-LFS is cross-sectional data instead of panel data. This makes it impossible to track the same individuals through time as they are randomized. And finally, the information on income per individual has many missing variables as people tend to refrain from sharing that personal information. These three implications make the direct estimation of someone climbing down the ladder impossible. That is why the dependent variable Climbing Down the Ladder now estimates workers to either be at risk of climbing down the ladder or not. And by doing so, it is used as a proxy for the deterioration of employability due to automation.

The counterfactual group

So, the set-up of the CDTL variable includes a check if the worker is confirmed to be (recently) unemployed and if this worker holds an automation risk that exceeds 70 percent. If this is the case, then this worker is considered to be at risk of climbing down the ladder. On the other hand, are the persons that do not fall into this category: the counterfactual group (the zero's in this binary variable). These are the persons that are either employed or unemployed with an automation risk that is lower than 70 percent.

A thing to note is that in this statistical analysis a specific check is made to assess the influence of automation risk on being more likely to climb down the ladder. This check consists of running the statistical analyses over the dataset without the employed persons. The logistic regressions run over this new dataset (only unemployed persons) is then compared to the logistic regressions over the entire dataset. If the results would be similar, then this would indicate that unemployment is the driving force influencing this dependent variable. The results show the same patterns but with much smaller log odds, indicating that both unemployment and automation risk is important for assessing the deterioration of employability of workers in this dependent variable.

3.2 Data editing

The final dataset consists of 3.442.664 workers, of which 3.91 percent are found to be at risk of climbing down the ladder, and can be considered to have suffered decreased employability due to job automation. This section will discuss what data editing had to take place to fully prepare this dataset.

The EU-LFS includes data on the economically active population, which includes both employed (also self-employed) and unemployed people. Additionally, economically inactive persons are included as well. These can include students, retirees, the permanently disabled, persons fulfilling domestics tasks, persons performing voluntary work/traineeships and persons in compulsory military service. As this study pertains to the active working population, the economically inactive persons will not be relevant for this study. This is because these persons can not have experienced a deterioration of their employability and thus would have otherwise severely skewed the data rendering the analysis weaker. Hence, these persons are dropped out of the dataset. This is done by using data on the main labour status of the individuals, which filters out these persons. Moreover, the individuals without any information on occupation have to be dropped as this is a crucial data point for this analysis. Lastly, a few occupations have to be dropped as for these the automation risk indexes of Frey and Osborne (2017) is not known. After this is done, the Frey and Osborne data is merged to the dataset. As mentioned before, this merging is done on the ISCO-codes of the occupations per individual. As an example, the dataset now shows that individuals who are primary school teachers (ISCO-code: 234) +are very low at risk of automation with a score of 0,083. On the other hand, an individual who is a secretary holds a very high risk of automation with a score of 0,96. An overview of all the occupation codes with its automation risk is included in appendix 2.

Furthermore, the OECD data on Active Labour Market Policy spending (ALMP) and level of Employment Protection Legislation (EPL) is added to the dataset. As this is national data, the data is merged into the respective nations. The ALMP data are recoded so a distinction can be made between low-, medium- and high-spending countries. The same is done for the EPL variable, where numeric values are recoded into three categorical values: mild, moderate and strict EPL. The splitting into three categories is done so a clear distinction is visible and because this allows the possibility to create dummies which makes the eventual analysis more clear and easier interpretable. However, do note that these three categories are not chosen at random. Three 'quartiles' are calculated and are the basis of the distinction made. This ensures that, for example, a low category for ALMP can be made as this is relative to the total average of the EU-countries.

Additionally, regional data adjustments are made, so that it coincides with the Eurostat NUTS 2 classification (Eurostat, 2016). Initially, the regional codes do not include the country codes. These are added to avoid overlap between regions in different countries. For example, there is a regional code of 21 for Belgium, Spain, France, Poland, Romania and Sweden. Adding country codes to these regional codes will stop this overlap (e.g. BE21, ES21, FR21 etc.). Fixing this will come in handy later when the phenomenon will be visualized in maps using GIS. The adjustment of the regional data is performed with a merge of the main dataset with a self-made excel dataset. In the excel dataset the countries, EU-LFS regional codes and its adjusted regional codes are added. This allows the dataset to be merged on both the country and regional code data and thus adds an adjusted regional code to each individual.

After this is done, the variable of regional exposure rates can be added to the dataset. This variable, which can give an indication of how the labour market structures in regions are performing in relation to automation risks, is then recoded appropriately. The recoding allows for a direct comparison between regions that are either: low, medium or highly exposed to automation risks. However, there are some complications with the regional data. For most countries data on NUTS 2 region is available, though for some countries either the regional data is collected on the NUTS 1 level (Austria) or the regional data is missing. The latter results in the phenomenon having to be visualized for these countries as a whole and thus loses its regional comparison. Because of this complication, the variable of regional exposure rates is also missing for certain countries, which leaves them out when run in the logistic regression. Therefore, a separate logistic regression model will be run with this variable specifically.

As for the individual demographic data, some variables are recoded whilst others only had to be relabeled to easier interpret the analysis later on. The variable of educational attainment is recoded and brought back from 8 (ISCED codes) to 3 categories on the basis of the Eurostat classification (Eurostat, 2019). Namely, Low education: “Less than primary, primary and lower secondary” (ISCED 0-2), Medium education: “Upper secondary and post-secondary non-tertiary” (ISCED 3-4), High education: “Short-cycle tertiary, bachelor or equivalent, master or equivalent and doctoral or equivalent” (ISCED 5-8). Additionally, age is recoded where 17 cohorts are brought back to 6 so that a more clear comparison can be done. The new cohorts are, 17-24, 25-34, 35-44, 45-54, 55-64 and 65/max. Note, that checks are made for persons (early) retired. Other variables did not have to be recoded, only a label change was needed. Examples include, 1’s and 2’s being changed to ‘Male’ and ‘Female’ with the variable gender, and degree of urbanization variable changed to ‘City’ (1), ‘Town or Suburb’ (2) and ‘Rural area’ (3).

The variable of mobility is not directly measured by the EU-LFS dataset. However, the dataset does include data on the current and previous region of residence (one year ago). With a comparison between these data points, the mobility of an individual is measured. For example, if the current region of residence differs from the previous one, the individual is recognized as having moved. There are some issues with this variable though. As this variable compares Nuts 2 regions, mobility will only be tracked when persons have moved between these (relatively large) regions. Thus, possibly a lot of close mobility will go unrecognized in this variable. To add to that, it is only measured in its own respective country as these regional codes did not yet include the country codes when they were established (so no comparison of regions between different countries can be done). Lastly, not all regional data is available for every country, as mentioned above. This means that for these countries no mobility factor can be measured. Taking all this into account, the variable of mobility will not be accurate but could only give an indication. For this reason, the analysis will be run with and without this variable to check if this variable improves the goodness-of-fit of the model or if only distorts the results due to its inaccuracy. If the latter is the case, this variable will be removed from the analysis.
An overview of the dependent variable and the main independent variables is shown in table 1 on the next page. Also, table 2 shows an overview of all the edited variables with its final labels.

Dependent variable	**Description**
Climbing Down the Ladder	Self-made dependent variable that tracks the deterioration of employability of workers at risk of job automation
Main independent variables	
Education	EU-LFS variable: Highest educational attainment of individuals
Training	EU-LFS variable: Did the individual follow any training in the last month?
EPL	OECD variable: strictness of Employment Protection Legislation
ALMP	OECD variable: country-level expenditure on Active Labour Market Policies
Individual and regional controls	Age, gender, degree of urbanization and regional exposure to automation
Countries	Country dummies
Year	Year dummy that allows comparison between 2011 and 2016

***Table 1**: Overview dependent variable and main independent variables*

Variable	Name in dataset	Labels	Percentages
Climbing Down the Ladder	CDTL	1 = Yes	3.91%
		0 = No	96.09%
Education	Edulvl	1 = High	27.41%
		2 = Medium	49.66%
		3 = Low	22.93%
Training	Training	1 = Training	91.12%
		0 = No Training	8.88%
Employment Protection Legislation	EPL	1 = Mild	27.29%
		2 = Moderate	49.35%
		3 = Strict	23.36%
Active Labour Market Policies	ALMP	1 = Low	36.81%
		2 = Average	49.00%
		3 = High	14.19%
Age	Age	17-24	7.42%
		25-34	19.73%
		35-44	26.10%
		45-54	27.86%
		55-64	17.14%
		65/max	1.75%
Gender	Gender	1 = Male	53.73%
		2 = Female	46.27%
Degree of Urbanization	DegUrba	1 = City	34.16%
		2 = Town or Suburb	29.07%
		3 = Rural area	36.77%
Regional exposure rate	Region_risk	1 = Low exposure	33.53%
		2 = Medium exposure	33.16%
		3 = High exposure	33.31%
Workers	Workerlevel	1 = Low-level worker	10.41%
		2 = Mid-level worker	53.31%
		3 = High level worker	36.28%
Automation Risk	Autom_risk	<0.3 = Low Risk	23.26%
		0.3 – 0.7 = Medium Risk	45.23%
		>0.7 = High Risk	31.51%

***Table 2**: The recoded/labelled variables with its percentages in the dataset*

3.3 Data analysis

To answer the first two research questions of this thesis a descriptive analysis combined with Pearson's chi-squared tests are performed. The first research question wants to know the extent of mid-level jobs at risk, and what the worker's characteristics and efforts are in dealing with this issue. To show this extent of mid-level jobs at risk, first, a distinction has to be made on the different levels of jobs. A low-, mid- and high-level jobs distinction is made for all the individuals in the dataset. This is done based on the ILO's classification of isco-08 major groups into skill levels (International Labour Office, 2012). With this classification, the isco-08 codes of the 'Occupation' and 'Previous Occupation' variables could be recoded into a new variable which shows the skill level of each individual according to the ILO's mapping. For example, the three isco-08 major groups of 1 (=managers), 2 (= professionals) and 3 (= technicians and associate professionals) are considered to be high in skill level. Thus, the occupation codes ranging from 100 till 399 are recoded as such.

Now, the different groups (based on skill level) can be set out against the automation risk variable. This is done with the help of a crosstab, which can give a clear overview of the distribution of the data. Moreover, Pearson's chi-squared test is run to test the relationship between the two variables. A chi-square test is designed to test a null hypothesis about the relationship between two variables. The null hypothesis in this kind of test is usually a statement that there is no relationship. Therefore, if the p-value is found to be significant, and the null hypothesis can be rejected, then the test would indicate that there does exist a relationship between the two variables. On the other hand, if no

significant p-value is found then it only indicates that there is insufficient evidence to reject the null hypothesis.
This analysis, using a crosstab in combination with a Pearson's chi-square test is also done for the relationships between educational attainment and automation risk, the following of training and automation risk and individual demographic factors such as age and gender with automation risk.

Then for the second research question, which has to show the extent of the CDTL phenomenon for the mid-level workers. A crosstab + chi-square test is shown for the relationship between the different groups of workers (based on skill levels) and the CDTL phenomenon.

With the third research question, the regional influences and differences across Europe are put forward. First, the regional differences in the extent of the phenomenon are visualized in a map using the program GIS. This will be done, where possible, on the NUTS 2 level. Reviewing the regional differences in the map could reveal certain patterns. Additionally, relationships between the regional factors and the phenomenon are investigated. For instance, the possible effect of a stricter employment protection legislation on the extent of the CDTL phenomenon. Moreover, active labour market policy spending, urban-rural differences and regional exposure rates to automation risks are investigated in relation to the phenomenon. The factors could also reveal certain patterns or may explain the patterns found in the created map.

The fourth and last research question, which seeks an answer to the extent that the individual and regional factors influence the phenomenon, will be analyzed using logistic regressions. Logistic regression is used as the dependent variable is binary (either 'yes' or 'no'). This is the first of the major assumptions that have to be met to use a logistic regression: the dependent variable should be dichotomous in nature, meaning a sharp division of things into two contradictory parts (Osborne, 2008). The second assumption is that there should be no outliers in the data. This was taken into account during the time all variable were carefully and logically recoded into either categorical or binary variables. Each variable was plotted and checked if certain data points were surprising or out of the ordinary.

Lastly, the assumption has to be met that no multicollinearity exists among the predictors, meaning no high correlations between the independent variables. To classify the correlations as acceptable the correlation parameters of Ratner (2009) are used, where values below 0.7 are deemed acceptable and multicollinearity can be ruled out. To double-check for multicollinearity the VIF (variance inflation factor) is calculated for each predictor. The VIF quantifies the extent of correlation between one independent variable and the other independent variables in the model. The resulting VIF values can then be used to diagnose if multicollinearity exists in the dataset. When these assumptions are met the logistic regression can be performed. The CDTL phenomenon will be regressed using the independent variables shown in table 1. To check if the model is achieving well, the pseudo-R-squared is used. A thing to note is that according to Wu & West (2013) pseudo-R-squared values cannot be interpreted independently or compared between different datasets or studies. A pseudo-R-squared has little meaning without context. It can only tell you something when the pseudo-R-squared values are compared on the same dataset, which are trying to predict the same outcome (Wu & West, 2013). Taking this into account, the regression is run multiple times, each time adding another one of the independent variables and checking if the pseudo-R-squared is improving. The highest pseudo-R-squared will indicate which model best predicts the outcome.
A final thing to note is that the standard errors in all logistic models have been clustered at the country level. This is done to account for the multilevel nature of the data. The final models will be shown in chapter 4.4. Before that the first three research questions are tackled, where the distribution of the data and certain (regional) patterns are investigated.

4. Results

This chapter will discuss the results that are found after performing the data-analyses as described in the previous chapter. The previously examined academic literature will be taken into account when discussing these results. Moreover, this chapter will allow to seek answers to the hypotheses that were set-up at the end of chapter two. These will then be discussed in the final chapter: the conclusions. For this chapter, the structure will follow the structure of the research questions and the set-up of the data analysis, which was made in the previous chapter.

4.1 Workers at risk of job automation and their characteristics

The tables below display how the respondents are distributed among the different categories. It is displayed in relative column percentages. This means that for every sub-group (e.g. low-/mid-/high-level workers) the distribution is shown across the categories. Additionally, the chi-square test is included at the bottom. If an asterisk is included besides the variable this means that the chi-square test was found to be significant. The note below the table shows at what level this significance is found. If a significant level is found, the null hypothesis of the chi-squared test (no relationship between the variables) can be rejected and thus a statistically significant relationship is found between the variables. This significant relationship means that the distribution of the data is not random across the cells. As a result, potential patterns can be investigated.

In table 3 the distribution of the workers is shown over the risk of automation. The results of the chi-square test show a significance at the 1 percent level. Therefore, a statistically significant relationship is found between the variables. Though, certain things are already pretty clear when looking at the relative percentages. A large part of the high-level workers is considered low at risk of automation. Only a fraction of these workers is considered high at risk, while for the low- and mid-level workers this is a substantial amount. This is especially the case for the mid-level workers of which 50.19 percent are considered high at risk of automation. This is not surprising taking into account the literature of Acemoglu & Autor (2011), who stated that the tasks of mid-level jobs generally comprise of routine tasks, and therefore, are more susceptible being high at risk of automation.

	Worker-level		
Automation risk*	Low-level	Mid-level	High-level
Low Risk	1.05%	2.44%	60.51%
Medium Risk	55.98%	47.37%	39%
High Risk	42.97%	50.19%	0.49%
	100%	100%	100%
Chi2	p = 0.000		

* Significant at the 1% level

***Table 3**: Distribution of workers over automation risk*

In table 4 the distribution of workers with their different automation risk levels is shown over the three different levels of education in the dataset. The chi-square test is shown to be significant at the 1% level, meaning a statistically significant relationship is present between the variables. When the table is observed a clear pattern is visible for the workers labelled as low at risk. Namely, this group comprises of 66,2% with a high level of education. These results are in line with the discussion in chapter two on higher educated people. Where it was explained that workers with higher education are, generally, more represented in occupations that comprise of tasks that are low at risk of automation. Hawksworth & Berriman (2018) stated that the tasks of these occupations consist of skills of intellectual reasoning and of supervision that will still be needed alongside computers and other AI-based systems, hence a consistently low automation risk can be expected for higher educated persons.

On the other hand, the workers labelled high at risk of automation have large percentages in the low and medium levels of education. Respectively, 31.10% and 58.01%. So, especially workers with a medium level of education are found to be high at risk. One could argue that the largest percentages of automation risk could be expected for low-level/lower-educated workers (both in table 3 and table 4), however, these findings are still as expected taking into account the literature. In chapter two, it is discussed that the occupations of low-level educated workers often include manual tasks, where situational adaptability, visual and language recognition and in-person interactions are required. These types of tasks are shown to be difficult to automate (Autor, 2015).

	Automation risk		
Level of education*	Low risk	Medium risk	High risk
Low	5.94%	25.98%	31.10%
Medium	27.86%	55.07%	58.01%
High	66.2%	18.95%	10.89%
	100%	100%	100%
Chi2	p = 0.000		

* = Significant at the 1% level

***Table 4**: Distribution of different levels of education over different levels of automation risk*

Yet, a 42.97 percent of low-level workers (table 3) and a 31.10 percent of lower-educated workers (table 4) being high at risk of automation is of course still a large percentage and is to a certain extent a surprising result when taking into account the data on job polarization. For example, Goos et al. (2014) show in figure 3 (chapter two) that it almost only seems to be the mid-level jobs that are disappearing and the number of low-level jobs are actually increasing. This brings up the question of why low-level jobs, of which quite an amount is found to be high at risk, are increasing while the amount of mid-level jobs is decreasing? This could be because even though some low-level jobs could be automated, employers make the conscientious choice of not implementing such automatable technologies as these are far less worthwhile compared to automating routine jobs. This might be the case as these low-level jobs hold low wages, as the supply of workers who can perform these tasks are very large. As a result, automating these jobs can be seen as far less cost-beneficial (Autor, 2015). Additionally, many of these jobs have to be performed on-site or in person, and thus these jobs are not subject to outsourcing which could further decrease the benefits of automation. However, according to Brynjolfsson & McAfee (2014), it can be expected that automatable technologies will learn to perform other tasks as well and do it even more efficiently. Plus, looking at figure 2 (chapter 2), the trend of automatable technologies becoming ever cheaper compared to labour costs might continue as well. Both these developments could make automating low-level jobs/tasks much more cost beneficial and result in these jobs disappearing as well in the future.

In table 5 and 6, the distribution of training over automation risk and the different levels of workers is shown. Both distributions are statistically significant at the 1 percent level, which indicates a significant relationship between the variables. Both tables show a clear pattern where in table 5 the higher the automation risk the lower the attendance of training is. In table 6 the different levels of workers also show a clear pattern. Workers with higher-level jobs following the most training and workers with lower-level jobs follow the least. These findings perfectly complement the literature on training discussed in chapter two. For instance, studies found that the odds of engaging in any type of training are significantly lower among workers with jobs at risk of automation (Nedelkoska & Quintini, 2018) (ESDE, 2018).

	Automation risk		
Training*	Low Risk	Medium Risk	High Risk
No	85.26%	91.83%	94.44%
Yes	14.74%	8.17%	5.56%
	100%	100%	100%
Chi2	p = 0.000		

* Significant at the 1% level

	Worker-level		
Training*	Low-level	Mid-level	High-level
No	96.26%	93.86%	85.62%
Yes	3.74%	6.14%	14.38%
	100%	100%	100%
Chi2	p = 0.000		

* Significant at the 1% level

Table 5 & 6*: Distribution of training over automation risk (5) and over workers (6)*

Lastly, the distribution of the data on age and gender over automation risk are shown in the tables in appendix 3**.** Both tables have a significant p-value of the chi-square test, which indicates that there exists a significant relationship between the variables. Where for age, young workers between the ages of 17 and 24 are shown to be relatively higher at risk than the other age groups. This might be the results of this group having more temporary jobs or because these workers are lower educated (as non-working students are filtered out of the dataset, thus workers at the age of 17-20 will probably not have a tertiary education). For gender, the table shows that there are more males than females in the dataset and that males may slightly be more at risk of automation. However, Leana & Feldman (1991) found that males generally tend to find new jobs quicker and have stronger labour market positions compared to females, which could result in the CDTL phenomenon to occur more for females as opposed to males.

4.2 Extent of the CDTL phenomenon for the mid-level workers

Of the total dataset of 3.422.664 workers, 133.783 (3.91 percent) workers were found to have suffered a decrease in their employability and could be forced to take down jobs at lower levels. In order to answer the second research question, what is the extent of the climbing down the ladder phenomenon for the mid-level workers table 7 is shown. This table shows per worker level what the relative percentages are that have experienced the phenomenon. A significant level is found for the chi-squared test, which indicates that a significant relationship is found between the variables. 5.46 percent of the total group of mid-level workers have experienced the phenomenon. After assessing the literature and polarization data in chapter two and tables 3 and 4 at the start of this chapter, one could argue that the highest percentage should be found for the mid-level worker group. Yet, the highest relative percentage is found for the lower-level workers. Here, 9.48 percent are found to have suffered a decrease in their employability. So, while mid-level workers were expected to be affected the most by automation, more low-level workers are found to have suffered from the risks of automation.

	Worker-level		
CDTL*	Low-level	Mid-level	High-level
No	90.52%	94.54%	99.96%
Yes	9.48%	5.46%	0.04%
	100%	100%	100%
Chi2	p = 0.000		

* Significant at the 1% level

***Table 7**: Climbing down the Ladder per worker-level*

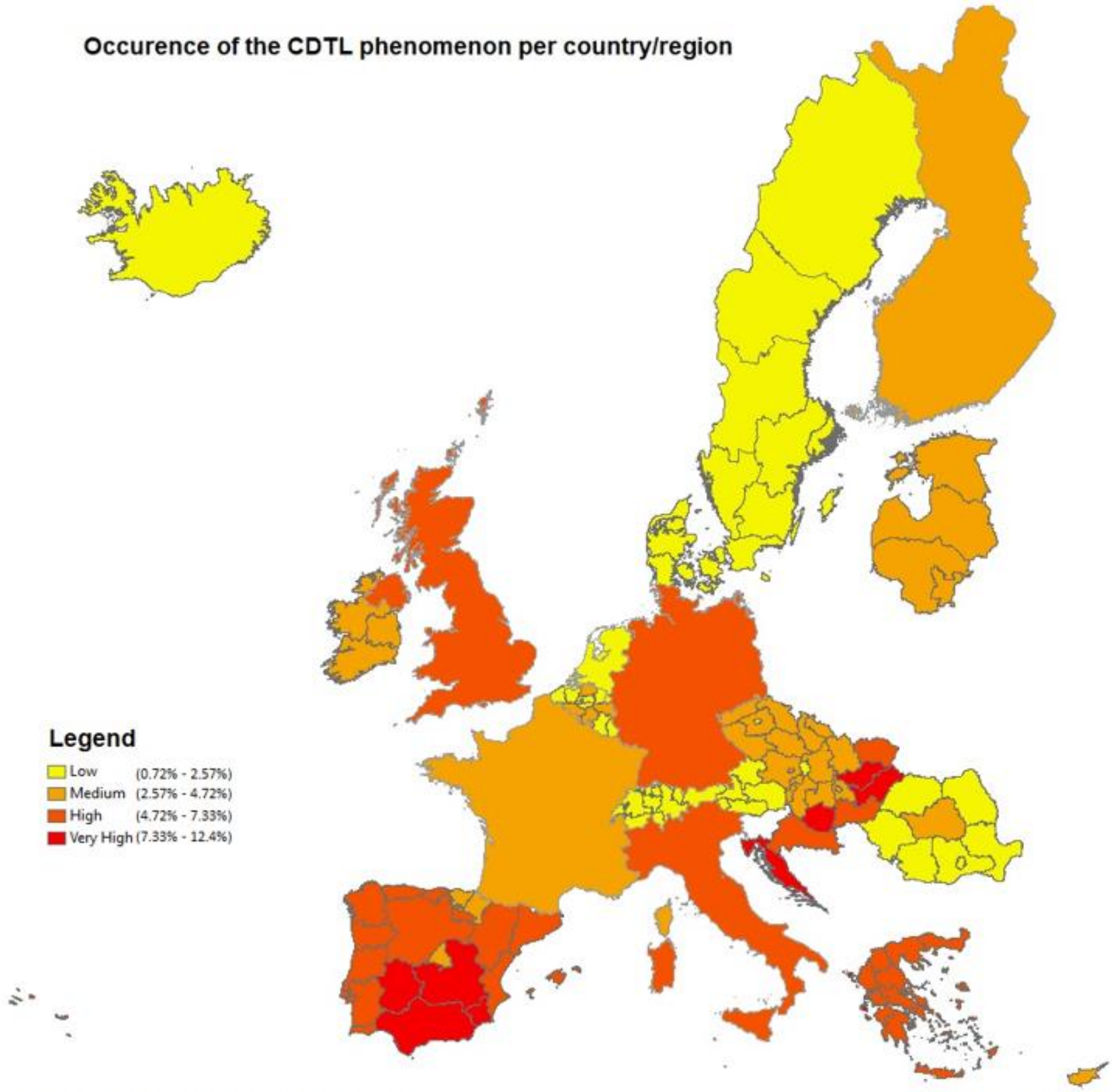
A possible reason for these results may be that, automating low-level jobs has become more worthwhile as adopting automated technologies becomes increasingly cheaper with time (ESDE, 2018; Servoz, 2019; figure 2). As a result, low-level jobs that were previously considered low at risk may have gained automation potential and may be the reason why more low-level workers are being displaced now.

Another reason might be that lower-level workers stay unemployed longer, as unemployment benefits could lower incentives to find new jobs. This is because unemployment benefits can come close to the wages they had before and could reduce the need to exert efforts in finding new jobs. On the other hand, these unemployment benefits could make it possible for workers to reject poor offers and continue to search for better jobs, which could make the chance of an actual drop to a lower level job smaller. However, the effects of unemployment benefits on this context go outside the scope of this research. But could possibly be an interesting topic for further research. A thing to note is that while the institutional variables used in this study do not directly measure these welfare systems, they are likely to be correlated with it.

4.3 The regional differences

Mapping the data is useful in order to make good distinctions in terms to what extent different countries or regions are experiencing this phenomenon. This is done using the mapping software ArcGIS. Figure 8 on the next page shows the end result. The occurrence of the CDTL phenomenon is mapped per country and per region where possible. As not all countries had regional data, certain countries have relative CDTL percentages shown for the entire country. In the map, a distinction is made between low, medium, high and very high occurrences of the phenomenon. These categories are not chosen at random. Four quartiles are calculated over all the cases and are the basis of the distinction made. The calculated percentages are shown in the legend for each category.

Countries that seem to be doing very well are Denmark, Sweden, the Netherlands, Iceland, Switzerland and regions of Austria and Romania. These countries and regions have an occurrence of the CDTL phenomenon that is lower than 2,57 percent. On the other hand, countries such as the United Kingdom, Germany, Portugal, Spain, Italy, Croatia, Greece and parts of Hungary are shown to have quite high occurrences of the phenomenon. Here, certain regions even experience the highest found occurrences of the phenomenon. For now, this map serves the purpose to be able to visualize the distribution of the phenomenon across Europe and to identify the countries and regions that are have experienced the phenomenon the most. Today, these countries and regions might still be highest at risk of having workers suffering decreased employability due to job automation. Identifying these countries/regions may be the first step in trying to alleviate these problems.



Source: EU-LFS + OECD; own creation using ArcGIS.

Figure 8

Additionally, countries have been put in country groups to identify if certain parts of Europe experience decreased employability due to automation more than others. The distribution of the phenomenon across the different country groups is shown below in table 8. What countries are included in each group can be seen in appendix 4. Looking at the relative percentages over each country group is it clear that certain parts of Europe experience the phenomenon to a greater extent than others. The chi-squared test is found to be significant at the 1 percent level, indicating that the distribution is indeed significant. Especially the Southern part of Europe holds a high percentage of the phenomenon compared to for example Scandinavian and Continental West-European countries.

CDTL*	Country Groups in Europe				
	Scandinavian	Anglo-Saxon	Continental West	East	South
No	97.95%	95.78%	97.06%	95.98%	94.18%
Yes	2.05%	4.22%	2.94%	4.02%	5.82%
	100%	100%	100%	100%	100%
Chi2	p = 0.000				

* = Significant at the 1% level

***Table 8**: Distribution of degree of urbanization over the CDTL phenomenon*

Besides showing the distribution over these country groups, these groups are run in the logistic regression using dummy variables. This allows to check if being in one of these parts of Europe can to a certain extent explain the occurrence of the phenomenon. Additionally, a separate model is run in the logistic regression which allows to add individual country dummies. In this model, direct comparisons can be made between the countries. If certain parts or individual countries of Europe pop out this could possibly spark an interest in a follow-up study in order to explain why this part of Europe is experiencing this phenomenon to such an extent.

Regional contextual factors

First, possible patterns of regional contextual factors on the phenomenon are explored though. This is done on the basis of the variables; employment protection legislation, active labour market policies and urban-rural differences and regional exposure rates.
The distribution of the phenomenon over employment protection legislation is shown in table 9 below. The chi-square test is shown to be significant at the 1% level, meaning a statistically significant relationship is found between the variables. The table shows that the most occurrences of the phenomenon are found in countries with strict employment protection legislation. A percentage of 4.81 is found. Interestingly, the percentage of CDTL occurrences for countries with mild employment protection legislation is close to this percentage. Here a percentage of 4.27 is found.

The distribution of data can be considered in line with the discussed literature in chapter two. Stringent EPL lowers the predisposition towards firings workers, but it also results in a decreasing willingness of employers to hire new workers in the first place. This is because employers can include future lay-off costs with current hiring decisions. These increased hiring costs can, as a result, become employment obstacles for job searchers (Bennett, 2016). This could result in workers staying longer unemployed and could, therefore, increase the occurrence of the CDTL phenomenon in this study. On the other hand, lenient EPL could result in quicker adaptations of automation processes (Samaniego, 2006). Furthermore, lenient EPL results in fewer barriers to firing and hiring workers, which could result in quicker turnovers in these labour markets. Could this mean that a moderately regulated employment protection legislation is the way to go? The logistic regression in the next chapter will elaborate on the extent it actually influences the CDTL phenomenon.

	Employment Protection Legislation		
CDTL*	Lenient	Moderate	Strict
No	95.73%	96.43%	95.19%
Yes	4.27%	3.57%	4.81%
	100%	100%	100%
Chi2	p = 0.000		

* = Significant at the 1% level

Table 9*: Distribution of the phenomenon over employment protection legislation*

Table 10 shows the distribution of the phenomenon over the active labour market policy spending. Goals of active labour market policies include job creation, job-search assistance, incentivizing workers to train, improve the quality of training and lowering barriers to training and many more. Because of all these aspects, this variable is used as a proxy of the extent of governmental interventions in labour markets to help workers in disadvantageous positions. The variable shows a clear pattern. Governments that spend more on ALMP have fewer CDTL phenomenon occurrences. This relationship is found to be significant at the 1 percent level with the chi-squared test.

	Active Labour Market Policy spending		
CDTL*	Low	Average	High
No	95.18%	95.89%	98.02%
Yes	4.82%	4.11%	1.98%
	100%	100%	100%
Chi2	p = 0.000		

* = Significant at the 1% level

Table 10*: Distribution of active labour market policy spending over the CDTL phenomenon*

One of the variables used to explore the regional context of the phenomenon is the variable which indicates urban-rural differences. The distribution of the phenomenon on this variable is shown in appendix 5. The chi-squared test is found to be significant at the 1 percent level and indicates a relationship between the variables. The distributions find that the most occurrences of the CDTL phenomenon are found in rural areas and the least in cities. This is in line with the views of Devaraj et al. (2020), who believe that rural areas can have substantial exposure to automation risks, as these areas can have specific occupations that hold high risks of getting automated. Furthermore, they state that rural areas, in general, have more vulnerable populations in terms of socioeconomic status and lower educational attainment, which might make workers in rural areas more at risk of suffering decreased employability due to automation. Another reason can be that job opportunities are more scarce in rural areas compared to urban ones (Bagchi, 1973). Cities hold far more employment opportunities and may therefore be better equipped to deal with automation risks.

Lastly, the variable that measures the automation risk exposure per region is also shown in appendix 5. This variable, which can give an indication of how the labour market structures in regions are performing in relation to automation risks, shows a clear pattern. Namely, that the higher the labour market structures in regions are exposed to automation risks, the higher the percentage is of workers suffering decreased employability. This goes in line with the literature of Vermeulen et al. (2018), who stated that certain labour market structures can be expected to be forced to undergo changes if they hold many occupations that are considered high at risk. Moreover, Böhm et al. (2019) stated that regions with higher exposure may hold less employment opportunities, which could be the reason laid-off workers, due to automation, may find it difficult to find new jobs again in this region. Add an increasing competition for jobs into the mix and workers may be forced to take on jobs at lower levels, which makes them climb down the ladder. The chi-square test is found to be significant at the 1 percent level, which indicates that the distribution is not random.

4.4 Effect of the individual and regional contextual factors on the phenomenon

Logistic regression

Besides the patterns of the CDTL phenomenon (reminder: a proxy for decreased employability of workers at risk of job automation), research is done to assess the effect individual-demographic and regional contextual factors have on the phenomenon across European regions. In order to assess this, logistic regressions are run. The logistic regression measures the relationship between the dependent variable; the CDTL phenomenon and the relevant independent variables by estimating log odds using a logistic function. These log odds show what the chance of certain categories (of the independent variables) is, compared to its reference category, on the occurrence of the phenomenon. For example, for the variable 'Gender' the log odds for the category 'Female' is found to be 1,142 in model 0, which indicates that females have a 14,2 percent higher chance of experiencing the CDTL phenomenon compared to males (as the reference category is 'Male'). This effect is found to be significant at the 1 percent level, indicated by three asterisks (***). When two asterisks (**) are found behind the log odds it indicates a significance at the 5 percent level. One asterisk indicates a significance at the 10 percent level and already needs to be interpreted carefully. When a variable is found to be insignificant then it indicates that no credible evidence can be found for a relationship between the category of this independent variable on the CDTL phenomenon compared to its reference category. The results of the logistic regressions are shown in tables 11 and 12. To create a better overview, the logistic regressions are split up into two tables showing individual-demographic factors in table 11 and the regional contextual factors in table 12.
As mentioned before, multiple logistic regressions are run with various models in order to find the strongest models to predict the occurrence of the CDTL phenomenon. The strongest models are shown in tables 11 and 12. In the columns, the log odds are added for each variable and model. The difference between the models is that model 0 only ran the individual demographic factors, hence it is left out in the regional contextual factors table. Model 1 holds all the variables and country groups in the EU are added. For model 2 the national institutional variables are removed, which allows for individual countries to be added. The institutional variables are national specific factors and are therefore the reason they have to be left out, otherwise, collinearity issues would arise. Finally, model 3 has the countries and the country groups removed, so it can focus on the effects of the regional factors. A thing to note is that worker levels, based on skill, (: low, mid and high-level workers) are not in the logistic regression. This is because it somewhat correlates to the variable of educational level. And as the variable of the educational level is more precise on the level of the individual, this variable is chosen.

Another thing to note is that the observations are lower for model 1 are lower because ALMP and EPL data are sporadically missing. Namely, for Greece and Romania. Moreover, model 3 also has lower observations as certain countries do not have the regional data available in the EU-LFS. As a result, these countries could not be run in this model and had to be left out.

4.4.1. Individual factors

The impact of individual-demographic factors on the CDTL phenomenon is studied on the basis of four variables. These include education, training and the demographic factors age and gender. From the results, it can be observed that both the level of education and training have substantial effects on the occurrence of the CDTL phenomenon. For instance, if a person has an educational level that can be considered low level then this person has between a 5.1 to 6.06 (taking into account the different models) times higher likelihood of experiencing the CDTL phenomenon to a person that has a high-level education. For people with a medium level education, a log odds of between 2.5 to 3.155 is found, meaning that these people have around a 2.5 to 3,2 higher likelihood of experiencing the CDTL phenomenon compared to people with higher-level educations. So, as expected, the likelihood of experiencing the CDTL phenomenon increases the lower the educational attainment is. This can be the case because of various reasons.

Logistic regression: Climbing down the Ladder								
Variables	Log odds; model 0		Log odds; model 1		Log odds; model 2		Log odds; model 3	
Individual-demographic factors								
Educational level; ref: High								
Low	5.434***	(0.833)	6.059***	(0.869)	5.116***	(0.772)	5.484***	(0.111)
Medium	2.984***	(0.292)	3.155***	(0.242)	2.933***	(0.218)	2.528***	(0.111)
Training; ref: Yes								
No	1.519***	(0.163)	1.250**	(0.143)	1.186*	(0.118)	1.261*	(0.154)
Gender; ref: Male								
Female	1.142***	(0.046)	1.123***	(0.038)	1.143***	(0.048)	1.123	(0.086)
Age; ref: 17-24								
25-34	0.847***	(0.050)	0.793***	(0.056)	0.796***	(0.049)	0.878	(0.093)
35-44	0.541***	(0.043)	0.492***	(0.052)	0.509***	(0.490)	0.562***	(0.065)
45-54	0.449***	(0.041)	0.418***	(0.052)	0.425***	(0.046)	0.461***	(0.053)
55-64	0.539***	(0.111)	0.538**	(0.141)	0.512***	(0.119)	0.463***	(0.069)
>65	1.528	(1.058)	1.694	(1.215)	1.315	(0.897)	0.158*	(0.025)
Year comparison; ref: 2011								
2016	1.213	(0.192)	1.128	(0.246)	1.130	(0.120)	1.168	(0.297)
Constant	0.012***	(0.003)	0.014***	(0.005)	0.019***	(0.003)	0.012***	(0.003)
Model characteristics								
Pseudo R-squared	0.0469		0.0703		0.0732		0.0586	
Observations	3.412.137		2.896.323		3.412.137		1.818.448	

Clustered standard errors in brackets behind the log odds
*** p<0.01 ** p<0.05 * p<0.10

***Table 11**: Results logistic regression individual demographic factors*

The main reason is that, persons that have better skills, due to higher education or training, have an easier time to adjust to new technologies and as a result have stronger employability (Groot & Van den Brink, 2000). Another reason is that workers with higher education are, generally, more represented in occupations that comprise of tasks that are low at risk of automation (Hawksworth & Berriman, 2018). For this reason, these workers already have a lower chance of experiencing decreased employability due to job automation (CDTL).

For the training variable, a log odds of 1.519 is found for model 0, which is a logistic regression model that only includes the individual-demographic factors. These log odds, which are statistically significant at the 1 percent level, show that workers not having followed training have around 52% higher chance of experiencing the CDTL phenomenon. For the log odds in model 1, which includes all the variables, a significance is found at the 5 percent level. These log odds are 1.25, meaning that not having followed training increases the chance of suffering decreased employability due to automation by 25%. With both percentages being considerably high, this again shows the importance of keeping up to date on relevant skills. For when someone has higher skills it is not only easier to prevent being laid-off from job automation but also to make it easier to find a new suitable job and to stay active in the labour market in case a lay-off occurs (Nedelkoska & Quintini, 2018).

For the demographic factor gender, log odds between 1.143 and 1.123 are found for the category females in the first three models. All of these log odds are significant at the 1 percent level. These log odds mean that females have a between 12,3 and 14,3 percent higher chance of experiencing decreased employability due to automation. These findings are in line with the academic literature, as males tend to find new jobs quicker and of higher quality (Leana & Feldman, 1991). Furthermore, males, generally, tend to have stronger labour market positions compared to females (Leana & Feldman, 1991).

For the age variable, the reference category is ages 17-24. So, all categories are compared to the youngest group of workers. The table shows that, across all models, the log odds seem to drop till age cohort 55-64. This indicates that the older someone is, the lower the chance becomes of suffering decreased employability due to automation when compared to the youngest group of workers. For example, in model 1 workers aged between 25 and 34 have a 20,7 percent lower chance of being labelled at risk of CDTL compared to workers aged between 17 and 24. And workers between the ages of 45 and 54 have a 58,2 percent lower chance compared to the youngest group of workers. According to the literature it was expected that younger workers would be more exposed to automation risk (Nedelkoska & Quintini, 2018). However, it was also expected that it could be counterbalanced by them being better equipped to deal with the issue compared to older workers (Nedelkoska & Quintini, 2018; Kanfer, et al., 2016; Hamil-Luker & Uhlenberg, 2002). And that through this expectation, older people could be considered more at risk of suffering decreased employability when laid-off due to automation. The findings of the logistic regressions may indicate that for younger people the higher exposure to automation outweighs the advantages of being better equipped in dealing with the risks of automation. Additionally, the results seem to be in accordance with the U-shaped relationship between automation and age (Nedelkoska & Quintini, 2018). Where the exposure to automation is highest for the youngest group and also relatively high for older workers. The age cohorts in-between experience less exposure, which may explain why the chance of suffering decreased employability due to automation decreases as workers get older (to a certain point).

4.4.2. Regional context

The impact of regional contextual factors on the CDTL phenomenon is studied on the basis of four variables. These include the two institutional variables of active labour market policies (ALMP) and employment protection legislation (EPL), and the two regional variables of the degree of urbanization and regional exposure rates. Moreover, country groups and the individual countries themselves are added as well.

From the results, it can be observed that ALMPs can have a substantial effect on the occurrence of the CDTL phenomenon. The log odds of average and high spending on active labour market policies are both close to each other. Namely, countries that have average ALMP spending have log odds of

0.577 (model 1) and 0.643 (model 3). This indicates that workers in countries with average ALMP spending have a 35,7 to 42,3 percent lower chance of experiencing the CDTL phenomenon compared to workers in countries that have low ALMP spending. For the high ALMP spending category these levels are slightly higher. Model 1 and 3 show 0.562 and 0.531 log odds, respectively. This means that workers living in countries that have high ALMP spending have a 43,8 to 46,9 percent lower likelihood of experiencing the CDTL phenomenon compared to workers in countries with low ALMP spending. So, governments that intervene in the labour market to help workers in disadvantageous positions seem to substantially lower the likelihood of suffering decreased employability due to automation. These findings are in line with the academic literature, as the International Labour Office (2017) stated the importance of ALMPs in the context of job automation. ALMPs can help ensure that job changes and losses deriving from technological advances are offset by other employment opportunities.

Logistic regression: Climbing down the Ladder						
Variables	Log odds; model 1		Log odds; model 2		Log odds; model 3	
Regional contextual factors						
Active Labour Market Policy spending; ref: Low						
Average	0.577***	(0.128)			0.643**	(0.178)
High	0.562***	(0.113)			0.531***	(0.124)
Employment Protection Legislation; ref: Lenient						
Moderate	1.153	(0.231)			1.131	(0.196)
Strict	0.621**	(0.132)			0.653**	(0.142)
Degree of Urbanization; ref: Rural area						
Town or suburb	0.953	(0.038)	0.971	(0.079)	0.831	(0.127)
City	1.033	(0.101)	1.029	(0.096)	1.020	(0.189)
Country Groups; ref: Scandinavian countries						
Anglo-Saxon	1.447*	(0.354)				
Continental West-Europe	1.061	(0.281)				
Eastern Europe	1.507*	(0.372)				
Southern Europe	3.675***	(0.799)				
Individual Countries; ref: Latvia (close to EU average)						
Complete overview			*Graph on page 40*			
Austria			0.493*** (0.017)			
Belgium			0.715*** (0.026)			
Switzerland			0.258*** (0.013)			
Cyprus			1.102*** (0.043)			
Czech Republic			0.879*** (0.036)			
Germany			1.387*** (0.042)			
Denmark			0.623*** (0.023)			
Estonia			0.809*** (0.040)			
Spain			1.792*** (0.058)			
Finland			0.932*** (0.044)			
France			0.859*** (0.016)			
Greece			1.531*** (0.047)			
Croatia			1.850*** (0.071)			
Hungary			1.525*** (0.047)			
Ireland			0.881*** (0.029)			
Iceland			0.313*** (0.022)			
Italy			1.218*** (0.037)			
Lithuania			1.410*** (0.050)			
Luxembourg			0.241*** (0.020)			

Netherlands			0.118***	(0.007)		
Portugal			1.186***	(0.038)		
Romania			0.359***	(0.012)		
Sweden			0.523***	(0.017)		
Slovakia			1.125***	(0.039)		
United Kingdom			1.407***	(0.047)		
Regional exposure; ref: Low exposure						
Medium exposure					1.132	(0.306)
High exposure					1.864***	(0.353)
Year comparison; ref: 2011						
2016	1.128	(0.281)	1.130	(0.281)	1.168	(0.297)
Constant	0.014***	(0.005)	0.019***	(0.003)	0.012***	(0.003)
Model characteristics						
Pseudo R-squared	0.0703		0.0732		0.0636	
Observations	2.896.323		3.412.137		1.818.448	

Clustered standard errors in brackets behind the log odds
*** p<0.01 ** p<0.05 * p<0.10

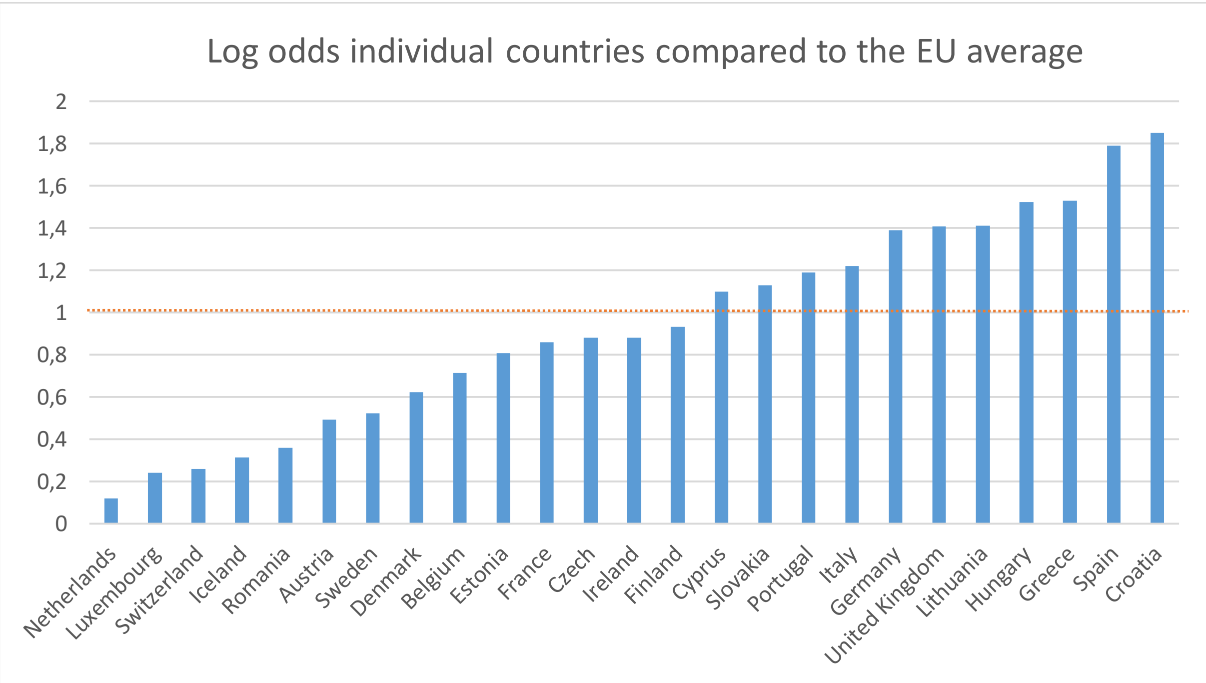
***Table 12**: Results logistic regression individual demographic factors*

The results of the second institutional factor, employment protection legislation, show that countries having strict employment protection legislation could make a large difference in the extent the CDTL phenomenon occurs. The log odds are shown to be 0.621 in model 1 and 0.653 in model 3. This means that workers living in countries with strict employment protection legislation have a 34,7 to 37,9 percent smaller likelihood of experiencing the CDTL phenomenon when compared to workers living in countries that have lenient employment protection legislation. These results are not entirely in line with the patterns found in the distribution of the data, as both lenient and strict EPL was shown to have the highest occurrences of the phenomenon. The reason for this can be because in the logistic regression the effect of EPL is calculated while taking into account all the other variables. The results can be considered in line with the academic literature though, as stringent EPL makes firing workers much more difficult and lowers the predisposition towards it (Bennett, 2016). Another possible reason that plays a role in these results, is that lenient EPL can result in quicker adaptations of automation processes (Samaniego, 2006). In turn, stringent EPL make firms less willing to adopt automatable technologies because firings costs are much higher. Therefore, automation becomes costlier to implement the more strict the EPL is. As a result, countries that have lenient EPL could see much quicker and/or more adaptations of automation processes, which could be the reason that workers living in countries with lenient EPL have a higher likelihood of suffering decreased employability due to job automation when compared to workers living in countries with strict EPL.

No evidence is found of a significant relationship between the degree of urbanization and the occurrence of the CDTL phenomenon and will therefore not be discussed. In appendix 5 the distribution of the data is shown for the different degrees of urbanization though. Here the chi-square test revealed that the distribution was not random. Still, no conclusions can be drawn regarding this variable.

For the regional exposure variable, a significant relationship on the occurrence of the CDTL phenomenon is found at the 1 percent level. This variable can give an indication of how resilient labour market structures in regions are in relation to automation risks. For the category of high exposure, a log odds of 1.864 is found. These log odds mean that workers living in regions that are highly exposed to the risks of automation have an 86,4 percent higher likelihood of the CDTL phenomenon. This is in line with the literature, as regions that are highly exposed are expected to be forced to undergo changes (Vermeulen, et al., 2018). Another reason that these regions can be considered less resilient in terms of experiencing the CDTL phenomenon is that these regions tend to hold more vulnerable workers. Since, these regional labour market structures that are high at risk could hold many low and medium educated workers, who are less equipped to deal with automation changes (Autor, et al., 2016). Additionally, according to Böhm et al. (2019), these regions may hold fewer employment opportunities. This can in part be the result of higher competition among workers for these opportunities. This can be the case, as more laid-off workers, due to automation, all have to compete for the same kind of jobs. This could explain the difference in the occurrence of climbing down the ladder phenomenon for these higher exposed regions.

Individual and country groups are added to the regression as well. For the added individual country dummies the reference category is the country Latvia. Latvia is chosen as it is very close to the average CDTL phenomenon percentage of all the European countries in the dataset. The average percentage of the EU is 3,69 and Latvia's percentage is 3,67. Thus, using Latvia as the reference group allows for all the other individual countries to be compared to the EU's average and makes interpretation easier. In the graph below the log odds of all the countries are shown in ascending order. This indicates that the Netherlands is experiencing the phenomenon the least and Croatia the most. Moreover, the orange line indicates the Latvia reference category and the EU's average, which allows seeing what countries are performing better or worse than the EU average.



Graph 1. Source: own creation. *Orange line: reference country Latvia / Average of the EU.*

The log odds of these countries can be interpreted as follows. Take for example Austria, here a log odds of 0.493 is found, meaning that workers living in Austria have a 50,7 percent lower likelihood of experiencing the CDTL phenomenon due to automation when compared to Latvia (and the EU average). Showing these log odds can also strengthen the identifications made in the map in 4.3, which showed the distribution of the CDTL phenomenon across European regions and countries. For example, the distribution identified that the countries Denmark, Sweden, the Netherlands, Iceland, Switzerland and regions of Austria and Romania experience decreased employability due to automation relatively little. The log odds of these individual countries back these findings up, where all these countries have log odds that are substantially lower than Latvia (the EU average). However, for the log odds of these individual countries, no check could be made for the institutional factors that are of influence on the phenomenon. The institutional factors are on the national level and would have resulted collinearity when run in the same model. Because of this, countries have also been put in country groups so these could be run with the institutional factors. What countries fall in each country group category can be seen in appendix 4. Scandinavian countries are chosen as the reference category, as these countries are considered to be best equipped to deal with the labour market risks of automation (Howell, 2005). This is in part due to these countries having strong socially regulated labour markets, high ALMP spending and training participation (Howell, 2005; Desjardins, 2015). The log odds of the country groups show that living in Southern Europe has a significant impact on the likelihood of experiencing the CDTL phenomenon when compared to living in a Scandinavian country. The log odds for this category are 3.675 and are significant at the 1 percent level. This indicates that workers living in Southern Europe have a 3.68 times higher likelihood of experiencing the CDTL phenomenon compared to workers living in Scandinavian countries. This substantially higher likelihood is in part explained because Scandinavian countries are better equipped to deal with risks of automation, but also because Southern European countries are not. This is because Southern Europe countries are generally lower educated and the quality of training is lower compared to the Anglo-Saxon, Western and Scandinavian parts of Europe (Desjardins, 2015).

For Continental West-European countries no significant log odds are found and therefore no conclusion can be drawn on this relationship. For the Anglo-Saxon and Eastern European countries, a significance is found at the 10 percent level. For this reason, conclusions have to be drawn very carefully for these parts of Europe. Yet, it seems that two country groups have around 44,7 to 50,7 percent, respectively, higher likelihood of experiencing the CDTL phenomenon compared to Scandinavian countries. The low ALMP and lenient EPL may be factors that help explain the 44,7 percent difference for Anglo-Saxon countries compared to Scandinavian ones. The Eastern European differences compared to the Scandinavian countries may be a result as generally, the educational levels are lower in Eastern Europe (Desjardins, 2015).

5. Conclusion

The goal of this research was to find new insights and discover potential patterns in the problem of the deterioration of employability of the mid-level workers at risk of job automation. The phenomenon of 'climbing down the ladder' is used in this research as a proxy to showcase this deterioration of employability due to automation. In other words, a person is considered to have suffered decreased employability when that person is susceptible to being forced to take on jobs at lower levels as a result of automated technologies.
On the basis of the goal of this research the following main research question was made:

To what extent are mid-level workers, at risk of job automation, susceptible to climbing down the career ladder in increasing polarized labour markets in Europe.

In this chapter, on the basis of the empirical results, each of the sub-questions will be discussed, from which the main research question can be answered. The chapter will end with a critical reflection on the research process and with recommendations for further research.

To answer the first two research questions of this thesis a descriptive analysis combined with Pearson's chi-squared tests are performed. The chi-squared test, if significant, shows that the distribution of the data is not random. This could indicate a pattern in the distribution.

1. What are the characteristics and efforts of the workers at risk of automation?

In line with previous academic research, this study also shows that the workers that are most at risk of automation are mid-level workers. Slightly more than half of the mid-level workers have a high automation risk. These results were not surprising as studies show that mid-level jobs often comprise of tasks that are more susceptible to being high at risk of automation. Besides mid-level workers, high-level workers are shown to have very few workers at risk. Many low-level workers, however, are also found to be high at risk of automation. Here, around 43 percent are found to be high at risk of automation. This substantial amount is somewhat surprising as automation is expected to polarize labour markets, where low- and high-level jobs are safe and mid-level jobs are at risk and disappearing.

The workers at risk predominantly have low and medium levels of education. Respectively, 31 percent low educated and 58 percent with a medium level education. Moreover, the data on training shows a clear pattern where the higher the automation risk the lower the occurrence of someone following training. This is directly in line with previous studies, which found that the odds of engaging in any type of training are significantly lower among workers that have high risks of automation. The literature states that this is not only due to their own willingness that is lacking, it is also because the provision of training is lacking. As a result, these workers at risk of automation likely stand a lower chance of receiving training, even though they can be considered to need it the most.
The last two characteristics are demographic ones. The distribution of the data shows that young workers are most at risk. And that for gender no clear pattern is found in the distribution.

2. To what extent are mid-level workers at risk of climbing down the ladder?

Of the total dataset of 3.422.664 workers, 133.783 (3.91 percent) workers were found to have suffered a decrease in their employability and could be forced to take down jobs at lower levels. To answer the second research question, the relative distribution of these cases are checked over the different types of workers. This showed that 5.46 percent of all mid-level workers are considered at risk of climbing down the ladder. One would expect, however, that this group would have the highest relative percentage. Yet, this is not the case, as for lower-level workers the highest relative percentage is found. Here, 9.48 percent are found to be considered at risk of climbing down the ladder and thus have suffered decreased employability due to automation. So, while mid-level workers were expected to be affected the most by automation, more low-level workers are found to have suffered from the risks of automation.

A reason for this surprising result might be that certain arguments do not hold true anymore as the development of automated technologies can go very rapidly. One of the arguments made in the academic literature as to why low-level jobs are deemed relatively safe from job automation is that automating these jobs is often not considered worthwhile. This because the supply of workers able to perform these types of jobs are very large, which means that wages are low. The argument continues that this makes investing in automated technologies relatively more expensive. Yet, as automation ingenuity improves, jobs that were previously perceived as being low at risk may start to gain more automation potential and undergo labour displacements. To add to this, as figure 2 in chapter two showed, labour costs keep increasing while automated technologies become ever cheaper. This in turn affects the relative cost of replacing workers with technology and may be the reason why more low-level jobs are being replaced as well now.

Another reason might be that lower-level workers stay unemployed longer, as unemployment benefits could lower incentives to find new jobs. This is because unemployment benefits can come close to the wages they had before and could reduce the need to exert efforts in finding new jobs. On the other hand, these unemployment benefits could make it possible for workers to reject poor offers and continue to search for better jobs, which could make the chance of an actual drop to a lower level job smaller. However, the effects of unemployment benefits on this context go outside the scope of this research. This could possibly be an interesting topic for further research though.

3. What are the regional differences across Europe where this phenomenon is experienced?

The main purpose of this sub-question was to identify what countries and/or regions experience decreased employability due to automation the most. This is done by visualizing the data into a map, which makes the distinction between the countries/regions much easier. The map for instance shows that countries that seem to be doing very well are the Netherlands, Iceland, Switzerland, Denmark, Sweden and parts of Austria and Romania. On the other hand, countries that have the highest occurrences of decreased employability due to automation are countries such as, the United Kingdom, Germany, Portugal, Spain, Italy, Croatia, Greece and parts of Hungary. The results of the logistic regressions confirm that these are indeed the best and worst, respectively, performing countries.

Country groups are added to a different model in the logistic regression as well. This allowed checking the results when taking institutional variables into account as well. Additionally, it allowed to point out areas of interest where policy changes can be considered important. One of the areas of interest discovered is Southern Europe. The results give evidence that workers living in Southern Europe have a substantially higher likelihood of experiencing decreased employability due to automation compared to workers living in Scandinavian countries. This substantially higher likelihood is, to an extent, explained because Scandinavian countries are better equipped to deal with the risks of automation. The strong socially regulated labour markets, high ALMP spending and high-quality training and participation in these countries can be a reason for this. On the other hand, Southern European lack in these aspects and have more vulnerable populations in regards to job automation.

For the Anglo-Saxon and Eastern European parts only an indication could be giving, as these results are significant at the 10 percent level. The indication is that workers living in these parts of Europe have a higher chance of experiencing decreased employability due to automation when compared to workers living in Scandinavian countries.

4. To what extent do individual-demographic and regional contextual factors influence the phenomenon across European regions?

Evidence is found that the level of educational attainment has considerable effects on the occurrence of the CDTL phenomenon. Low and medium educated workers are much more likely to experience decreased employability due to automation than high educated workers are. This is especially the case for low educated workers. Following training is also shown to have an important influence, where following training results in a lower occurrence of the CDTL phenomenon. This again shows the importance of having better skills in relation to employability. For when someone has higher skills it is not only easier to prevent being laid-off from job automation but also to make it easier to find a new suitable job and to stay active in the labour market in case a lay-off occurs.

Demographically, the evidence is found that young workers and females are more at risk of experiencing a decrease in employability due to automation compared to other age groups and to males. That females are more at risk is in line with the academic literature. The argument is that males generally tend to have stronger labour market positions compared to females. Moreover, males tend to find new jobs quicker and of higher quality. For age, it was expected that young workers would be more exposed to automation, but that older people would be more likely to suffer decreased employability due to automation. This because they are deemed less equipped to deal with the risks of automation. However, the results indicate that the higher exposure to automation seems to outweigh the benefits younger people have in relation to dealing with the risks of automation.

For the institutional variables, the results give evidence that workers living in countries with either average or high active labour market policy spending result in a substantially lower likelihood of being at risk of climbing down the ladder. The likelihood is lowest for countries with higher ALMP spending. So the conclusion can be drawn that, governments that intervene in the labour market to help workers in disadvantageous positions seem to substantially lower the likelihood of these workers to experience decreased employability due to job automation.

For employment protection legislation the results show evidence that countries having strict EPL could make a large difference in the extent the CDTL phenomenon occurs. Precisely, workers living in countries that have strict EPL results in a lower likelihood of being at risk of climbing down the ladder when compared to countries with lenient EPL. These results are in line with previous studies, where strict EPL was shown to make firms less willing to adopt automatable technologies because firings costs are much higher. When lenient EPL is in effect, firings costs are much lower and the adoption of automated technologies is far less costly. As a result, this could be the reason more workers are laid-off and experience the risk of climbing down the ladder in countries that have lenient EPL.

For the regional variable of the degree of urbanization, no evidence is found of a significant relationship with the occurrence of the CDTL phenomenon. Because of this, no conclusions can be drawn for this variable. For the regional variable that gives an indication of how resilient labour market structures in regions are in relation to automation risks does show evidence. Namely, workers living in these regions that are highly exposed to automation have a substantially higher likelihood of experiencing a drop in their employability due to this automation when compared to regions that have low exposure. The reason that a decrease in employability occurs in these regions can be because employment opportunities are rare in these regions, in part due to more workers having to compete for the same jobs. This could force more workers to take on jobs at lower levels, hence more workers at risk of climbing down the ladder.

Reflection and recommendations for further research

This study has contributed by making workers at risk of climbing down the ladder due to automation empirically measurable. As a result, this allowed identifying workers that may suffer decreased employability. Moreover, with the identification of these workers, relevant variables on employability and its influences on the phenomenon were able to be checked. In this study, many of these relevant variables were able to be checked in the same models, which allowed to more precisely show the relative influences the different variables can have. Additionally, regional differences where these workers are at risk of climbing down the ladder are identified. Identifying where problems lie, can often be the first step in trying to alleviate the. However, to alleviate these problems for specific countries or regions, a more in-depth analysis is warranted as to set-up relevant policies in order to improve the employability of the workers at risk. Perhaps a more in-depth analysis on a smaller scale in this regard. This because certain countries could have panel data available, contrary to the cross-sectional data available in the EU-LFS. With panel data individuals can be tracked through time, this could allow to directly track if workers have climbed down the ladder and suffered decreased employability. Additionally, more precise estimations on regional levels may be achieved. This because the EU-LFS dataset has no regional data available for certain countries, which made regional comparison impossible for these countries.

Another thing to add is that this study may have started to indicate a shift happening where automated technologies are now also being used to replace more low-level jobs. This is contradicting to the polarization effect automation was expected to have. Yet, researchers often mentioned the incredibly rapid rate at which automatable technologies can develop. Because of these developments, jobs that are deemed safe from automation at one point may become at risk in the future. Therefore, it would be beneficial to repeat this study from time to time. New automation risk estimations per task or occupations that is more up-to-date may be necessary for that though.

However, it should also be noted that this research has certain weaknesses. Many of the variables that may influence employability (in this context) are added in this study. Yet, it is likely that there are also other variables that play a role in the extent where workers are becoming at risk of climbing down the ladder. If a study does not control for all the factors of influence, then the effect of these missing factors could have been allocated to others that are included. Moreover, this study could not assess certain causal mechanisms with the available data. For instance, the data in this study remains imprecise when it comes to what type of training or quality of training is followed. On the regional level, the causal mechanisms that explain higher exposure rates to automation are missing and the content of the active labour market policies could not be derived from the data (which is why it was used as a proxy for the extent governments intervene in the labour market to help workers in disadvantageous positions). Thus taking in the regard that this is a partial analysis, conclusions have to be drawn carefully. Further research could focus on these specific aspects to explain certain unidentified causal mechanisms in the context of decreasing employability due to automation.
A final thing to note is that the automation risk index used in this dataset is based on estimations. This study does try to protect against certain biases in this regard, however, one should still be careful drawing conclusions on the basis of estimations.

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Appendix

1. EU-LFS variables

All the EU-LFS variables that were necessary for this dataset

https://ec.europa.eu/eurostat/documents/1978984/6037342/EULFS-Database-UserGuide.pdf

ISCO3D	Occupation
ISCOPR3D	Occupation of last job
HATLEV1D	Level of education
COURATT	Training last month
AGE	Age
SEX	Gender
COUNTRY	Country classification
DEGURBA	Degree of urbanization
REGION	Region of the household
REGIONW	Region of place of work
REGION1Y	Region of residence one year before survey
MAINSTAT	Main labour status
DURUNE	Duration of unemployment

2. Risk of Automation per occupation

ISCO3D	RoA	Job description
111	0,072	Legislators and senior officials
112	0,0875	Managing directors and chief executives
121	0,24948	Business services and administration managers
122	0,01933	Sales, marketing and development managers
131	0,047	Production managers in agriculture, forestry and fisheries
132	0,23525	Manufacturing, mining, construction, and distribution manage
133	0,035	Information and communications technology service managers
134	0,06921	Professional services managers
141	0,04345	Hotel and restaurant managers

142	0,16	Retail and wholesale trade managers
143	0,21025	Other services managers
211	0,31117	Physical and earth science professionals
212	0,1484	Mathematicians, actuaries and statisticians
213	0,03881	Life science professionals
214	0,04779	Engineeringprofessionals (excluding electrotechnology)
215	0,0825	Electrotechnology engineers
216	0,15008	Architects, planners, surveyors and designers
223	0,02	Traditional and complementary medicine professionals
224	0,14	Paramedical practitioners
225	0,038	Veterinarians
226	0,03769	Other health professionals
232	0,1344	Vocational education teachers
233	0,0078	Secondary education teachers
234	0,08295	Primary school and early childhood teachers
235	0,06551	Other teaching professionals
241	0,60722	Finance professionals
242	0,13856	Administration professionals
243	0,19405	Sales, marketing and public relations professionals
251	0,18736	Software and applications developers and analysts
252	0,03	Database and network professionals
261	0,205	Legal professionals
262	0,4517	Librarians, archivists and curators
263	0,12922	Social and religious professional
264	0,20672	Authors, journalists and linguists
265	0,15586	Creative and performing artists
311	0,55331	Physical and engineering science technicians
312	0,11867	Mining, manufacturing and construction supervisors
313	0,68758	Process control technicians
314	0,64167	Life science technicians and related associateprofessionals
315	0,39337	Ship and aircraft controllers and technicians
321	0,58821	Medical and pharmaceutical technicians
322	0,058	Nursing and midwifery associate professionals
324	0,4445	Veterinary technicians and assistants
325	0,42223	Other health associate professionals
331	0,6511	Financial and mathematical associate professionals
332	0,51425	Sales and purchasing agents and brokers
333	0,59369	Business services agents
334	0,631	Administrative and specialised secretaries
335	0,4605	Regulatory government associate professionals
341	0,395	Legal, social and religious associate professionals
342	0,24295	Sports and fitness workers

343	0,3407	Artistic, cultural and culinary associate professionals
351	0,405	Information and communications technology operations and use
352	0,72	Telecommunications and broadcasting technicians
411	0,97	General office clerks
412	0,96	Secretaries (general)
413	0,9	Keyboard operators
421	0,84367	Tellers, money collectors and related clerks
422	0,75829	Client information workers
431	0,96933	Numerical clerks
432	0,89889	Material-recording and transport clerks
441	0,83471	Other clerical support workers
511	0,37117	Travel attendants, conductors and guides
512	0,732	Cooks
513	0,835	Waiters and bartenders
514	0,34983	Hairdressers, beauticians and related workers
515	0,84667	Building and housekeeping supervisors
516	0,34721	Other personal services workers
521	0,92	Street and market salespersons
522	0,46333	Shop salespersons
523	0,9	Cashiers and ticket clerks
524	0,82136	Other sales workers
531	0,32	Child care workers and teachers' aides
532	0,48333	Personal care workers in health services
541	0,39635	Protective services workers
611	0,595	Market gardeners and crop growers
612	0,76	Animal producers
613	0,76	Mixed crop and animal producers
621	0,792	Forestry and related workers
622	0,7075	Fishery workers, hunters and trappers
634	0,8	Subsistence fishers, hunters, trappers and gatherers
711	0,64961	Building frame and related trades workers
712	0,67807	Building finishers and related trades workers
713	0,805	Painters, building structure cleaners and related trades work
721	0,79367	Sheet and structural metal workers, moulders and welders
722	0,87481	Blacksmiths, toolmakers and related trades workers
723	0,52373	Machinery mechanics and repairers
731	0,53432	Handicraft workers
732	0,78167	Printing trades workers
741	0,28136	Electrical equipment installers and repairers
742	0,55971	Electronics and telecommunications installers and repairers
751	0,75944	Food processing and related trades workers
752	0,84833	Wood treaters, cabinet-makers and related trades workers

753	0,58583	Garment and related trades workers
754	0,57637	Other craft and related workers
811	0,80935	Mining and mineral processing plant operators
812	0,88	Metal processing and finishing plant operators
813	0,91833	Chemical and photographic products plant and machine operators
814	0,84594	Rubber, plastic and paper products machine operators
815	0,87167	Textile, fur and leather products machine operators
816	0,816	Food and related products machine operators
817	0,8	Wood processing and papermaking plant operators
818	0,90146	Other stationary plant and machine operators
821	0,899	Assemblers
831	0,61975	Locomotive engine drivers and related workers
832	0,52615	Car, van and motorcycle drivers
833	0,51087	Heavy truck and bus drivers
834	0,70382	Mobile plant operators
835	0,725	Ships' deck crews and related workers
911	0,63167	Domestic, hotel and office cleaners and helpers
912	0,6675	Vehicle, window, laundry and other hand cleaning workers
921	0,88333	Agricultural, forestry and fishery labourers
931	0,68333	Mining and construction labourers
932	0,59667	Manufacturing labourers
933	0,698	Transport and storage labourers
941	0,8625	Food preparation assistants
952	0,94	Street vendors (excluding food)
961	0,70475	Refuse workers
962	0,827	Other elementaryworkers

3. Distribution of data over age and gender

Distribution of the data over age.

	Automation risk		
Age*	Low Risk	Medium Risk	High Risk
17-24	3.32%	7.74%	9.99%
25-34	20.19%	19.51%	19.71%
35-44	28.14%	25.92%	24.86%
45-54	28.47%	28.13%	27.03%
55-64	17.98%	17.06%	16.62%
>65	1.92%	1.63%	1,80%
Chi2	p = 0.000		

* = Significant at the 1% level

Distribution of the data over gender.

	Automation risk		
Gender*	Low Risk	Medium Risk	High Risk
Male	53,62%	53,22%	54,54%
Female	46,38%	46,78%	45,46%
Chi2	p = 0.000		

* Significant at the 1% level

4. Countries in the country groups with their CDTL percentages

Country Groups	Percentage at risk of climbing down the ladder
Scandinavian countries	
Denmark	5.84%
Sweden	1.92%
Finland	3.11%
Iceland	1.50%
Anglo-Saxon countries	
United Kingdom	5.90%
Ireland	3.28%
Continental West-European countries	
Netherlands	0.44%
Belgium	2.58%
Luxembourg	0.86%
Germany	5.84%
France	3.34%
Austria	2.00%
Switzerland	0.92%
Eastern European countries	
Estonia	2.97%
Latvia	3.67%
Lithuania	4.43%
Czechia	3.26%
Slovakia	4.08%
Croatia	6.93%
Hungary	5.98%
Romania	1.62%
Southern European countries	
Portugal	6.03%
Spain	7.26%
Italy	5.39%
Greece	6.34%
Cyprus	4.05%
Average of all countries	**3.69%**

5. Distribution of data over degree of urbanization and regional exposure rates

Distribution of the data over degree of urbanization

	Degree of Urbanization		
CDTL*	City	Town/Suburb	Rural Area
No	96.35%	96.03%	95.90%
Yes	3.65%	3.97%	4.10%
Chi2	p = 0.000		

* = Significant at the 1% level

Distribution of the data over regional exposure rates

	Regional Exposure		
CDTL*	Low	Medium	High
No	97.62%	97.13%	94.71%
Yes	2.38%	2.87%	5.29%
	100%	100%	100%
Chi2	p = 0.000		

* = Significant at the 1% level