Connecting regional automation resilience and regional inequality: evidence from Sweden

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Abstract

Through advances in automation, certain jobs are made obsolete, displacing human workers; at the same time, automation creates new jobs for human workers. The occupational structure of regions is continuously altered by the progress of automation technology. At the same time, regional inequality is growing across European regions, with automation being one of the primary causes. Because automation impacts tasks and jobs differently, the same holds true for regions: jobs are not necessarily lost and created in the same locations. This study builds on the analysis on occupation automation risk conducted by Frey & Osborne (2017), and proposes the use of regional automation resilience as a measure for regional inequality, by looking at the job loss risks and job creation abilities of 21 Swedish regions. The analysis finds small regional differences in mean automation risk, and substantial regional inequality in terms of job creation potential and job creation ability. Furthermore, it finds that low-risk job creation, while addressing the growing skills mismatch, is the key to maintaining wage growth and improving living standards within regions.

1. Introduction

Regional inequality has become an important subject matter in the field of economic geography, inspired by the works of prominent scholars like Milanovic (2016), Piketty (2014), and others (Iammarino, Rodríguez-Pose & Storper, 2019; McCann, 2020; Rosés & Wolf, 2018; Storper, 2018). There is a clear trend towards economic divergence between European regions, with clear winners and losers (Rosés & Wolf, 2018). One of the most important causes of this ongoing economic divergence is automation, which hitherto primarily impacted the employment in regions with a dominant manufacturing sector (Houseman, 2018; Iammarino, Rodríguez-Pose & Storper, 2019). Nonetheless, the surge of artificial intelligence (AI) might lead to the replacement of jobs at such a pace that society cannot adjust anymore, and thus starts to resist such innovation to protect their living standards (Korinek & Stiglitz, 2017). Owing to the changing nature of automation, combined with the continuous price decline of automation technology, more and more tasks can be automated, putting numerous jobs at risk of disappearing either partially or completely. Simultaneously, automation also creates opportunities for new jobs to appear (Brynjolfsson & McAfee, 2014; Ford, 2015; Frey & Osborne, 2017; Lund et al., 2019; Manyika et al., 2017).

Because automation impacts tasks and jobs differently, the same holds for regions; regions with a high share of highly automatable jobs are at risk of mass unemployment in the future. Especially in the case that they cannot create enough new jobs to compensate for the automation job loss; this can become a major driving force behind growing regional inequality (Lund et al., 2019). Automation thus creates both winning and losing regions, impacting the employment and living standards of many workers (Furman, 2018). Furthermore, the risk of automation is increased further due to the worldwide COVID-19 pandemic, as employers seek ways to increase the resilience of their production facilities (Chernoff & Warman, 2020). Despite the concerns about growing regional inequality due to the forces of automation, there is little focus on the regional geography of automation, as differences in automation job loss and job creation ability can provide more insight into regional inequalities, beyond mere GDP/capita comparisons (Crowley & Doran, 2019; Iammarino, Rodríguez-Pose & Storper).

In Sweden, regional inequality is low compared to other EU member states. Employment numbers are high throughout all regions (NUTS 2-level), ranging from 74 percent in North-Central Sweden to 79 percent in Stockholm (OECD, 2018a). While the statistics on the number of jobs do not raise concern, Swedish regions do experience slightly differing GDP per capita growth rates, pointing to possible differences in the quality (and automatability) of jobs (OECD, 2018b). Swedish data on regional GDP/capita confirms that inequality among regions has increased slightly since 2000, both with and without controlling for regional population (Statistics Sweden, 2021). This follows the trend of increasing inequality throughout most OECD countries, despite the interventionist nature of the Swedish government (Harris, Kimson & Schwedel, 2018).

Nevertheless, the main factor in choosing Sweden as the location for this study is the extensiveness of the regional statistical database in Sweden, which makes it possible to look into 4-digit occupational data on the NUTS 3-level (Statistics Sweden, 2021). The case of Sweden is also interesting for studying the relationship between innovation and population density, as most of its regions are very sparsely populated compared to other European regions. The notable exception to this is the Stockholm region, which is almost three times more densely populated as the second-most dense region, Skåne, and 130 times more densely than Norrbotten, the least densely populated region (Eurostat, 2021).

1.1 Aim of the research

This research aims to study interregional disparities in automation resilience, built on the research on occupational automation risk conducted by Frey & Osborne (2017). I combine their results with data from the Swedish regional statistics database and the EU statistical database. Within this research, automation resilience is defined as the combination of automation job loss risk and the capacity to attract jobs created by automation. The main research aim of the thesis is to measure regional inequality in Sweden by comparing the automation resilience of different regions. The thesis firstly addresses how regions differ in terms of mean automation risk. This is done by connecting the Swedish regional occupation database to the automation risk data as determined by Frey & Osborne (2017). Secondly, it examines how regions differ in both their potential and their ability to create and attract high-quality jobs, to maintain or improve the living standards of their citizens. This is done by analysing the relatedness density of Swedish regions to complex occupations, and how the economic composition of Swedish regions is changing over time (2014-2018)

The thesis tries to map and explain the differences between regions regarding the risk of automation job loss by comprehensive data analysis. This comprises looking at the current occupational composition of NUTS 3-regions (21 in total) in Sweden, and how it is changing over time, and subsequently connecting this with data on potential job growth in Swedish NUTS 2-regions, built on the concepts of relatedness density and complexity; this is relevant because automation creates new jobs that are relatively complex, and thus require related occupations to be present in the region (Balland & Boschma, 2019; 2021; Balland et al., 2019). It is expected that the differences in regional automation resilience reinforce the existing regional inequality. Regional inequality in this study is defined as the difference in living standard, and the availability and quality of job opportunities, between regions. Within Europe, rural regions are typically the ones lagging behind urban regions, although this differs between countries (Iammarino, Rodríguez-Pose & Storper, 2019).

This type of top-down regional analysis serves as the foundation of future regional economic policy, most notably the smart specialisation strategy (European Commission, 2012; McCann, 2015; McCann & Ortega-Argilés, 2016). As indicated by Storper et al. (2015), 'knowing your place' is crucial for institutions that are in charge of creating regional economic policy, highlighting the relevance of extensive data analysis as the foundation for decision-making. This thesis tries to contribute by providing relevant insight into the regional automation resilience, as well as providing policy recommendations for underperforming regions.

2 The changing nature of automation and its impact

Ongoing automation impacts occupations and sectors in varying degrees, dependent on the specific tasks that encompass a specific occupation. Automation is by no means a modern phenomenon; it dates back to the First Industrial Revolution, where a substantial number of labour-intensive manual tasks were taken over by machines. During the Second and Third Industrial Revolution, a growing number of routine physical tasks were made obsolete. It is important to note that automation does not target occupations or jobs as a whole. Automation targets tasks that are performed within these jobs. This in turn makes it possible to use human resources more productively in other places (Autor, 2015; Arntz, Gregory & Zierahn, 2017).

Concurrently, automation created many different new jobs, in different sectors of the economy. In 1850, more than half of the US population worked in agriculture. Since then, its employment share has steadily declined, to 2.9 percent in 2019 (Bureau of Labor Statistics, 2021; Manyika et al., 2017). The displacement of agriculture jobs through automation has not led to mass unemployment; workers found jobs in other growing sectors of the economy. So far, automation job loss and job gain have balanced each other out (Autor, 2015). Most importantly, the new jobs that automation has created are less labour-intensive, less dangerous, and more productive, and thus allowed mankind to become more prosperous than ever before (Acemoglu & Restrepo, 2019).

2.1 The two sides of the automation debate and their common challenges

There is an ongoing debate among academics about the impact the changing nature of automation will have on society as we know it today (Autor, 2015; Ford, 2015; Manyika et al., 2017; Wajcman, 2017). Roughly, two sides can be identified: the automation optimists and the automation pessimists. The optimists point at the impact of automation in the past industrial revolutions, as it has not decreased the demand for human labour (Autor, 2015; Wajcman, 2017). Pessimists allude to the changing nature of automation as a disruptive force. They argue that the broadening range of automatable jobs will cause mass unemployment in the future, once robots become cheaper than human labour (Ford, 2015).

Both sides of the argument agree that the nature of automation is changing, however. In practice, this means it is no longer limited to automating routine physical tasks, primarily in agriculture, transportation, and manufacturing (Autor, 2015). The accelerating development of AI makes it possible to take over routine cognitive tasks as well at an increasing pace; routine cognitive tasks have already been on the decline, albeit slowly (Acemoglu & Restrepo, 2018; Brynjolfsson & McAfee, 2014; Cortes, Jaimovich & Siu, 2017). This also means automation does not only threaten low-skilled workers anymore; there are also medium- and high-skilled occupations that might become obsolete in the future, and most importantly, on a scale never witnessed before (Chui, Manyika & Miremadi, 2015; Frey & Osborne, 2017; Lund et al., 2019; McClure, 2018). However, even if automation simply continues its progress as witnessed previously, the changing labour economy still provides some comprehensive challenges, in which policymakers could play a crucial role (Furman, 2018).

2.2 Automation-induced wage pressure

There is a clear consensus that low-skilled workers are affected the most by automation in the short term, as the ever-cheapening automation technology is suppressing their wages (Brynjolfsson & McAfee, 2014; Zhang, 2019). Many low- and medium-skilled workers perform routine tasks within their jobs. Because of their repetitive and predictable nature, these routine jobs are easier to automate, compared to non-routine jobs which are mostly carried out by high-skilled workers (Frey & Osborne, 2017). This causes automation-induced wage pressure, known in the literature as the displacement effect: tasks previously undertaken by workers, are now automated, provided that automation technology can do the job at a lower cost (Acemoglu & Restrepo, 2020). Thus, low-skilled workers are de facto directly in wage competition with automation technology. The displaced jobs are either taken up by technology or offshored to low-wage countries (Goos, Manning & Salomons, 2014).

Due to the wage pressure, medium-pay occupations are disappearing relative to high- and low-pay occupations. These medium-pay occupations under threat by AI are found mostly in the financial sector, sales, logistics, and trade (Acemoglu & Restrepo, 2019). The displaced workers from medium-pay occupations often end up in low-pay occupations, creating job polarisation (Frey & Osborne, 2017; Michaels, Natraj & van Reenen, 2014). In a deregulated market, one would expect to see increasing wage polarisation between high- and low-skilled workers, given the automation-induced wage pressure; evidence from the US suggests this is indeed the case (Autor & Dorn, 2013; Kaltenberg & Foster-McGregor, 2020).

2.3 The financial consequences of job displacement

The wage competition between workers and automation technology is one with a predictable outcome. Automation technology will only become cheaper in the future, and human labour costs will continue to increase; inevitably, workers will get on the short end of the stick at some point in time (Ford, 2015). Furthermore, the replacement of human labour decreases their share of value added within industries, leading to productivity outgrowing workers' wages (Acemoglu & Restrepo, 2019). The owners of automation capital are the ones reaping the rewards of automation: every time a human employee is replaced by a machine, the owner increases productivity while also reducing their tax payments. This is because tax policy in many countries is built around taxing human labour; robots do not pay taxes, while human workers do. Automation thus has the potential to threaten the tax revenue, and in turn worsen inequality, if the system does not adapt accordingly (Abbott & Bogenschneider, 2018).

Some economists and policymakers are willing to fight this fight, however (Delvaux, 2017). Through market interventions, like a robot tax, employment in highly automatable occupations can be forcefully retained for a longer period, slowing the impact of disruptive automation technologies. This would be a controversial measure, however, and one which is heavily debated between scholars (Abbott & Bogenschneider, 2018; Gasteiger & Prettner, 2020; Guerreiro, Rebelo & Teles, 2017; Zhang, 2019). Another rigorous band-aid for automation-induced joblessness that is commonly proposed, most notably by Democratic primary candidate Andrew Yang in the US, is the introduction of a universal basic income (UBI). UBI guarantees a certain income for every citizen, and would thus guarantee an acceptable living standard for displaced workers. The downside of UBI that it disincentivises working. Moreover, it can potentially increase the tax burden on those who remain employed (Glaeser & Hausman, 2020). Therefore, an easy solution to the automation-induced job displacement does not seem to be at hand, unfortunately.

2.4 Automation job growth and the skills mismatch

On the positive side, automation increases productivity throughout industries, creating new non-routine tasks for human labour, complementary to the technology (Acemoglu & Restrepo, 2018). This changing nature of automation provides a challenge for the current labour market, however, as workers need to shift their focus towards the new jobs that are created by automation. These new non-routine jobs will require different skills from workers: skills where human labour still holds a comparative advantage over automation technology. The most important non-routine skills are flexibility, human interaction, problem-solving ability, and creativity (Acemoglu & Autor, 2011; Autor, 2015; Cortes, Jaimovich & Siu, 2017; Nedelkoska & Quintini, 2018). These skills are largely unrelated to the skills required for routine jobs, however, and this makes switching from a routine to a non-routine job difficult for the average worker. This begs for a few questions. Are displaced lumberjacks, for instance, capable to learn a non-routine task, and secondly, do they even want to? It goes without saying that education plays a vital role in combatting the skills mismatch. The displacement of workers specifically asks for investing in their skills development, to allow them to transition back into the labour market and take on newly created jobs. To achieve this, businesses could be incentivised to enrol displaced workers into training programs (Glaeser & Hausman, 2020; Nedelkoska & Quintini, 2018).

The observed mismatch between the skills of the labour force and the skills required for newly created jobs threatens the ability to profit from progress in automation technology (Vandeplas & Thum-Thysen, 2019). Moreover, the skills mismatch might worsen inequality. If the demand for these non-automatable skills increases more quickly than the supply, the high-skilled people who are already able to take on the newly created jobs benefit from ever-increasing wages. Meanwhile, the other workers are left behind in this winner-takes-all economy (Brynjolfsson & McAfee, 2014; Wajcman, 2017).

2.5 The spiky geography of job generation

In addition to the challenge created by the skills mismatch, there is also a geographical component to consider: created jobs do not necessarily appear in the same location as where jobs are lost. The geography of job creation is spiky, as not all regions have the capabilities to attract newly created jobs. This means that new jobs tend to cluster in a limited number of regions, reinforcing the already growing regional inequality (Balland & Boschma, 2021). Regional inequality specifically affects the economic performance and political stability of regions, dividing people based on where they live (Iammarino, Rodríguez-Pose & Storper, 2019; Marchand, Dubé & Breau, 2020). The rise of within-country inequality is an increasingly important policy priority in European countries, and other countries, including the US and China. The main reason for this is the adverse effect inequality has on economic performance, through various underlying factors. In the short term, inequality leads to lower aggregate demand for goods and services, as the highest income earners invest relatively less of their money back in the economy. In the long term, inequality leads to less opportunities for children that grow up in low-income households. This way, the inequality of opportunity hurts the future labour market and exacerbates the aforementioned skills mismatch (Stiglitz, 2016; Zhou & Tyers, 2019).

A question central to this thesis is what constitutes a winning region. In the context of the changing nature of automation, winning regions are those who can adapt successfully to the new economic landscape, by creating a sufficient number of low-risk jobs (Brynjolfsson & McAfee, 2014; Storper, Kemeny, Makarem & Osman, 2015). It has become evident that the winning regions are almost exclusively large urban centres. In the US, large metropolitan areas are significantly outperforming smaller urban and rural areas in terms of job growth, dating back to the Computer Revolution in the 1980s (Berger & Frey, 2016; Lund et al., 2019; Shearer, Vey & Kim, 2019).

In Europe, a similar trend is visible: the McKinsey Institute reports 48 of the largest cities and superstar hubs were accountable for 35 percent of total job creation from 2010 to 2019, with this number expecting to rise towards 50 percent through 2030 (Smit et al., 2020). Numerous lesser developed regions will be faced with employment stagnation or decline. These regions have a relatively high share of employment in shrinking sectors, including transportation, manufacturing, construction, utilities, and agriculture. Moreover, these regions do not possess the regional capabilities required to attract new employment in growing industries (Balland & Boschma, 2021; Iammarino, Rodríguez-Pose & Storper, 2019).

These developments do not come out of nowhere. The changing nature of work has made geography arguably more important than ever before, despite the forces of globalisation making the world more interconnected than ever before (Florida, Mellander & King, 2020; Moretti, 2012). Innovation is the key to a successful economy and fostering long term economic growth. Because of agglomeration economies, cities are able to produce innovations at a disproportionate rate, relative to more rural regions. This is known as superlinear scaling (Arbesman, Kleinberg & Strogatz, 2009; Balland et al., 2020; Carlino & Kerr, 2015). Following the literature, these agglomeration economies explaining the superlinear scaling can be unpacked into three separate mechanisms. The first is that cities are home to universities and other public research facilities, as well as other R&D-facilities. The second pertains to the quality of life in cities, which attracts creative, high-skilled workers. The third mechanism is the role of spatial proximity, which allows for knowledge spillovers between related industries, fostering innovation (Carlino & Kerr, 2015; Florida, Adler & Mellander, 2017; Puga, 2010). Given the knowledge on superlinear scaling and agglomeration economies, it seems inevitable that less urban regions will fall behind at some point in time. However, the relationship is not as clear-cut as often suggested (Glaeser & Hausman, 2020). It is indeed the case that innovations are mostly registered in cities, however, there is no way of knowing for sure whether the innovation actually originated from the city itself (Shearmur, 2012). Geographically, the trend of innovation concentrating in a few urban centres is not as evident in other regions as it is in the US. Within the European context, there are quite a few non-urban regions that are outperforming more urban regions (Fritsch & Wyrwich, 2021). Maybe, there is still potential for regions, other than large cities, to successfully diversify their economies.

2.6 Building on the principles of relatedness and complexity

New industries locate themselves near industries with similar human capital requirements, where complementary industries are situated, and where there is local synergy with other industries (Farinha Fernandes, Balland, Morrison & Boschma, 2019; Hidalgo et al., 2018). This is the revealed behaviour that entails the principle of relatedness in a nutshell, and it is upon this principle that regional economic policy is built in Europe. Put more simply, related industries are industries with similar human capital and knowledge requirements. The principle of relatedness can also be used to predict where automation job creation will take place. Regions tend to diversify into industries that are related to existing activities (Boschma, 2017). Because all regions have different existing economic structures, they also have different potential for diversification into new industries. This is known in the literature as path-dependency (Cecere & Ozman, 2014; Neffke, Henning & Boschma, 2011).

Notwithstanding, to sustain economic growth, merely diversifying into related industries is insufficient. The reasoning for this is not all industries are equally valuable to a region (Balland & Rigby, 2017). Ideally, a region wants to diversify into related industries with a high degree of complexity. The complexity of an industry is inferred by taking its geography and ubiquity into account. An industry only present in a few regions, is likely to be complex. This is especially the case when other non-ubiquitous industries are present alongside that industry in the same regions (Hidalgo & Hausmann, 2009). An example of this is the aircraft industry, which is present in a minimal number of places. As a region, being specialised in producing aircraft provides more economic added value than specialising in producing bread, as that is an omnipresent industry.

The consequence of only being able to diversify into related industries is that one-size-fits-all economic diversification policies are bound to fail. Policy needs to be place-sensitive, which means discovering regional competences and building upon them (Iammarino, Rodríguez-Pose & Storper, 2019). Whether this solves the problem of growing regional inequality, as the EU smart specialisation policy aims to do by building upon these principles, is another question, however. The inherent problem is that already economically successful regions have more diversification potential than the regions already lagging behind, especially in the sectors of the economy with the most added value (Balland & Boschma, 2019). Nonetheless, place-based policy is necessary to fulfil the potential of the region (Iammarino, Rodríguez-Pose & Storper, 2019). Job creation, through building upon relatedness and complexity, is the key to achieve future economic growth.

3 Methodology

This research utilises secondary data from two sources as the basis for regional analysis in Sweden; primarily the analysis conducted by Frey & Osborne (2017), who estimated the automation risk of 702 occupations based on the extent to which individual tasks can be computerised. I combine their results with a Swedish occupational database to determine the susceptibility of occupations in 21 Swedish counties. The dataset used, derived from Statistics Sweden (2021a), comprises 426 different occupations (4-digit SSYK-2012) over five years (2014-2018). This allows for detailed analysis of the regional labour markets, and how they are changing over time. Due to a change in the classification system, the changes over time of the employment in 4-digit occupations cannot be analysed for 2013 and any previous years (Sweden Statistics, 2021a).

These occupations can be individually linked to their automation risk as determined by Frey & Osborne (2017), using a crosswalk from the American SOC-2010 classification to the European ISCO-08, and subsequently using a crosswalk from ISCO-08 to the Swedish SSYK-2012 classification. The detailed crosswalk from ISCO-08 to SSYK-2012 is found in Appendix I. For 9 occupations, there is no automation probability available, as the Frey & Osborne study calculated the automation risk for 702 out of 840 total occupation categories. This leaves 417 occupations for analysis, allowing for calculating the mean automation risk for every region, which is done by weighing every individual occupation's risk by its prevalence within the region.

The 417 occupations present within the Swedish regional dataset can be categorised into 9 major groups, numbered 1-9, with category 1 being the most complex occupation category overall, and 9 the least complex occupation category. Within this thesis, occupations with 0-30 percent automation risk are considered low-risk, 30-70 percent medium-risk, and 70-100 percent high-risk, which is similar to the classification used by Frey & Osborne (2013; 2017) and Vitáloš (2019).

To determine to what extent Swedish regions are under threat of automation job loss, the regional automation risk is calculated by weighing all individual occupational automation risks relative to their total share in the regional labour market. Regional automation risk (RAR), as well as the mean category automation risk (MCAR), are calculated using this formula:

$$RAR/MCAR = \sum automation\ risk\ of\ X * \frac{Jobs\ within\ X\ in\ region\ R}{Total\ jobs\ in\ region\ R}$$

The X stands for the occupation (4-digit) in the calculation of the RAR, and an occupation category (2-digit) in the calculation of the mean automation risk of the occupation categories.

To estimate regional automation resilience, the regional automation risk is combined with EU-wide data on relatedness density of 40 occupational categories (2-digit level ISCO-08), provided by Pierre-Alexandre Balland. To determine the regional job creation potential, the mean relatedness density (MRD) is calculated by taking the average relatedness density (RD) of all categories with a complexity (CO) of more than 50 (on a scale of 0-100), while weighing for their complexity. This ensures that the most complex categories are assigned the most weight, as regions seek to diversify into the most complex industries possible (Balland & Boschma, 2019; 2021; Boschma, 2017). The following formula is used:

$$MRD = \sum \frac{RD\ of\ occupational\ category * CO\ of\ occupational\ category}{Total\ occupation\ categories\ in\ region\ R}$$

It should be noted that the data on relatedness density and complexity is on the NUTS 2-level. When comparing the job loss and job creation statistics, the NUTS 3-data is aggregated to the NUTS 2-level. Analysis based on this should thus be conducted carefully, as the locations of the related industries underlying the data are unknown. For the revealed automation job growth, the growth of jobs in low-risk occupations is used as a proxy. This way, the potential job creation ability, and the revealed job creation can be compared.

The use of occupational data for determining automation risk is very practical for comparing regions, as it provides insight into the economic structure of regions, and how it might change in the future. However, the use of occupational data has its shortcomings. Frey & Osborne (2017) used the help of experts to determine the automation risk of occupations, rather than the individual jobs that together make up an occupation. This can lead to a somewhat misleading representation of an occupation, failing to take the diversity of jobs within an occupation into account (Arntz, Gregory & Zierahn, 2017). Overall, Arntz, Gregory & Zierahn (2017) find that the occupation-level approach overestimates the automation risk, as workers tend to specialise in non-automatable tasks within their occupations. This does not render the occupation-based analysis useless, however, the results should be very carefully interpreted.

4 Analysis and results

In table 1, the results of the mean automation risk of major occupation categories in Sweden are shown. The data shows a clear link between required education and automation risk; occupations that require higher education are less susceptible to automation. There is also a negative correlation between job growth (between 2014 and 2018) and automation risk in Sweden, although very minor and not statistically significant (r= -0.068; p= 0.178), which tells us that less automatable sectors are growing faster than highly automatable sectors. The limited time frame of the dataset makes it hard to draw reliable conclusions, however. Moreover, job loss within occupations cannot be blindly attributed to automation technology; technological progress in a broader sense can make certain occupations obsolete as well (Bessen, 2016).

4.1 Regional differences in mean automation risk

Zooming in on individual occupations on the 4-digit level, table 2 illustrates that some of the most common and least complex occupations are very much at risk of being automated. At the same time, there is a huge inequality among these occupations in terms of automatability. Human workers have a comparative advantage in common occupations that require a high amount of social interaction, such as in teaching or healthcare. These are more difficult to automate because of the human comparative advantage in social intelligence (Frey & Osborne, 2017).

Based on the occupation-level geographical analysis, significant differences in mean automation risk are found between counties, although the differences between most counties are very small (M= 48.57, SD= 1.76). The risks range from 44.8 percent (Uppsala) to 52.5 percent (Jönköping), as visualised in figure 3. The two positive standout regions are Uppsala and Stockholm, both of which have a higher relative share of jobs in low-risk occupations, compared to other regions. On the other side, Jönköping, Kalmar, and Halland are under high threat of automation job loss, relative to other regions. Comparison of these numbers with the findings of similar Frey & Osborne-based studies shows that the share of high automation risk occupations in Sweden is low, compared to other countries within Europe (Nedelkoska & Quintini, 2018; Vitáloš, 2019). Furthermore, Bowles (2014) found that the share of high-risk occupations in Sweden is the lowest in Europe. Although the average automation risk is relatively low in Sweden, the high wage level means that the point in time where computers will become price competitive with human labour is reached more quickly (Autor & Dorn, 2013; Frey & Osborne, 2017).

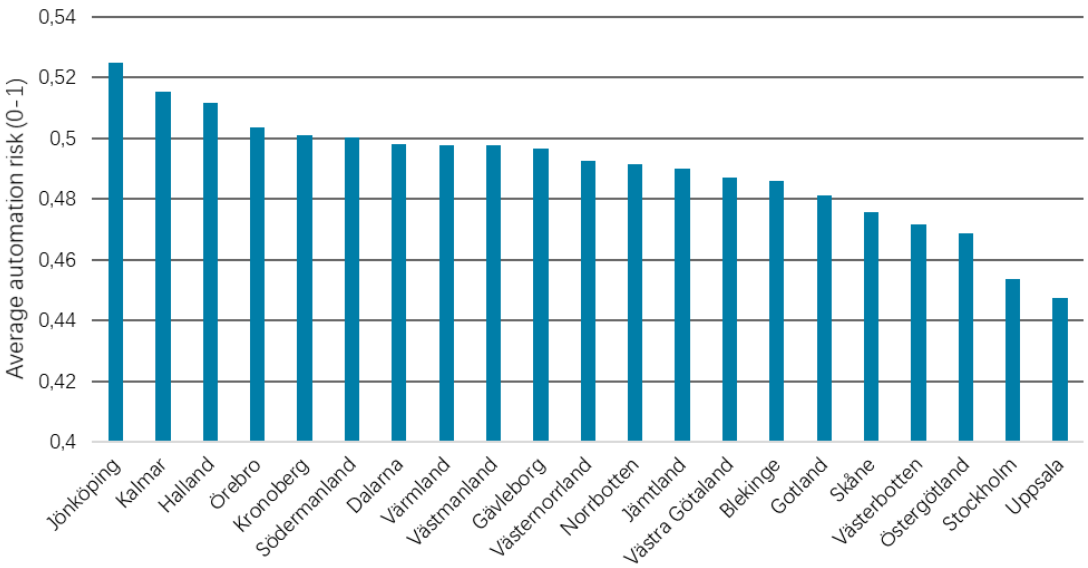
Table 1 The 9 major occupation categories and their automation risk (2018, 1-digit level SSYK-2012)

Category number	Major occupation category	Total jobs	Mean automation risk
1	Managers	301,386	12.0 %
2	Occupations requiring advanced higher education	1,094,556	11.7 %
3	Occupations requiring higher education	594,840	43.7 %
4	Administration and custom service clerks	362,768	77.8 %
5	Service, care and shop workers	983,639	54.5 %
6	Agricultural, horticultural, forestry & fishery workers	34,781	77.8 %
7	Building and manufacturing workers	402,690	71.8 %
8	Mechanical manufacturing and transport workers	317,621	84.8 %
9	Elementary occupations	245,465	82.2 %

Table 2 The 10 most common occupations in Sweden and their automation risk (2018, 4-digit level SSYK-2012)

Rank	Occupation	Total jobs	Automation risk
1	Assistant nurses	135,263	30.0 %
2	Specialty store sales workers	109,526	92.0 %
3	Primary school teachers	106,080	0.4 %
4	Commercial sales representatives	90,286	85.0 %
5	Child care workers	90,008	8.4 %
6	Warehouse and terminal staff	86,491	85.7 %
7	Grocery shop workers	84,252	92.0 %
8	Software- and system developers	77,319	13.0 %
9	Personal care workers	76,698	39.0 %
10	Cleaners and helpers	74,797	57.3 %

Figure 3 Mean automation risk for Swedish counties (NUTS 3, 2018)



4.2 Observing the revealed regional automation resilience

As the data in figure 3 has shown, regions have different automation risks, however, the differences are small. Nonetheless, every region is under significant threat of automation job loss. The data on automation job gain suggests that are greater differences in the regional capabilities to attract new jobs. This is the case on the NUTS 2- (2-digit ISCO-08, figure 4) and NUTS 3-level (4-digit SSYK-2012, figure 5 and 6). The relatedness density data on the NUTS 2-level indicate substantial variance between regions in terms of job creation potential (M = 37.60, SD = 4.68), especially when compared to the variance in mean automation risk (M = 48.57, SD = 1.76). In terms of mean relatedness density (MRD), the best performing region, West Sweden, scores 47.6 percent higher than the worst-performing region, North Middle Sweden. There is no significant correlation found between mean relatedness density and mean automation risk on the NUTS 2-level (r=0.012; p=0.978).

To dig deeper into the connection between automation risk and job growth, the change in the occupational structure of regions (NUTS 3) is analyzed over the 2014-2018 period. Whereas the MRD merely measures the regional job creation potential, the change in regional job growth composition reveals the actual job creation taking place. In 2018, 41.5 percent of all workers in Sweden possessed jobs within the high-risk category, 18.3 percent within the medium-risk category, and 40.2 percent within the low-risk category. In 2014 these percentages were 42.2, 18.7 and 39.1 respectively (Frey & Osborne, 2017; Statistics Sweden, 2021a). On the national level, employment within low-risk occupations is increasing faster compared to medium- and high-risk occupations. Due to this, the national mean automation risk has been on the decline. Nevertheless, there are notable regional differences, as presented in figure 5. Three regions have seen a main automation risk increase from 2014 to 2018: Västernorrland, Norrbotten, and Västra Götaland. In Stockholm county, 53.2 percent of new jobs added from 2014 to 2018 are within low-risk occupations. This presents a stark contrast to the northernmost region Norrbotten, where only 25.5 percent of jobs added are considered low-risk, and more than half (54.7 percent) in high-risk occupations. These results connect to the findings of Frank et al. (2018), who observed that larger cities tend to have more automation resilience, and the findings of Balland et al. (2020), who found that complex economic activities take place disproportionally in large cities, as the Stockholm region is by far the most densely populated in Sweden.

Figure 4 Regional automation risk and relatedness density in Swedish regions (NUTS 2-level, 2018)

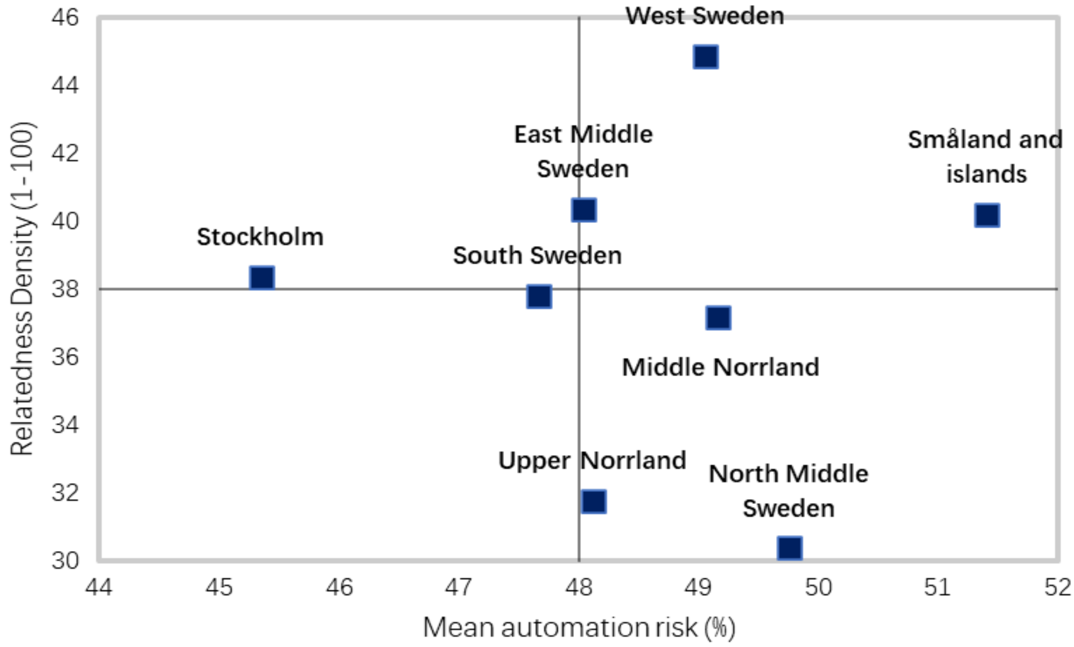
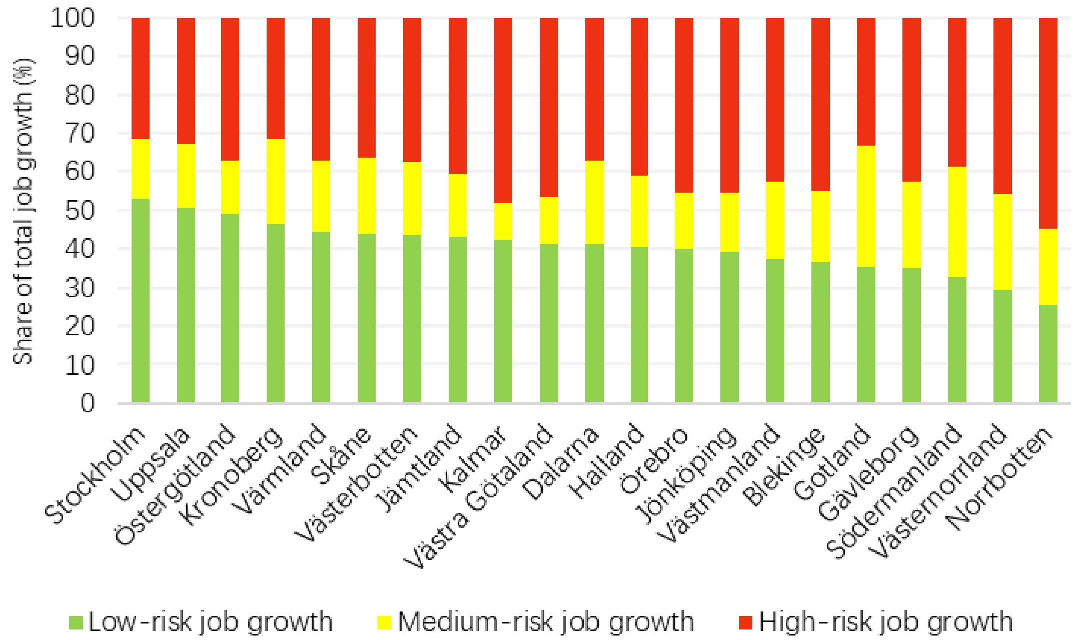


Figure 5 Regional composition of job growth in Sweden based on automation risk, (NUTS 3-level, 2014-2018)



By using low-risk job growth as a proxy for automation job growth, the relationship between automation job loss and automation job growth can be scrutinised at the NUTS 3-level. The results are displayed in figure 6 (For the regional coding, see appendix II). The winning regions are those in the upper left quarter while the losing regions are those in the lower right quarter. Again, the variance in low-risk job growth (M= 40.53, SD= 6.77) is greater than the variance in mean automation risk (M= 49.31, SD= 1,87). Moreover, there is no significant correlation between low-risk job growth and mean automation risk on the NUTS 3-level as well (r= -0.334, p= 0.139). The results show that the regional automation resilience of Swedish regions is largely determined by their ability to create jobs in low-risk occupations.

While the best-performing regions in terms of low-risk job growth are also those with the lowest MAR (Stockholm (01) and Uppsala (03)), the same cannot be said about the regions with the highest MAR. Some of the regions that were found to be most a risk based on their current occupational composition are performing above expectations in terms of low-risk job creation. Examples of such regions are Kronoberg (07), Kalmar (08) and Värmland (17). This provides a positive narrative for the regions with a highly automatable occupational composition relative to other regions: the creation of low-risk jobs is an achievable objective for the regions that are currently lagging behind.

4.3 Automation-induced wage pressure and the displacement effect

To better understand the relationship between the changing regional composition of job growth and regional inequality, it is necessary to understand the relationship between occupational wage and occupational automation risk. When looking closer at this relationship, the data find a significant correlation between the two variables (r= -0.49; p= 0.000), similar to the results found by Chui, Manyika & Miremadi (2015). The data shows that those occupations under threat of automation provide lower wages than occupations that are relatively safe from automation. The correlation is visualised in figure 7. Despite the strong correlation, the automatability of a job is not a very strong predictor of its wage, as there is quite a significant unexplained variance (r^2 = 0.24). There are a few occupations with relatively high wages, despite being in the high-risk category, which are clear outliers in figure 7. The most notable outliers within this category are administration and planning managers, insurance sellers and advisors, commercial sales representatives, and accountants (Frey & Osborne, 2017; Statistics Sweden, 2021a).

Figure 6 Mean automation risk and low-risk job growth share in Swedish regions (NUTS 3-level, 2014-2018)

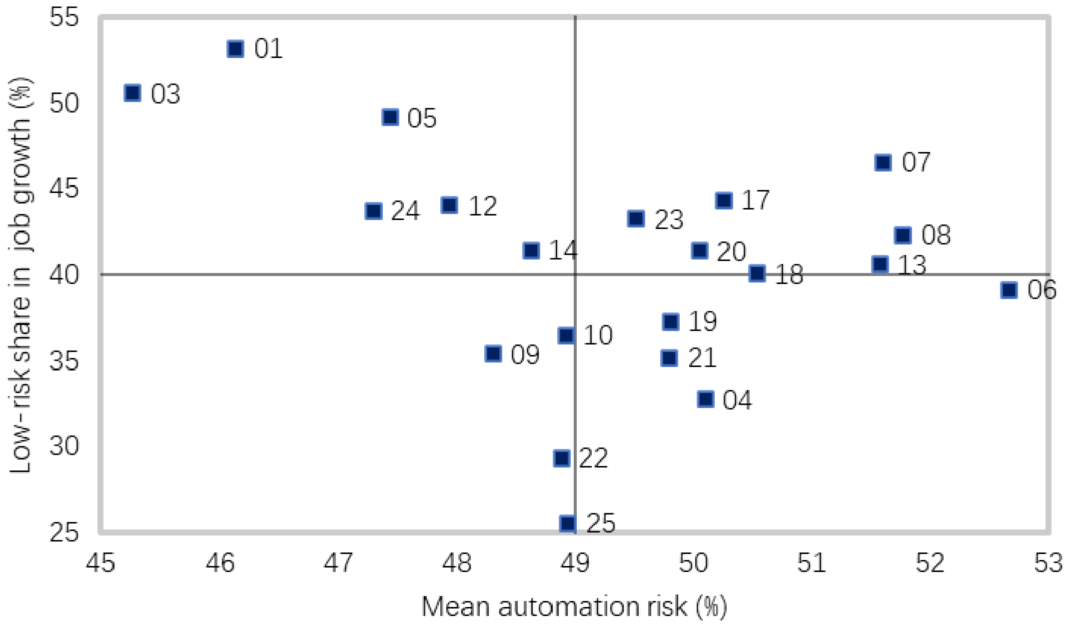
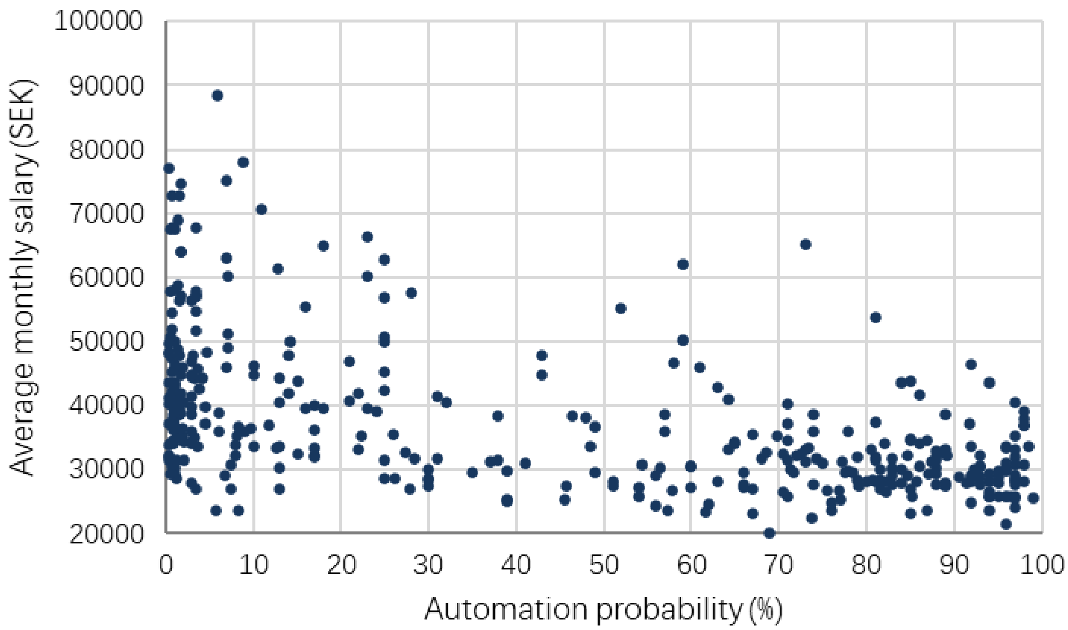


Figure 7 Link between automation risk and average occupational wage (4-digit SSYK-2012)



It also becomes apparent that the found correlation can be explained by the difference in wage variance between low-risk and high-risk occupations. There is a large inequality of wages within the low-risk occupations, whereas the high-risk occupations are much more homogeneous in terms of average wages. As the number of jobs in low-risk occupations is growing relative to the jobs in medium- and high-risk occupations, an overall rise in within-region inequality is to be expected because of this (Kaltenberg & McGregor, 2020).

Naturally, this also impacts regional inequality, as the regions with high low-risk job growth also have faster-growing average wages than the regions lagging behind in low-risk job creation. The regional differences in average wage growth are displayed in table 8. Analysis of the relationship between low-risk job growth and average wage growth finds a significant and strong correlation between the two ($r= 0.544$, $p= 0.011$). The Stockholm region already has the highest average wage by a sizeable margin and the highest average wage growth. The lead they hold over other regions can be expected to increase in the future, as they have been able to create the most low-risk jobs. Regions that are lagging behind in low-risk job creation, are bound to fall further behind in average wage growth (Sweden Statistics, 2021b; 2021c).

The wage statistics also reveal an interesting discrepancy between relatedness density (measured at the NUTS 2-level) and average wage growth. As more complex, less ubiquitous occupations are assumed to render higher wages, the regions with the highest relatedness density to complex occupations are expected to experience the largest average wage growth (Balland & Rigby, 2017). However, the data from 2014 to 2018 shows that the counties within the NUTS 2-regions outperforming Stockholm in this regard, do not experience larger wage growth.

Finally, the displacement effect in Sweden is underlined by the significant negative correlation ($r= -0.108$; $p= 0.032$) between occupation growth and occupation wage from 2014 to 2018. Many of the fastest-growing occupations have relatively low average wage levels, while many of the declining occupations have above average wage levels. At the same time, wages have increased significantly across the board in the same period: the mean monthly wage has increased by 10.2 percent, from 31,400 to 34,600 SEK (3106 and 3423 euro, respectively) per month (Statistics Sweden, 2021c).

Table 8 Average wage and average wage growth in Swedish regions (NUTS 3-level)

Region code	Region name	Average monthly wage (SEK)	Wage growth 2014-2018
01	Stockholm	40,491	12.78 %
03	Uppsala	36,792	12.75 %
05	Östergötland	34,068	12.50 %
24	Västerbotten	31,661	12.43 %
07	Kronoberg	32,845	12.33 %
14	Västra Götaland	34,649	11.90 %
18	Örebro	33,196	11.86 %
13	Halland	32,196	11.43 %
17	Värmland	31,828	11.35 %
04	Södermanland	32,413	11.18 %
22	Västernorrland	32,331	11.09 %
23	Jämtland	30,351	10.99 %
08	Kalmar	31,545	10.57 %
25	Norrbotten	33,288	10.31 %
20	Dalarna	32,050	10.27 %
06	Jönköping	32,223	9.94 %
12	Skåne	34,321	9.88 %
21	Gävleborg	31,861	9.28 %
19	Västmanland	33,542	8.77 %
10	Blekinge	32,171	7.74 %
09	Gotland	31,011	6.07 %

5 Conclusion and discussion

It has become clear that the changing nature of automation comes with comprehensive challenges, even in the case that the predicted shocks caused by disruptive technologies do not come about as forcefully as expected. It is observed that regional economic structures are continuously changing, partially because of automation job loss and automation job growth (Autor, 2015; Acemoglu & Restrepo, 2019). However, the connection between automation job loss, automation job creation and the development of regional inequality is often underexposed in the existing literature. This study specifically aimed to reveal regional differences in automation resilience for 21 Swedish regions, and connecting this with the growing regional inequality in Sweden. Furthermore, the study proposes to use automation resilience as an important measurement for regional inequality. Regional inequality is a problem observed across many European countries, and one without realistic one-size-fits-all solutions (Glaeser & Hausman, 2020; Iammarino, Rodríguez-Pose & Storper, 2019).

Firstly, analysis has found that Sweden is relatively safe from automation job loss, compared to other European countries. The differences in mean automation risk are small across all regions, ranging from 44.8 to 52.5 percent. Secondly, the study also found that there are larger regional differences in relatedness density to complex occupations and the revealed low-risk occupation job creation from 2014 to 2018. This means that there is a considerable regional inequality in the ability to provide low-risk, higher-wage jobs to citizens.

No significant correlation was found between mean automation risk and the ability to create new jobs, meaning that the regions that are found to be most at risk of automation job loss are not necessarily losing regions. Furthermore, the discrepancy between job creation potential and revealed job creation indicates that some regions have untapped potential in high complexity occupations. The results also indicate that compared to the very urban Stockholm region, less densely populated regions are capable of creating low-risk jobs, which is in line with the results found by Iammarino, Rodríguez-Pose & Storper (2019) and Fritsch & Wyrwich (2021). As low-risk job growth is strongly associated with higher average wage growth, regions that are lagging behind in terms of wage growth need to embrace place-based policy towards creating more jobs in low-risk occupations (Balland & Boschma, 2021; Iammarino, Rodríguez-Pose & Storper, 2019).

Nevertheless, because of the significant differences in job creation potential and wage growth between regions, the trend of rising regional inequality can be expected to continue. At the same time, within-region inequality is a point of concern, due to the automation-induced wage pressure and job displacement affecting mainly low-skilled workers. Regions most at risk of automation job loss need to pay closer attention to the skills mismatch that affects the employment opportunities for displaced workers. This is especially the case in less densely populated areas, as their economies tend to be less diversified and thus more specific in their human capital requirements (Lund et al., 2019). Investing in regional human capital can lead to better economic performance and opportunities for upward mobility (Glaeser & Hausman, 2020; Nedelkoska & Quintini, 2018).

On a final note, it is important to note that the scope of this study is limited, as the available data is not detailed enough to truly grasp where jobs are at risk and where new jobs are created. Furthermore, the occupational data provided by Frey & Osborne (2017) lacks detail, as their data do not account for the diversity of jobs within occupations (Arntz, Gregory & Zierahn, 2017). The automation risk data also fails to control for wages. To get a clearer picture of which jobs are most at risk, comparison between the costs of automating specific tasks and the costs of human labour carrying out these tasks is required. Further research should be conducted with more accurate data, using jobs instead of occupations as the base. Moreover, the discrepancy between job creation potential and revealed job creation asks for further analysis into the capacity of regions to fulfil their potential, and what the differences are between underperforming and overperforming regions.

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Appendix I Crosswalk ISCO-08 to SSYK-2012

SSYK-2012	ISCO-08 translation	SSYK-2012	ISCO-08 translation
0110	0110	1712	1411
0210	0110, 0210	1721	1412
0310	0310	1722	1412
1111	1111	1731	1420
1112	1112	1732	1420, 5221, 5222
1113	1114	1741	1213, 1431
1120	1120, 1420	1742	1213, 1431
1211	1211	1791	1439
1212	1211	1792	1120, 1439
1221	1212	2111	2111
1222	1212	2112	2112
1230	1213, 1219, 3343	2113	2113
1241	1222	2114	2114
1242	1222, 2431, 2432	2121	2120
1251	1221	2122	2120
1252	1221, 2431	2131	2131, 2265
1291	1213, 1219, 1223	2132	2131
1292	1213, 1219, 1223, 5151	2133	2131
1311	1330	2134	2132, 3142
1312	1330, 2519	2135	2132, 3143, 6224
1321	1324, 1330	2141	2141
1322	1324, 1330, 1439, 3323, 3341, 4321, 4322	2142	2142
		2143	2151, 2152, 2153
1331	1223	2144	2144
1332	1223	2145	2145
1341	1213	2146	2146
1342	1213	2149	2149
1351	1219	2161	2161
1352	1219	2162	2162
1361	1323, 3123	2163	2164
1362	1322, 1323, 3123	2164	2165
1371	1321	2171	2163
1372	1321	2172	2166
1380	1311, 6112, 6113, 6114, 6121, 6122, 6123, 6129, 6130	2173	2166, 2651
		2179	2163, 3435
1411	1345	2181	2263
1412	1345	2182	3257
1421	1341	2183	2133, 2143
1422	1341	2211	2211, 2212
1491	1345, 5165	2212	2211
1492	1345, 5165	2213	2211
1511	1342	2219	2211
1512	1342	2221	2221
1521	1342, 1344	2222	2222
1522	1342, 1344	2223	2221
1531	1343	2224	2221
1532	1343	2225	2221
1540	2636	2226	2221
1591	1213, 1349	2227	2221
1592	1213, 1349	2228	2221
1611	1346	2231	2221
1612	1211, 1346	2232	2221
1711	1411	2233	2221

2234	2221	2643	2643
2235	3211	2651	2651, 3433, 7318, 7323, 7522
2239	2221, 2267	2652	2652
2241	2634	2653	2653
2242	2634	2654	2654
2250	2250	2655	2655
2260	2261	2661	2422, 2635
2271	2269	2662	2635
2272	2264	2663	3412
2273	2269	2669	2635
2281	2262	2671	2636
2282	2265	2672	2635
2283	2266	3111	3115, 3323, 3339
2284	2267	3112	3112
2289	2269	3113	3113, 3114, 3522
2311	2310	3114	3115
2312	2310	3115	3116, 3119
2313	2310	3116	3117
2314	2310	3117	3118
2319	2310	3119	3119
2320	2320	3121	3121, 3123
2330	2330	3122	3122
2341	2341	3151	3151
2342	2342	3152	3152
2343	2342	3153	3153
2351	2351, 2352	3154	3154
2352	2423	3155	3155
2359	2330, 2353, 2354, 2355, 2359	3211	3211
2411	2411	3212	3212
2412	2411	3213	3213
2413	2412, 2413	3214	3214
2414	2412	3215	3111, 3142, 3143
2415	2631	3230	3230, 3255, 3259
2419	2412, 2413, 2422	3240	3240
2421	2421	3250	3251
2422	2421, 2422	3311	2412, 3311
2423	2423, 2424	3312	3312, 3339, 4211
2431	2431, 2433	3313	3313
2432	2432	3314	3315
2511	2511	3321	3321
2512	2511, 2512, 2513, 2514, 2521	3322	2433, 2434, 3322
2513	2513	3323	3323
2514	2519	3324	3339
2515	2522	3331	3324, 3331
2516	2529	3332	3332, 3339
2519	2519, 2529	3333	3333
2611	2611	3334	3334
2612	2612	3335	3334
2613	2611	3339	3339
2614	2619	3341	3341, 3343
2615	2619	3342	3342, 3411
2619	2619	3343	3343
2621	2621	3351	3351
2622	2621, 2622	3352	3352
2623	2632, 2633	3353	3353
2641	2641	3354	2263, 3115, 3257, 3354
2642	2642	3355	3112, 3115, 3354

3359	3343, 3354, 3359
3360	3355, 5412, 5414
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3412	3413
3421	3421
3422	3422, 3423
3423	3412, 3423
3424	3423
3431	3431, 3521
3432	3432, 3435
3433	3435
3439	2656, 2659, 3435
3441	5165
3449	2353, 2354, 2355, 2356, 2359, 2424
3451	3434
3452	3434
3511	3511, 3513
3512	3512
3513	2521, 2522, 3514
3514	2523, 3513
3515	3514
3521	3521
3522	3435, 3521, 7115
4111	4311
4112	4313, 4416
4113	4312
4114	4419
4115	4322
4116	4110
4117	3341, 3344
4119	3314, 3343, 4110, 4120, 4131, 4132, 4312, 4413, 4419
4211	4212
4212	4213, 4214
4221	4221, 4225
4222	4222, 4225
4223	4223
4224	4224
4225	4226
4226	4227
4321	4321
4322	4321,4322
4323	3341, 4323
4410	4411, 4415
4420	4412
4430	3257, 3313, 3343, 3411, 4110, 5322, 9629
5111	5111
5112	5112
5113	5113
5120	5120
5131	5131
5132	5132
5141	5141
5142	5142
5143	3255
5144	5142

5149	5142
5151	3343, 5151, 5152
5152	5153
5161	5163
5169	5161, 5162, 5169
5221	1420, 5221, 5222
5222	5223
5223	5223, 7549
5224	3254
5225	5245
5226	5223, 5249
5227	5329
5230	4211, 5211, 5230
5241	5241, 5242, 5243
5242	5244
5311	5311
5312	5312
5321	5321, 5322
5322	5321
5323	5321
5324	5321
5325	5321
5326	3258
5330	5321, 5322
5341	5321
5342	5321, 5322
5343	5322
5349	3259,5321, 5322, 5329
5350	3251
5411	5411
5412	5413
5413	3351, 5414
5414	3152, 4223
5419	3411, 5419
6111	6111, 6112, 6114
6112	6113
6113	3142, 6113
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6122	5164, 6121
6129	5164, 6121, 6123, 6129
6130	6130
6210	3141, 6210
6221	6221
6222	6222, 6223
7111	7111, 7115
7112	7112, 7122, 7123
7113	7114
7114	7112, 7119, 7126, 9312
7115	7541
7116	7119
7119	7111, 7114, 7119
7121	7121
7122	7122
7123	7124
7124	7125
7125	7126
7126	7127

7131	7131
7132	7132
7133	7133
7134	7133, 7544, 9129
7211	7211
7212	7212
7213	7213
7214	7213
7215	7214, 7215
7221	7221
7222	7222
7223	7223
7224	7224
7231	7231, 7234
7232	7232
7233	7233
7311	7222, 7311
7312	7313
7319	7312, 7314, 7315, 7316, 7317, 7318, 7319
7321	7321
7322	7322
7323	7323
7411	7411
7412	7412
7413	7413
7420	3123, 7421, 7422
7521	7521
7522	7115, 7522
7523	7523
7531	7531, 7532
7532	7533, 7534
7533	7534
7534	7535, 7536
7611	7511
7612	7512
7613	7515
7619	7513, 7514
8111	8111
8112	8112
8113	8113
8114	8114
8115	7542
8116	7113
8121	8122
8122	8121
8129	8121
8131	8131
8132	8131, 8132
8141	8141
8142	8142
8143	8143
8151	8154, 8157, 9129
8159	8151, 8152, 8153, 8155, 8156, 8159
8161	8160
8162	8160
8163	8160
8169	8160
8171	8171
8172	8171
8173	8172
8174	7521
8181	8183
8189	7549, 8181, 8189
8191	3131, 3132, 8182
8192	3133, 3134
8193	3135
8199	3139
8211	8211
8212	8212
8213	8189, 8219
8214	8219
8219	8219
8311	8311
8312	8312
8321	8322
8329	8321, 8322, 9331
8331	8331
8332	8332
8341	8341
8342	8342
8343	8343
8344	8344
8350	8350
9111	9111, 9112
9119	5311, 9111
9120	9121, 9122, 9123, 9510
9210	9211, 9212, 9213, 9214, 9215, 9216
9310	9312, 9313
9320	9321, 9329
9331	9333
9332	9332, 9333, 9334
9411	9411
9412	9412
9413	5246
9520	5211, 5212, 9520
9610	9611, 9612, 9613
9621	9621
9622	9621, 9622, 9629
9629	8189, 9510, 9621, 9622, 9623, 9629

Appendix II Regional coding scheme (NUTS 2 to NUTS 3)

NUTS-2 region	NUTS-3 region
Stockholm	01 Stockholm
East Middle Sweden	03 Uppsala
	04 Södermanland
	05 Östergötland
	18 Örebro
	19 Västmanland
Småland and the islands	06 Jönköping
	07 Kronoberg
	08 Kalmar
	09 Gotland
South Sweden	10 Blekinge
	12 Skåne
West Sweden	13 Halland
	14 Västra Götaland
North Middle Sweden	17 Värmland
	20 Dalarna
	21 Gävleborg
Middle Norrland	22 Västernorrland
	23 Jämtland
Upper Norrland	24 Västerbotten
	25 Norrbotten