Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Economics and Management
Department of Economics

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Has technology replaced routine jobs in Norway?

An empirical study testing the Routinization Hypothesis

Master's thesis in Economics
Supervisor: Costanza Biavaschi
June 2020

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Preface

This master thesis marks the end of a 2-year master program in Economics at the Department of Economics at the Norwegian University of Science and Technology. Working on our thesis has been interesting, challenging, fun, and sometimes frustrating.

We especially want to express our gratitude to our amazing supervisor, Costanza Biavaschi, for her enthusiasm and excellent guidance throughout this process. For always answering our questions, and welcoming us with a big smile (over video calls).

Thank you to Maria Forthun Hoen, for providing us with helpful data. We would also like to thank our fellow students for making the last two years fly by, filled with laughter, late nights at the campus and great memories.
Finally, we wish to thank each other for a good partnership throughout the semester.

(Part of) the data used in this thesis is gathered from the "Labour Force Survey 1972-2019". The data is in an anonymous form, made available from Statistic Norway through NSD - Norwegian Center for Research data AS. Statistic Norway and NSD are not responsible for the analysis of the data, or the interpretations done in this thesis.

Summary

This thesis test whether technology has substituted routine tasks and complemented high-skilled workers, looking at the Norwegian case during the period 1996-2018. Using information from the Norwegian Labour Force Survey, combined with information on occupational task characteristics from the O*NET database, we analyze employment trends using a task-based method. To the best of our knowledge, we provide first-evidence on the routinization hypothesis over the last twenty years in Norway. We believe this thesis could provide useful information to the government and policymakers in Norway, in regards to the future demand for jobs and skills. In addition to looking at the economy as a whole, we analyze the trends within the two sectors, manufacturing and services, as well as genders.

We find that the routine-biased technical change appears in the first decade, and then towards the end of our time period. The findings are more evident in routine manual tasks, whereas support for the routinization hypothesis is mostly absent in routine cognitive tasks. Our findings suggest that it is essential to take other considerations into account when exploring employment trends within tasks, including cyclical variations in the economy.

Oppsummering

Formålet med denne oppgaven er å teste hvorvidt teknologi har erstattet typiske rutineoppgaver, i tillegg til å komplimentere de oppgavene som ikke er preget av rutine. Ved å bruke data fra Arbeidskraftsundersøkelsen, kombinert med informasjon fra O*NET om hvilke typer arbeidsoppgaver ulike yrkesgrupper utfører, analyserer vi sysselsettingstrenden innenfor ulike arbeidsoppgaver i Norge i tidsperioden 1996-2018. Så vidt vi vet, er vi de første som tester rutiniseringshypotesen i Norge over de siste 20 år. Vi tror denne oppgaven kan gi nyttig informasjon til myndighetene og beslutningstakere i Norge, med tanke på hvordan etterspørselen etter jobber og ferdigheter utvikler seg.

Vi analyserer trender for hele økonomien, i service- og produksjonssektoren, og for kjønn. I oppgaven finner vi bevis som støtter hypotesen i det første tiåret og mot slutten av vår tidsperiode. Vi ser en klarerer tendens til at teknologi erstatter manuelle rutineoppgaver, sammenlignet med kognitive rutineoppgaver. Våre funn indikerer at det er viktig å ta hensyn til andre faktorer som kan påvirke sysselsettingstrenden, for eksempel konjunktursvingninger i den norske økonomien.

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1 Introduction

Technological development has had a rapid growth in the last decades, and it does not seem to slow down. The general public, as well as some economists, fear that technology will replace workers, and as a result, the employment rate will decrease. Some even propose that almost half of all the existing jobs could end up being replaced by technology within the next 20 years (Blit, Amand & Wajda, 2018). On the other hand, new technology can also be a driver in creating new jobs. However, despite new jobs occurring, there is a risk that there will be an increase in unemployment, and that a larger share of the population will be permanently forced out of the labour market, this due to skills mismatch.

These concerns have motivated a vast literature to explore the relationship between technology and the labour market. Obtaining information on the development of the labour market and on which factors might have affected it, and probably will affect it in the future, is essential to the economy. By increasing our understanding of such patterns, we can better predict what kind of jobs will be in demand in the future and what type of education and skills that will be important. Increased knowledge of this topic, can advise governments and policymakers to implement guidelines and polices to sustain the most vulnerable segments of the labour market, which in turn can decrease the impact of shocks in the economy.

As technology can both substitute and complement the labour force, it can, in that manner, change the type of tasks performed in different occupations. In countries such as the U.S, Portugal, Germany, and the U.K, economists have been able to document this effect and found that routine tasks are more likely to be substituted, compared to non-routine tasks (Acemoglu & Autor, 2011; Bachmann, Cim & Green, 2019; Fonseca, Lima & Pereira, 2018; Goos & Manning, 2007). Despite the importance of this topic, evidence for Norway remain limited. To the best of our knowledge, this thesis provides the first evidence on whether technology has disproportionally replaced routine tasks in Norway, using a task-based method. It does, however, complement studies by Asplund, Barth, Lundborg & Nilsen, (2011) and Salvanes and Førre (2003), who have instead looked more generally at polarization and alternative explanations to their findings.

Using the task-based method, as suggested originally by Autor, Levy & Murnane (2003), we empirically analyze the trends in the employment share within various tasks, over multiple decades and across industries. In particular, we study the evolution of employment rates for groups of workers that hold a comparative advantage in a given task at the beginning of our sample period. The model is estimated for the economy as a whole, between genders and the manufacturing and service sector.

Previous findings on the Nordic labour market indicates that demand for labour could be subject to both skill-biased technical change and routine-biased technical change (Asplund et al., 2011). Our findings show that in Norway, the labour distribution is sensitive to shocks in the economy. We find some evidence supporting the routinization hypothesis, especially in regards to employment in routine manual tasks for the period 2011-2018. These findings are especially evident in the manufacturing sector, but not substantially different between genders. Subsequently, our results indicate that non-routine tasks are harder to automate, as we see a significant increase in employment performing abstract tasks.

The remainder of the thesis is structured in the following way: In the 2$^{\text{nd}}$ chapter, we will briefly review some of the literature related to the topic and discuss how their contributions and methods apply to our work. We will explain the data sources, and how they are used, to empirically test our research question in the 3$^{\text{rd}}$ chapter. Important factors related to Norway are presented in chapter 4. In chapter 5, we present the empirical model used, the obtained results and additional robustness checks. In the 7$^{\text{th}}$ chapter, we discuss our findings, and present possible explanations driving the observed results, before giving our concluding remarks in chapter 8.

2 Literature review

The recent literature on the relationship between technological change, skills and tasks focuses on how these factors drive the changes in the wage distribution and the distribution of the labour force. Here, a central topic is job polarization, defined as the presence of employment growth at both the bottom and the top of the income distribution, while the share of middle-wage workers decrease, indicating a u-shaped pattern in the labour force distribution

The literature has developed two core theories that could explain job polarization. The first is skill-biased technical change, meaning that new technology favours the more skilled workers.[1] A notable contribution in this topic is given by Card and Dinardo (2002), who analyze likelihood of computer use at the workplace among college and high school graduates. Their results showed that college graduates in the U.S are twice as likely to employ computers than high school graduates. Conversely, high school graduates are almost four times more likely to employ computers than high school dropouts. These findings substantiate the correlation between education and technology.

Autor, Levy & Murnane (2003) (referred to as ALM henceforth) criticize this theory, as they believe that it merely labels the correlation without further explanations of the causes behind. They state that the theory fails to explain what computers do - or what it is people do with computers - that causes educated workers to be relatively more in demand. To address this gap, ALM formalizes and test a simple theory of how the rapid adoption of computer technology, and a decline in the price of computer capital, change the tasks performed by workers and, ultimately, the demand for human skills. They developed the "Routinization hypothesis", or the "routine-biased technical change" hypothesis, which refers to technology replacing workers performing routine tasks. By measuring the tasks performed in jobs rather than the educational credentials of workers performing those jobs, the study supplies a missing conceptual and empirical link in the economic literature on technical change and skill demand. The conceptual model developed by ALM suggests that, when the price of computer capital declines, industries and occupations with

[1] Berman, Bound & Machin (1997), Machin and Van Reenen (1998), Surendera, Wulong and Zhengxi (2001).

relatively high intensity of labour input of routine tasks will reduce the demand for labour used in conducting these tasks. Conversely, the demand for relatively highly educated workers, who hold a comparative advantage in non-routine tasks, will increase (Autor et al., 2003). They find that the substitution of machinery for repetitive human labour has been a thrust of technological change throughout the industrial revolution. Their results show that the employment share in occupations with intensive use of non-routine analytic and non-routine interactive tasks increased substantially during the last four decades.

Acemoglu and Autor (2011) develops a conceptual framework with a task-based approach, which consists of a continuum of tasks that produce a unique final good. An essential feature of the task-based model is that it allows for new technologies that could directly replace workers in specific tasks. The model treats skills (labour), technology (capital), and trade or offshoring, as offering competing inputs to accomplish various tasks. In this framework, technological development can change the productivity of different types of workers in all tasks, thus changing their comparative advantage. Based on the patterns found in the analysis, as well as the general characterization of machine-task substitution offered by Autor et al. (2003), they believe the set of tasks that are most likely to be replaced by machines in the current era are those that are routine or codifiable.

To empirically test their theory, Autor et al. (2003) presented a classification of tasks. They divide tasks between routine-and non-routine manual and cognitive. Here they use information on the activities performed by workers on the job to classify jobs in terms of task intensity. They use the Dictionary of Occupational Titles (DOT) to collect information on the task composition of occupations, finding which tasks, and at what level, they are used in specific occupations. More recent literature has redeveloped the tasks measure categorization by connecting the two different routine categories (Autor, 2013; Autor, Katz & Kearney, 2006; Cortes, 2016; Goos & Manning, 2007; Sebastian, 2018). Tasks are classified as manual, routine and abstract, or non-routine manual, routine and non-routine cognitive. Most of the studies using this method of task categorizing have similar results like the ones presented by Autor et al. (2003) and Acemoglu and Autor (2011); abstract and manual (non-routine) tasks are harder to automate than routine tasks.

One of the authors using the three-way classification of tasks (routine, non-routine cognitive and manual) is Cortes (2016). In his paper, he explores the effects of routine biased technical change on occupational transition patterns and wage changes of individual workers in the U.S. In the paper, he classifies occupations into three broad groups, where the categorization of jobs is based on the aggregation of three-digit occupational codes. Using data from the Panel Study of Income Dynamics from 1976 to 2007, he focuses on individual-level predictions in terms of occupational switching patterns and wage changes, shedding light on what happens to these workers over time. His evidence shows that routine workers have a higher probability of becoming unemployed than non-routine workers with the same demographic characteristics. Also, his results show that those who stay in routine jobs rather than those who switch occupations are the ones hardest affected in the long run by the effects of technological change (Cortes, 2016).

Goos and Manning (2007) looks for evidence of job polarization in the U.K, exploring both the skill-biased technical change (SBTC) and the routine-biased technical change hypothesis. As the SBTC hypothesis is assumed to increase demand for more educated labour, the authors argue that this will not provide a u-shaped pattern explaining polarization. Their paper does provide evidence supporting the routinization hypothesis developed by Autor et al. (2003) in regards to increased job polarization in the U.K. Sebastian (2018) finds evidence supporting the routinization hypothesis in Spain, using a task perspective method.

Adopting the methodology presented by Cortes (2016), and the task classification developed by ALM, Bachmann et al. (2019) uses longitudinal data to study the long-term pattern of labour market polarization in Germany. Their research provides important information regarding the actual process of job-loss and reemployment at the individual work level, particularly the nature of individual worker transitions that results from the reduction in demand for routine intensive work. Their results show that the risk of becoming unemployed is higher for workers in occupations with high routine task intensity. They also find that routine task work is associated with reduced work stability and a higher probability of transitioning to unemployment (Bachmann et al., 2019).

Although most of the literature is based on the three-way classification, some studies still use the categorization of ALM. When looking at job polarization, technological change and routinization in Portugal, Fonseca et al. (2018) follows the task classification developed by ALM. They find it essential to separate routine manual and routine cognitive tasks, as the different routine groups have different importance in the service and manufacturing sector. Using these task measures to classify jobs, they find support for the routinization hypothesis as an explanation for most of the employment and wage patterns observed in Portugal.

To the best of our knowledge, the literature does not provide many studies focusing on Norway, but when looking at polarization on the Nordic labour markets, Asplund et al. (2011) found evidence of polarization in Norway. Although they do not test the routinization hypothesis, their results could indicate that the Nordic countries have experienced a shift from skill-biased technical change to routine-biased technical change, but more likely, a combination of the two. Similar results were found in Salvanes and Førre (2003), where they concentrated on trade and technology-related explanations for the changes in compositions of skills on a business-level in Norway.

Berglund, Dølvik, Rasmussen & Steen (2019) study the distributional changes in employment within occupational/wage structure in the three Nordic countries Denmark, Sweden and Norway. In doing so, they use a wage approach estimating which skills that are increasing or decreasing in demand, looking for patterns supporting either the SBTC or RBTC hypothesis. For Norway, they find clear tendency of upgrading, indicating that higher-skilled workers are more in demand.

In this thesis, we complement existing evidence provided by Asplund et al. (2011), Salvanes and Førre (2003) and Berglund et al. (2019), by directly testing the routinization hypothesis for Norway. We use data collected from the Norwegian Labour Force Survey (LFS) between the years 1996 and 2018, and the classification of tasks developed by Autor et al. (2003). We follow the empirical approach used by Fonseca et al. (2018) to test whether employment movement in Norway is consistent with the routinization hypothesis. With our data, we can distinguish between four tasks: Abstract, routine cognitive, routine manual and manual. We believe separating between routine manual and routine cognitive tasks is especially important in our case, as we are focusing on a country with a growing service sector, and a manufacturing sector highly dependent on the petroleum industry. Therefore, it is likely that technology will have different effects on the two routine tasks.[2] Our contribution to the field of study is to look for evidence that can support the routinization hypothesis in the case of Norway.

[2]We do, however, compare the results obtained when combining the two routine tasks in section 6.1.1 p.33.

3 Data

In this chapter, we describe the data used in our analysis, as well as adjustments made to obtain a continuous data set for both periods. We will explain the task measures used, and how we, by following previous literature, are able to find the specific task associated with each occupation.

3.1 Labour Force Survey

The data used in this analysis is the National Labour Force Survey of Norway (LFS), which is collected by Statistic Norway (SSB). The survey started in 1972 with the purpose of providing information on the employment structure in the population and its developments over time. Participants in the survey are randomly chosen households, where all individuals within the ages of 15-74 are interviewed. Participation is mandatory, but per now, there have not been any repercussions to those refusing to answer[3]. Each quarter approximately 24 000 individuals, in about 12 000 households, are asked about their attachment to the labour market, based on a specific reference week.[4] The interviews are primarily conducted directly by phone, but if the participant is unable to answer, the interview will be done indirectly by having near family members answering the questions. About 14-15 % of the interviews are carried out indirectly. The participants answer background questions about age, gender, educational level, marital status and whether they have kids or not. Regarding their involvement in the labour market, they answer questions about their employment status, work contract (full or part-time, temporary employment), what kind of county they work in, if they have had any absent, and if yes, for what reasons.

In the analysis, we look at two different time periods, 1996-2010 and 2011-2018. We focus on individuals working full time at one job only, within the ages 15-74. We include individual characteristics such as age, education, gender, industry and occupation. We use information about the participant's employment status to limit

[3]The response rate differ each year, but on average, the response rate is 88%.

[4]From 1996, the participants are interviewed for eight consecutive quarters, but because individuals are not linked, we do not have access to a panel dimension.

the data to those with active employment status.[5]

Similar to the literature, we have excluded military occupations from our data (Acemoglu & Autor, 2011; Cortes, 2016). National defence occupations are hard to classify as there are different national practices to the classifications. In many countries, it is impossible to collect information on the work that members of armed forces do and how they do it. Since it is hard to get information on each occupation, ISCO classified them all together (ILO, n.d.). In Norway, serving in the national defence is compulsory for both males and females, and as these occupations are not likely to erupt or be replaced, this justifies removing these observations.

3.2 Changes in the survey

The questions and definitions used in the survey changed several times during the years, so in order to make our periods consistent, some manual adjustments were necessary. An example is a question related to educational level. In earlier years, the levels were divided in more detail, whereas later they used broader standards. Here we have manually adjusted the values into broader educational groups. Even though the survey started in 1972, we are limited to use data between 1996 and 2018. The reason for the time limit is the changes in the occupational code classification.

In the years 1996-2010, the standard occupation classification used is STYRK-88 (Standard for yrkesklassifisering), which is the Norwegian occupational codes based on ISCO-88 (International Standard Classification of Occupations). In 2011, the LFS implemented the updated version STYRK-08, based on ISCO-08. This was due to significant changes in the labour market in the last 20 years, among other things, an increasing number of occupations within information and communication technology (ICT) (ILO, n.d.). However, even though STYRK-88 and STYRK-08 are both based on ISCO, we are unable to create a continuous data set due to a more detailed classification in the updated version. The occupational codes used before 1996 are not based on the same classifications, making it difficult for us to create a consistent data set.

[5]Active employment status is defined as workers who are currently employed, and not absent from work in the reference week. We exclude workers who are temporarily absent in the reference week, this due to little knowledge about the length of absent.

The code system in the occupational codes is hierarchical built, where the first number of the code describes the field of occupation. In total, there are ten major groups, ranging from 0-9. The second number describes the occupation area, divided into 29 sub-major groups in STYRK-88 and 42 in STYRK-08. The third number shows the occupational group, consisting of 108 (STYRK-88) and 121 (STYRK-08) minor groups, and the fourth represents the profession. At the four-digit level, we have 365 (STYRK-88) and 406 (STYRK-08) different unit groups.

An example of this:

2	Professionals
21	Physical, mathematical and engineering science professionals
212	Mathematicians, statisticians and related professionals
2122	Statisticians

3.3 Industry codes

The industry variable is vital for our work as it captures the fact that workers with similar occupations can work in different industries, and therefore also in different sectors.

Due to changes in economic structure and organizations, the standards need to be updated. The relevance of the classifications shrink over time because new industries emerge and old ones change (ILO, n.d.). In the period 1996-2018, the LFS uses three different versions of the industrial codes. In 1996, the labour force survey started using NOS C 182, which was industry classifications based on the EU-standard NACE Rev.1. This classification had some minor changes in 2002, and then changes of another magnitude in 2007. The industry codes reported in the LFS are on a 2-digit level, so the minor changes on a 4-digit level in 2002 did not affect our variable. To make the variable consistent, we had to manually connect the 2002 version with the updated version from 2007, using the correspondence provided by Statistics Norway (n.d).

Following Eurostat (n.d.), we assemble the industry standards into ten broader groups.

1. Agriculture, forestry and fishing
2. Manufacturing, mining and quarrying and other industries
3. Construction
4. Wholesale and retail trade, transportation and storage, accommodation and food service activities
5. Information and communication
6. Financial and insurance activities
7. Real estate activities
8. Professional, scientific, technical, administration and support service activities
9. Public administration, defence, education, human health and social work activities
10. Other services

3.4 Challenges with the data

The most challenging part of our research has been to put together the data needed to conduct the analysis. As the Norwegian administrative register on occupational data lacks information about occupation-specific characteristics in regards to tasks, we have adapted the task measures provided by The Occupational Information Network (O*NET) database [6]. O*NET is a source of occupational information that is essential for understanding the rapidly changing nature of work and how it impacts the workforce. The database contains hundreds of standardized and occupation-specific descriptors on almost 1000 occupations covering the entire U.S. economy. It is continually updated from input by a broad range of workers in each occupation (O*NET, n.d.). Because O*NET provides detailed information about characteristics associated with the Standard Occupational Classification (SOC) codes used in the U.S, we have used a crosswalk between the Norwegian occupational codes (STYRK) and SOC. This is not a straightforward process and is in that manner, done in several steps. Because of the many differences between SOC and STYRK, we first had to match SOC with the Occupational Census Classification (OCC) codes and match OCC with STYRK. The OCC is used as a link between STYRK and SOC because it provides more aggregated occupational codes than SOC, creating a better mapping between STYRK and SOC.

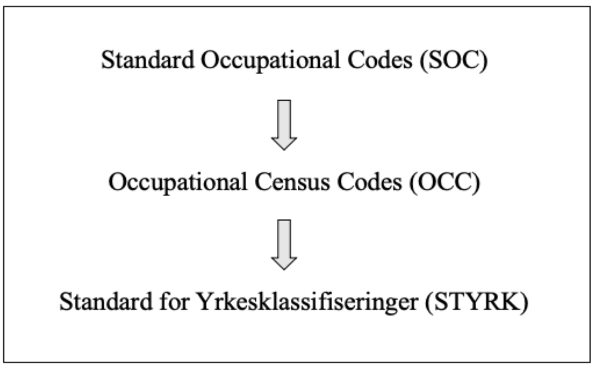

Figure 1: The figure shows the direction of the crosswalk connecting SOC and STYRK.

Maria Forthun Hoen (2020) kindly provided a crosswalk for matching STYRK-88 with OCC-00, whereas the crosswalk for matching OCC-00 to SOC-00 was provided

[6]Cedefop (2013) found that it is methodologically valid to use O*NET data to construct occupational measures in European countries.

by the Institute of Structural Research (2016). For the second period (2011-2018), we followed the same steps as in the previous period, only using updated SOC-10, OCC-10 and STYRK-08 codes. The crosswalk between STYRK-08 and OCC-10 was done by first matching STYRK-88 and STRYK-08 manually, with the use of the correspondence provided by Statistics Norway (2016a). The correspondence between OCC-00 and OCC-10 was provided by the U.S. Bureau of labor statistics (2016). The final step was connecting STYRK-08 with OCC-10.

3.5 Task measure construction

As mentioned in the literature review, there are several ways to classify tasks. The classification based on occupational titles could, in our opinion, be subject to selection bias based on the researcher's selection of tasks.[7] Therefore, we believe the best method is to use information about occupational tasks provided by workers. Since the Norwegian occupational codes lack this information, we follow the task measure construction used by Autor et al. (2003). In their study of the labour market in the U.S, they use DOT (Dictionary of Occupational Titles) to collect information on the occupation's task composition, creating categories of tasks. The crosswalk linking STYRK to SOC makes it possible for us to use the information provided by DOTs successor, the O*NET database.

We follow in Autors footsteps and use raw O*NET files on work activities, work context, abilities and skills to find the task composition used in specific occupations. These files contain information on occupation-specific characteristics provided by a broad range of workers in each occupation. Given the magnitude of the files, we used principal component analysis (PCA) on the task scales (Table 1) best representing the task measures used in our research, and find the most important task input in each occupation.

Acemoglu and Autor (2011) address a limitation with using O*NET, as they state that the task scales are loosely defined and weakly differentiated. Despite these limitations, we believe this method is best suited for our analysis. However, we are aware of possible biases arising from this issue.

[7] A classification of tasks based on broad occupational groups yields similar results as the method used here. See section 6.1.2 p.34.

Table 1: O*NET descriptors

O*NET descriptors		Scale type
Abstract: Non-routine Cognitive: Analytical and interpersonal		
4.A.2a.4	Analyzing data or information	Importance
4.A.2b.2	Thinking creatively	Importance
4.A.4.a.1	Interpreting the meaning of information from others	Importance
4.A.4.a.4	Establishing and maintaining personal relationships	Importance
4.A.b.4	Guiding, directing and motivating subordinates	Importance
4.A.4.b.5	Coaching and developing others	Importance
Routine cognitive		
4.C.3.b.7	Importance of repeating the same tasks	Context
4.C.3.b.4	Importance of being exact or accurate	Context
4.C.3.b.8	Structured vs. Unstructured work (reverse)	Context
Routine manual		
4.C.3.d.3	Pace determined by speed of equipment	Context
4.C.2.d.1.i	Spend time making repetitive motions	Context
4.A.3.a.3	Controlling machines and process	Importance
Manual: Physical adaptability		
4.A.3.a.4	Operating determined by speed of equipment	Context
1.A.2.a.2	Manual dexterity	Importance
1.A.1.f.1	Spatial orientation	Importance
4.C.2.d.1.g	Spend time using hands to handle, control or feel objects, tools or controls	Context

Note: O*NET measures selected for construction of each task measures following Fonseca et al. (2018). Reverse means that the scale has been transformed in order for the lower values to be at the top and for the higher values to be at the bottom. Source O*NET (n.d.).

Table 1 shows the task scales used in creating the composite task measures, providing us with the task categories; Abstract, routine cognitive, routine manual and manual. We combine non-routine cognitive analytical- and interpersonal, which we call abstract tasks. These tasks require intuition and ability to think creatively and analyze data or information, e.g., perform tasks associated with problem-solving, coaching and developing others. Routine cognitive tasks is typically defined as the importance of being exact or accurate, and the importance of repeating the same skills. These are skills typically required in jobs like sales and office clerks. Manual tasks require in-person interactions, such as abilities to operate vehicles, mechanized devices or equipment. Routine manual tasks require skills related to controlling machines and processes and making repetitive motions.

3.6 Occupations and task measures

Using the two-digit level of occupational codes, and the task measures calculated using the O*NET task descriptors, we find a set of task measures for each occupation, which provides information about the intensity of each task in specific occupations.

From Table 2, we can see the distribution of tasks within occupations and see which task has the highest intensity in each occupation.

Table 2: Task importance measure STYRK-88

Styrk Title	STYRK-88	Abstract	Manual	Routine Manual	Routine Cognitive
Small enterprises and corporate managers	12+13	1.31	-0.77	-0.79	-0.52
Realists, engineers	21	0.90	-0.60	-0.56	0.01
Biology and health professionals	22	1.12	-0.05	-0.50	0.38
Teaching professionals	23	1.69	-1.04	-0.92	-0.70
Other professionals	11+24+25	1.02	-1.08	-0.99	-0.26
Engineers and technicians	31	0.31	0.33	0.10	-0.08
Biology and health associate professionals	32	0.77	-0.16	-0.63	0.40
Teaching associate professionals	33	1.28	-1.09	-0.93	-0.51
Other associate professionals	34	0.42	-0.69	-0.79	-0.07
Office clerks	41	-0.49	-0.08	0.29	0.44
Customer service clerks	42	-0.04	-0.42	0.12	0.88
Personal and protective service workers	51	-0.01	0.13	-0.33	-0.23
Models and salespersons	52	-0.32	-0.14	0.10	0.50
Agriculture professionals	61	0.70	1.80	0.77	-1.44
Forestry occupations	62	-0.14	1.29	1.25	-0.47
Fish farming occupations	63	-1.35	1.81	-0.12	-1.58
Fishing professionals	64	-1.35	1.81	-0.12	-1.58
Stone and building trades workers	71	-1,24	1.10	0.87	-0.54
Metal, machinery and related trades workers	72	-0.68	1.33	0.83	-0.32
Precision, handicraft, print and related trades workers	73	-1.32	0.21	0.86	-0.58
Other craft and related trades workers	74	-1.32	0.21	0.86	-0.58
Process operators	81	-0.91	0.71	1.74	-0.35
Machine operators	82	-1.10	0.76	2.10	-0.25
Drivers and mobile-plant operators	83	-0.35	1.94	1.08	0.00
Sales and services elementary occupations	91	-1.69	0.33	0.42	-1.28
Agriculture associate professionals	92	-1.12	1.49	0.22	-1.41
Labourers in building and industry	93	-1.44	0.96	0.71	-0.74

Note: Task importance measures calculated using principal components of several O*NET measures. All scores are standardized to mean 0 and standard deviation 1.

Table 2 summarizes the results for the first period, displaying the standardized principal components (mean 0 and standard deviation 1) for each task measure. As can be seen from the table, managerial, health- and teaching occupations rank highest in abstract tasks. Given that abstract tasks require cognitive abilities such as problem-solving and coaching skills, which can be found in professions such as teaching, financial directors and biologists, supports this measure. Manual tasks have the highest intensity in occupations, such as drivers of different vehicles and workers in fish farming industries. Workers in occupations such as machine operators and process operators require the most routine manual tasks, whereas customer service clerk related occupations have the highest intensity of routine cognitive tasks.

Table 3: Task importance measure STYRK-08

Styrk Title	STYRK-08	Abstract	Manual	Routine Manual	Routine Cognitive
Chief executives, senior officials and legislators	11	1.24	-0.43	-0.41	-0.43
Science and engineering professionals	21	1.51	-0.50	-0.85	-0.53
Teaching professionals	23	1.62	-0.91	-1.11	-1.58
Business and administration professionals	24	0.85	-0.68	-0.93	-0.01
Other professionals	25+26	0.69	-0.29	-0.42	-0.18
Other associate professionals	31+34	0.50	0.48	0.11	0.03
Information and communication technicians	35	-0.02	-0.23	-0.04	0.62
Administrative and commercial managers	12	1.61	-0.73	-0.83	-0.45
Production and specialized services managers	13	1.61	-0.73	-0.83	-0.45
Hospitality, retail and other services managers	14	1.41	-0.39	-0.47	-0.43
Health professionals	22	0.81	0.00	-0.13	0.24
Health associate professionals	32	0.68	0.03	-0.08	0.54
Business and administration associate professionals	33	0.40	-0.59	-0.88	0.03
General and keyboard clerks	41	-0.40	-0.69	-0.22	0.68
Numerical and material recording clerks	43	-0.11	0.04	0.63	1.36
Other clerical support workers	44	-1.62	0.92	0.90	1.76
Personal services occupations	51	-0.33	0.33	0.42	-0.22
Personal care workers	53	-0.09	-0.01	-0.51	-0.46
Protective services workers	54	0.80	0.64	-0.28	0.60
Customer services clerks	42	-0.20	-0.61	-0.11	1.47
Sales workers	52	0.39	0.94	0.20	0.76
Cleaners and helpers	91	-0.40	0.48	0.88	-0.55
Food preparation assistants	94	-0.21	0.70	0.93	-0.87
Refuse workers and other elementary workers	96	-0.64	1.74	1.56	0.29
Handicraft and printing workers	73	-0.22	0.38	0.44	0.30
Electrical and electronics trades workers	74	0.45	1.57	0.64	0.40
Food processing, woodworking, garment and other craft workers	75	-0.30	1.09	1.47	0.35
Stationary plant and machine operators	81	-0.46	1.25	2.23	0.69
Assemblers	82	-0.32	1.03	1.22	0.20
Building and related trades workers, excluding electricians	71	-0.07	1.96	1.40	-0.18
Metal, machinery and related trades workers	72	-0.31	1.82	1.13	-0.08
Drivers and mobile plant operators	83	-0.55	2.17	1.22	-0.24
Labourers in mining, construction, manufacturing and transportation	93	-0.49	1.73	1.72	0.05
Market-oriented skilled agricultural workers	61	0.07	0.39	0.31	0.03
Market-oriented skilled forestry, fishing and hunting workers	62	-1.28	1.96	0.66	-1.89
Agricultural, forestry and fishery labourers	92	-1.25	1.25	0.78	-1.46

Note: Task importance measures calculated using principal components of several O*NET measures. All scores are standardized to mean 0 and standard deviation 1.

Table 3 summarizes the results for the second period (2011-2018). As can be seen, the updated STYRK-08 version includes more occupations than STYRK-88. Occupations such as production and specialized service managers and teaching professionals have the highest intensity of abstract tasks, with 1,62 and 1,61 scale points. Similar to the first period, drivers and mobile plant operators also require the most manual skills in the second period. Stationary plant and machine operators and workers in occupations related to construction, manufacturing and mining perform mostly routine manual tasks. Also here, occupations related to clerical work score highest in routine cognitive tasks. In contrast, clerical occupations require the least abstract skills, while teaching professionals have the lowest intensity of manual tasks.

4 Norwegian economy and labour market

In this chapter, we will provide some relevant background information about the Norwegian economy and labour market. We believe these factors could help explain the patterns found in our analysis.

4.1 Trends in the economy

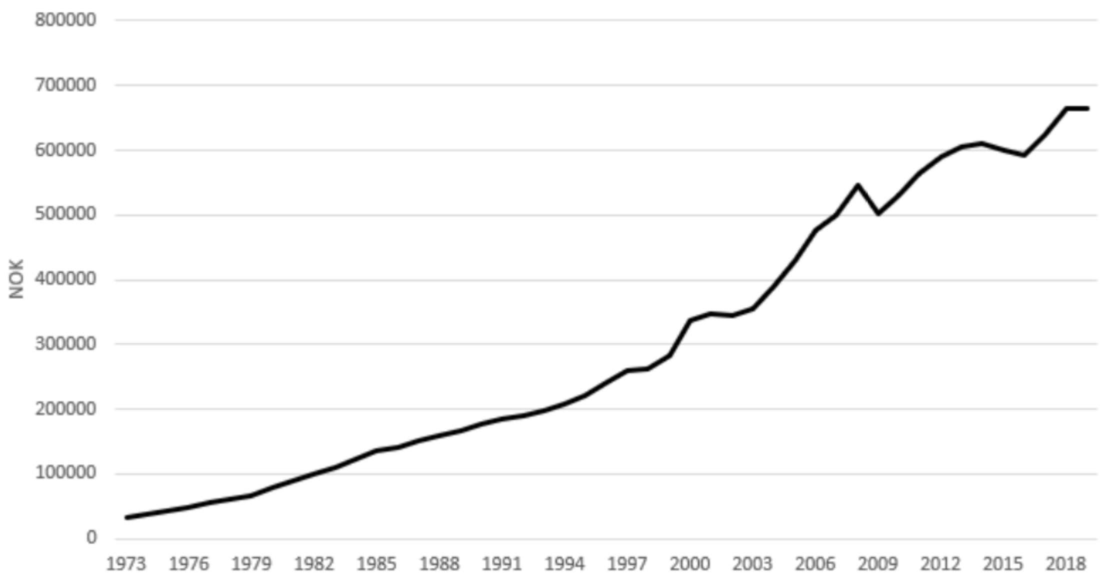

Figure 2: The graph displays the trend in GDP per capita in Norway, between 1973-2018. Source: National accounts, Statistics Norway (2020).

The trend in the Norwegian economy is mainly captured by growth and stability in the years between 1973-2018, with a few exceptions. The financial growth is to a large extent due to increased investments in the petroleum industry, which in 2018 consisted of 16% of the total GDP in Norway (Department of Finance, 2018).

However, in 2007-2009 the economy experienced a recession, where high interest rates led to a fall in real estate investment and demand for goods and services by households. In the autumn of 2008, the financial market is profoundly affected by the international financial crisis. As economic growth in Norway showed signs of recovery already in 2010 (Statistisk sentralbyrå, 2011), it could be argued that the Norwegian economy is more robust than most. Growth continued until the price of oil decreased in 2014, which led to a slight increase in the unemployment rate, especially among men (Lindbeck, 2017; Nilsen, 2018).

4.2 Labour force market

The Norwegian labour market score well on most indicators related to employment rate, job quality[8] and labour market inclusiveness[9] (OECD, 2018). One of the main reasons for Norway's prosperous labour market is cooperation between employers organizations, government and trade unions (Bivens et al., 2017). In 2018, the unionization rate in Norway was 49% (OECD, 2020), which indicates that the Norwegian labour market and wage structure are impacted by high unionization in industries.

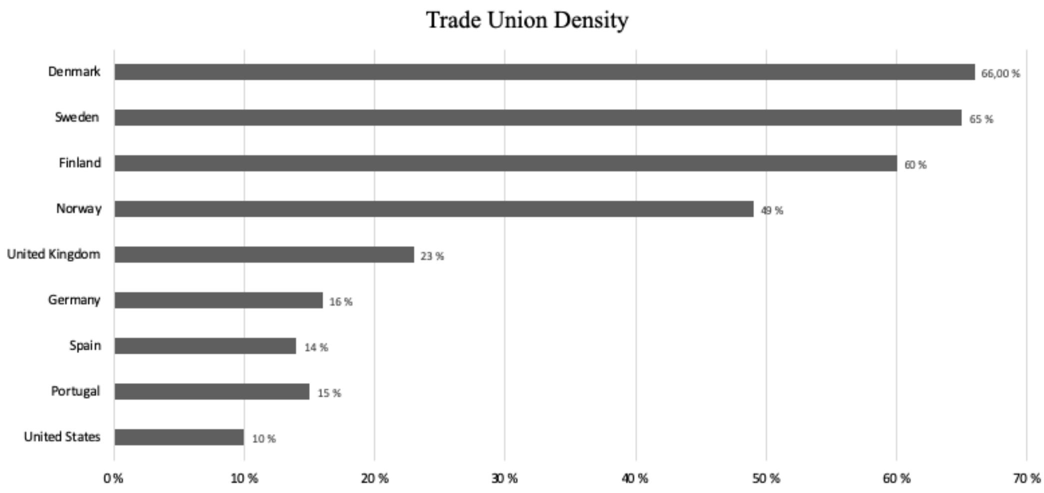

Figure 3: Trade Union Density. All numbers are registered in 2018, except for Portugal, which are registered in 2016. Source: OECD, (2020).

Nordic countries are ranked high when it comes to social and economic performance, to a large extent due to safety provided by welfare states (Brezis, 2018; Stende, 2017; Tiemer, 2018). In Norway, the government aspire to give the population incentives to participate in the labour market, this through publicly financed education and family arrangements such as child care facilities (Andersen et al., n.d.). Other initiatives the government has implemented, like gender points when applying for education related to occupations which are typically male - or female-dominated, have helped decrease the gender gap in Norway (Dabla-Norris & Kochhar, 2019).

However, despite the many positive effects on the labour market, it has been argued that the welfare system and a unionized society comes with some disadvan-

[8]Job quality is measured by working environment, pay and job security.

[9]By inclusiveness, they mean gender equality, wage equality and job access for disadvantage groups.

tages. For Norway, the biggest concern is related to unemployment rates, and how members of the labour force receiving disability benefits could conceal the actual unemployment rate (Lindbeck, 2017; Nilsen, 2018).

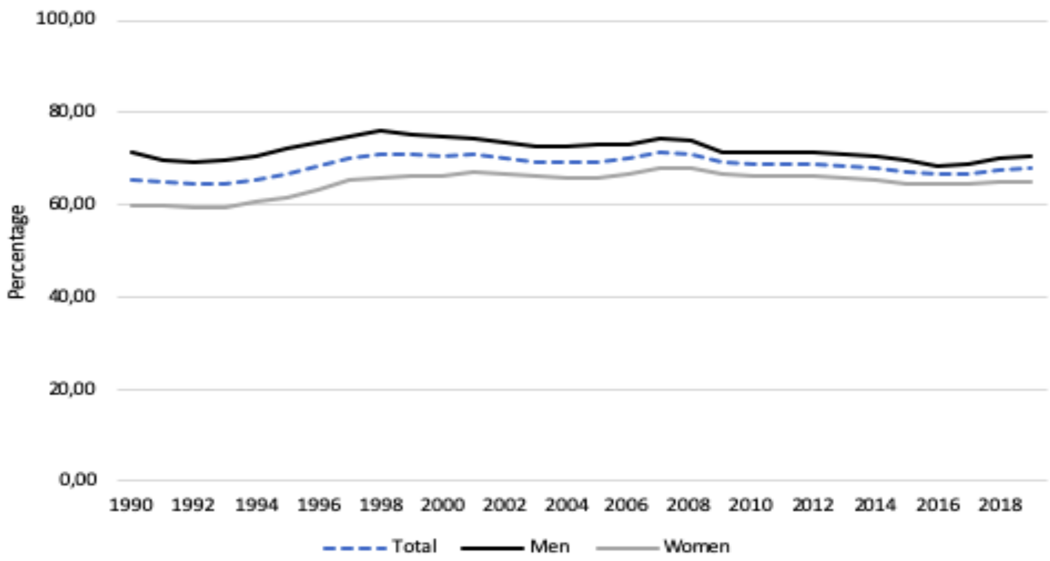

Figure 4: The graph displays the employment trends in Norway between 1990 and 2019, for workers aged 15-74. Source: Statistics Norway, (2020).

The graph in Figure 4 showing the employment rate for all workers aged 15-74 indicates an increase in the years from 1992 to 1998. From 1998, the trend is rather stable until 2008, where the observed decrease can be explained by the financial crisis, which affected economies worldwide. From 2009 the trend is again stable, until a small decrease in the years when the price of oil decreased by almost 60% between 2014 and 2015 (Statistics Norway, 2016c). The graph also shows how the gender gap in Norway has decreased between 1990 and 2018.

The Norwegian economy and labour market have shown signs of high dependence on the petroleum industry. According to Statistics Norway (2016b), the decrease in the price of oil had minimal impact on workers directly employed in oil companies, reducing the employment with only 10%. The industries producing goods and services used in production by oil companies were the ones taking the biggest hit. The high dependency can also be seen in terms of adapting to new technology. According to Norwegian Petroleum (2019), the innovative power of the petroleum industry has had a significant positive effect on technological utilization in other industries.

5 Empirical testing

To empirically study the routinization hypothesis, we follow the methodology used by Autor et al. (2003) and Fonseca et al. (2018). We resort to cells constructed by grouping the variables age, gender, education and industry variables, which are defined by age (<25, 25-34, 35-44, 45-54, 55-64, 65-74), gender, education (<high school, high school, university, Ph.D., unanswered) and ten industry codes.[10] For each cell, we calculate yearly employment, along with initial employment share for each task (abstract, routine cognitive, routine manual and manual) at the beginning of each period (1996 or 2011). On average, the number of workers in each cell is 1332 in the first period and 492 in the second period. Our dependent variable is the log employment per cell, and the coefficient of interest are from the interaction between the initial task at time 0 and time dummies. We perform the estimation for each period separately. Applying fixed effects for the cells provides us with the model:

$$\log(employment)_{it} = \beta_0 + \beta_1 T_{it0} \cdot t_t + a_i + u_{it} \tag{1}$$

The variable T_{it0} represents the initial employment share per task for cell i at time t_0. The omitted category is manual tasks, so all results are compared to changes in employment shares holding manual tasks as their comparative advantage at time t_0. The interaction between T_{it0} and t_t captures the trend in employment for cells that hold a comparative advantage in a given task in time t_0. Cell fixed effects are represented by the variable a_i, which controls for individual heterogeneity. The estimates of interest are represented by β_1.

Our assumption is that, as time passes, the share of workers in occupations with a comparative advantage in routine tasks will decrease, as we expect technology to substitute these workers. On the other hand, given that technology can compliment workers performing non-routine tasks, i.e., abstract tasks, we expect to find results showing an increase in workers holding abstract tasks as their comparative advantage in the initial period.

[10] Unlike other studies, our data do not provide information about regions.

In addition to looking at the changes in the whole economy, we also estimate the changes within sectors and genders. We believe estimating the changes between sectors might provide insight to the observed patterns for the economy, especially since the service sector is more than twice as large as the manufacturing sector.

Using the industry groups, we focus on two sectors: manufacturing and services. The manufacturing sector includes workers in the industry groups related to production, being agriculture, manufacturing and construction. For both periods, workers in the manufacturing sector represent 30% of the total labour force. The service sector encompasses a wide range of industries, but broadly speaking, industries related to producer services, distribution services, private services, health-related and social services (Table A3 in Appendix). In both periods, workers in the service sector represent 70% of the total labour force. Before estimating the changes for the economy as a whole, we look at the employment share trends by task in the economy, within sectors and by gender.

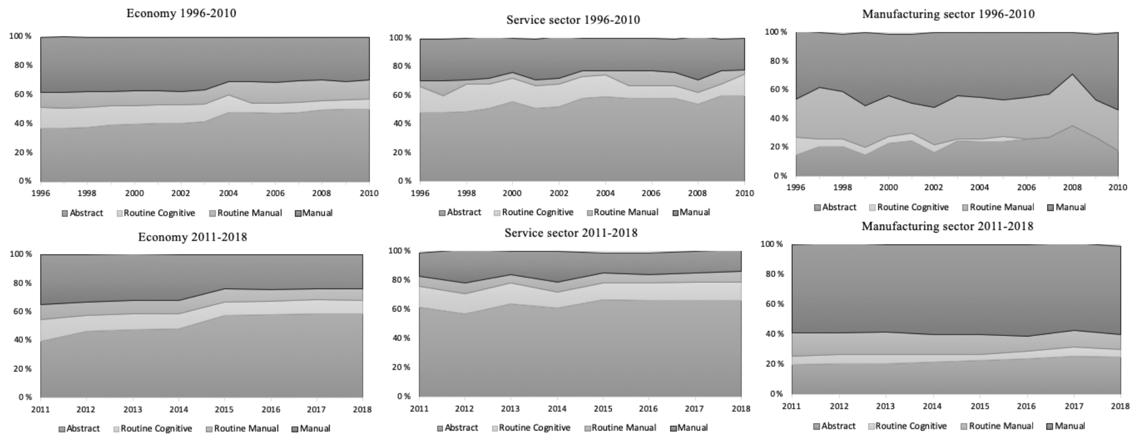

Figure 5: Employment share trends by task and sector

Figure 5 shows the evolution of employment share trends by tasks for the economy as a whole, as well as within sectors. In both periods, the service sector have the highest share of workers performing abstract tasks, and the lowest share of workers performing routine manual tasks. In contrast, the manufacturing sector have the highest share of workers performing manual tasks, and the lowest share of workers performing routine cognitive tasks. In the service sector the trends are relatively stable in both periods, whereas the trends in the manufacturing sector are more stable in the second period.

As the Norwegian government has implemented several policies to increase gender equality, it is interesting to look at the distribution of employment between genders and see if the trends between males and females follow the same pattern. Figure 6 shows that female workers are highly represented in abstract tasks, compared to manual tasks. For males, the figure shows that the distribution between abstract and manual are almost identical in the second period, whereas manual is slightly higher in the first period. Male workers represent 57% of the participants used in the data, while female workers represents 43%.

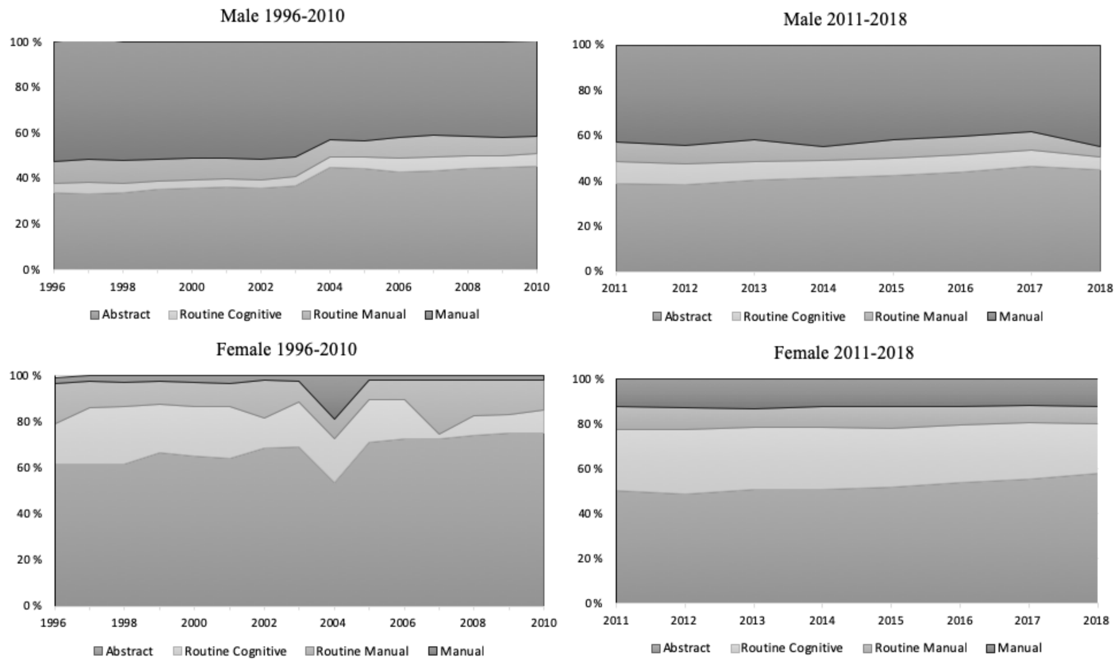

Figure 6: Employment share trends by task and gender

5.1 Results

We display the results showing the changes for the whole economy, as well as changes within the manufacturing and services sectors, and by gender. In the main text we plot the estimates of the interaction term between the initial task at time 0 and time dummies. All results presented are relative to demographic groups holding manual tasks as their comparative advantage in the initial period (1996 or 2011). The results from the regressions are presented in Table A6 and A7 in the appendix.

5.1.1 Economy

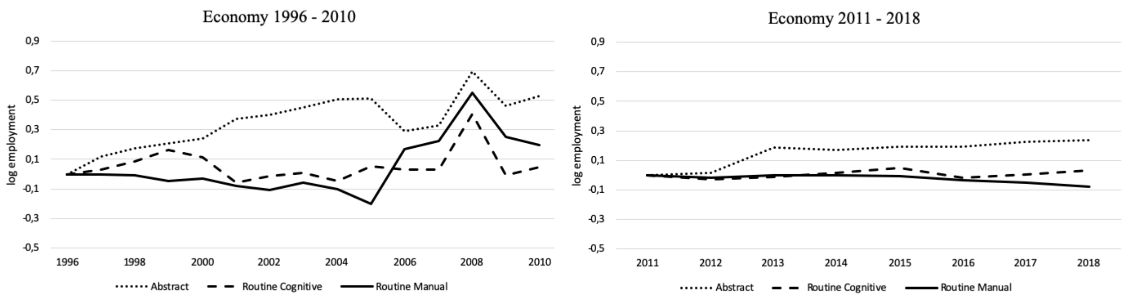

Figure 7: The estimates displayed are for the interaction term between initial task and time dummies for the economy as a whole. The model contains fixed effects for cells.

For both time periods, the results show a significant increase in the employment share among workers within abstract tasks. The results are consistent in both periods, indicating a shift in the demand for more skilled labour.

Employment among demographic groups holding routine cognitive tasks as their comparative advantage, in both time periods, does not show a clear pattern of increase or decrease relative to manual. The estimated effect is mostly insignificant, with a few exceptions in the first time period.

Regarding workers holding routine manual tasks as their comparative advantage, the changes relative to manual are somewhat in line with the assumption that workers performing routine tasks are being substituted. In the first period, we see a relative decline at the beginning of the period, but an increase from 2006-2008. The results showing a relative increase are significant on a 5% and 10% level. However, in the second period, the share of workers holding routine manual tasks decrease, relative to manual.

5.1.2 By sector

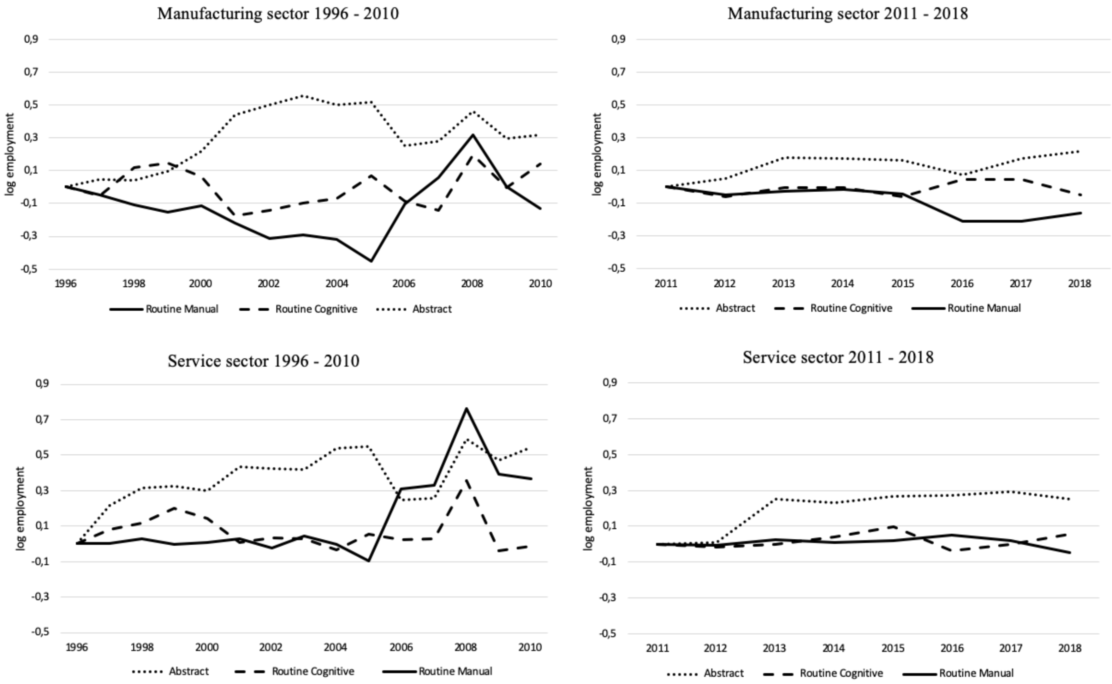

Figure 8: The estimates displayed are for the interaction term between initial task and time dummies by sector. The model contains fixed effects for cells.

For both sectors, the trend in employment in cells with a comparative advantage in abstract tasks is similar to those of the economy in both periods. The trends showing the employment share for workers performing routine cognitive tasks are somewhat similar between sectors. A distinct pattern is hard to find, as the share both increase and decrease in this period. For workers holding routine manual tasks in the initial period within the manufacturing sector, the employment share decrease until 2005, where the trend turns to a significant increase until it reached a top in 2008, and then again decrease.

Looking at the results, the increase in the service sector accelerates faster relative to the manufacturing sector. For workers holding routine cognitive tasks as their comparative advantage, the employment share in the service sector has a small, but steady, increase until 2015. The opposite is true for the same group in the manufacturing sector, where the employment share increased in 2015.

For workers holding routine manual tasks as their comparative advantage in the manufacturing sector, the employment share decreases for the whole period, but more significant from 2015. In the service sector, employment among the same group stays relatively flat until 2016.

5.1.3 By gender

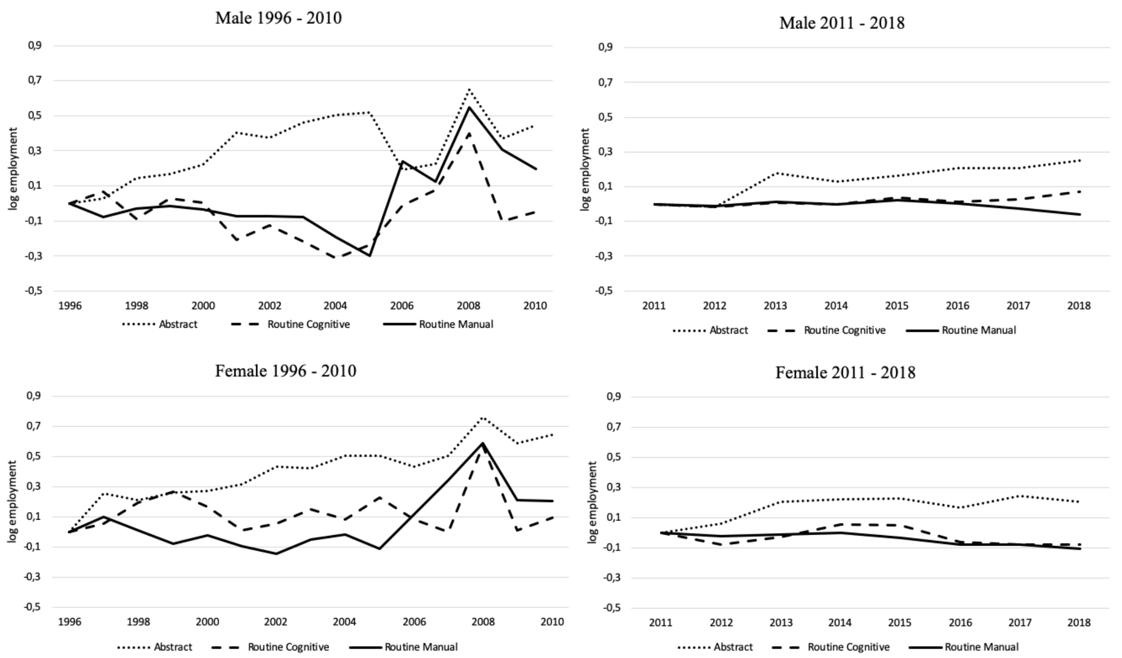

Figure 9: The estimates displayed are for the interaction term between initial task and time dummies by gender. The model contains fixed effects for cells.

Looking at figure 9, the trend in employment among females holding abstract tasks is similar to the results of the economy, showing a significant increase relative to manual. For males, the trend is overall similar, but with a drop between 2005 and 2008. In line with the results for the economy as a whole, the results are positive and significant for both. The results for the second period for the same groups are similar to the results for the economy.

Between the two periods, we see a shift between genders in the groups performing routine cognitive tasks. In the first period, the employment share among females is mostly increasing, whereas the share of male workers is mostly decreasing. The opposite is true for the second period, where the employment share of females decreases and males increases. For the second period, none of the results are significant.

Similar to the results for the economy in the first period, the share of workers in routine manual tasks follow the same pattern between genders. The employment share of both female and male workers decrease until 2005, where the trend turns to an increase. For the second period, females performing routine manual tasks decreased for the whole period, whereas the trend for males shows a relatively flat trend up until 2015.

5.1.4 F-test

In order to see whether the estimated patters over time are jointly significant, we conduct an F-test for each of the two samples. The results using an F-test shows that the variables are jointly significant at a 1% significance level for both periods for the economy as a whole. The same is true for the service sector. In the second time period, the variables are jointly significant at a 10% level in the manufacturing sector, whereas the same variables are significant at a 1% level in the first period.

As a precaution, we have used the variance inflation factor (VIF) to test whether the collinearity between the regressors in the model is too high to provide evidence for the routinization hypothesis. Even though the maximum value to be accepted has been discussed, the "rule of thumb" says that the VIF cannot transcend the value of 10 (Daoud, 2018). For our model, the average value is 3,29 for the first period, and 5,86 in the second period. Following the rule of thumb, we can assume that the level of collinearity in our model is not a great cause of concern.

5.2 Robstness checks

In order to see whether the model chosen best represents the effects technology has on employment opportunities, we conduct several robustness checks in which we modify the original model. The robustness checks is done to lessen possible remaining biases, such as omitted variables and selection bias. As patterns are similar across sectors, we perform this analysis for the economy as a whole.

We start by checking the robustness of the results to our sample definition. As there have been concerns about concealed unemployment rates due to disability benefits[11], we excluded workers who are temporarily absent in the reference week. We perform a robustness check to see whether inclusion of these workers affects the results. The share of workers who are temporarily absent is 15% and 16% in the two periods, respectively.

Finally, another type of concern could be that the fixed effects in the original model do not control for the possibility of changes in the effect of education over time or the possibility of changes within industries over time. Hence, we estimate the model including two-way fixed effects, controlling for these possibilities. The results from the robustness checks are displayed in table A8 in the appendix.

5.2.1 Temporarily absent

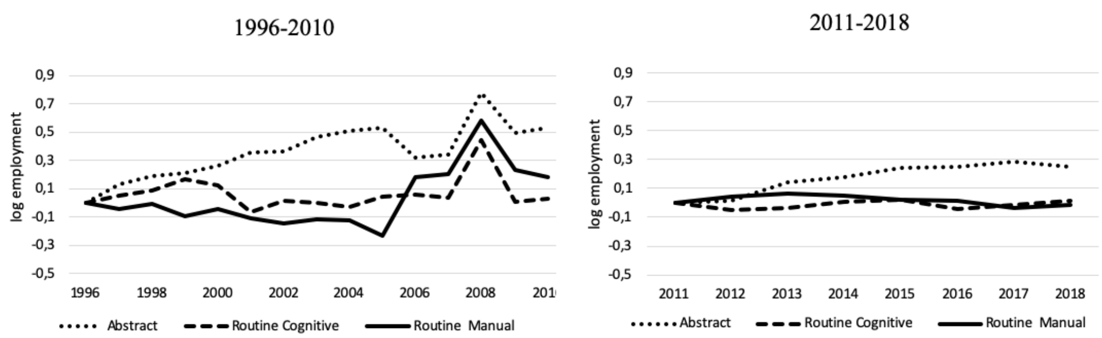

Figure 10: The estimates displayed are for the interaction term between initial task and time dummies for the economy as a whole, now also including workers who are temporarily absent in the reference week. The model contains fixed effects for cells.

For the robustness check including workers who are temporarily absent, the regression and cells are defined in the same way as the original model.

[11]See section 4.2 about the labour force market, or Lindbeck (2017), Nilsen (2018).

The results in the modified model are in both period similar to those found in the original model. Employment share holding abstract tasks as their comparative advantage increases in both periods, relative to manual. Also here, it is difficult to distinguish a clear pattern for employment in routine cognitive tasks in the first period, whereas the trend is relatively stable in the second period. For employment in routine manual tasks, the trends in the modified model also follow the same pattern as the original model for both periods. These findings indicates that excluding workers who are temporarily absent in the reference week do not affect the results in the main model.

5.2.2 Including two-way fixed effects

Given that Norway is a country with a high share of highly educated workers, and that our results show a significant increase in employment among groups holding abstract tasks as their comparative advantage in the initial period (1996 or 2011), we want to make sure that this effect does not mask secular employment trends.

Similar, as new occupations emerge and industries change, we believe controlling for secular changes in employment that are specific to each industry group is important. To account for time-specific education and industry factors, we first include an interaction term between education level and time dummies (equation 2), and then in a separate model, an interaction term between industry groups and time dummies (equation 3). The results are displayed in figure 11 and 12.

Education

As we estimate changes over a longer time frame, it is likely that requirements from employers, in regards to education among employees and applicants, change over time. Figure 10 display the trends in the modified model including the additional fixed effect controlling for the possibility of shocks in educational requirements. We expand the original model, and estimate equation (2):

$$\log(employment)_{it} = \alpha_0 + \alpha_1 T_{it0} \cdot t_t + \alpha_2 Education_g \cdot t_t + a_i + u_{it} \tag{2}$$

The regression is the same as the original model, but now including the additional fixed effect, represented by α_2. Educational level (<high school, high school,

university, Ph.D., and unanswered.) is defined with the subscript $_g$.

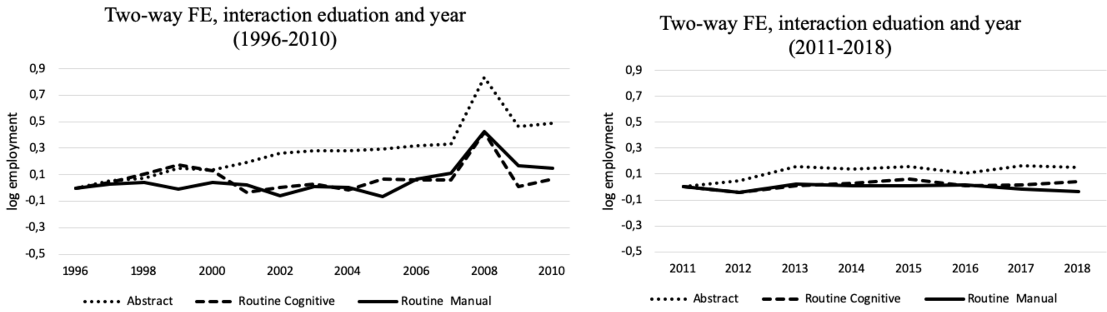

Figure 11: The estimates displayed are for the interaction term between initial task at time 0 and time dummies for the economy as a whole. The model contains fixed effects for cells, and education level and year.

We see that, when including an additional fixed effect, the trend in employment holding abstract tasks has a weaker increase than in the original model. We believe this could be explained by higher requirements in terms of education. The same could be said about routine manual, as the trend is relatively more stable in the modified model. Employment in routine cognitive tasks is overall similar in the modified and original model.

Industry

As the first period is subject to several shocks, for example the economy boom in the years before 2007 and the financial crisis affecting the economy from the end of 2008, we want to introduce a industry fixed effect to see whether this will affect the results obtained in the original model. We estimate equation (3):

$$\log(employment)_{it} = \pi_0 + \pi_1 T_{it0} \cdot t_t + \pi_2 Industry_g \cdot t_t + a_i + u_{it} \tag{3}$$

The regression is defined in the same way as the original model, but now including the additional fixed effect, represented by π_2. Industry groups (ten industry groups, listed on p. 13) are defined with the subscript $_g$

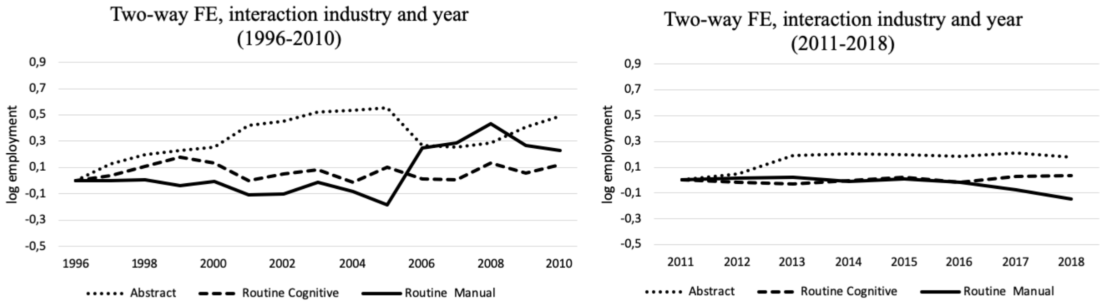

Figure 12: The estimates displayed are for the interaction term between initial task at time 0 and time dummies for the economy as a whole. The model contains fixed effects for cells, and industry groups and year

We see that when including an additional fixed effect controlling for possible changes in industries over time, the model better account for shocks in the economy. This is more apparent in the time before and after the financial crisis. The trend for employment holding abstract tasks do not experience the same increase in this period, as they do in the original model. The same is true for employment in routine manual tasks. Also, the share of workers performing routine manual tasks decrease more towards the end of the second period, than in the original model.

When including fixed effects for education and industry, we see that the results are not considerably different from the original model, substantiating the results observed in the baseline model.

6 Possible mechanisms and discussion

The routinization hypothesis assumes that technology is biased towards workers performing routine tasks. In light of the hypothesis, we expected our findings to show a decrease in employment shares holding routine tasks, relative to those holding manual tasks. Looking at the economy as a whole, the trends for routine manual tasks are somewhat in line with the hypothesis, where we do see a small but steady decrease in the first decade and towards the end of the second period. However, we are unable to distinguish a clear pattern in employment holding routine cognitive tasks. Despite the weak evidence supporting the routinization hypothesis, our findings show a steady increase in employment performing abstract tasks, which could indicate that technology is biased towards more skilled labour.

Past literature exploring the effects of technology on the labour market find that non-routine tasks are harder to automate.[12] This is in line with the findings provided by ALM (2003), who found that occupations with non-routine tasks increased substantially in the four decades investigated in their paper. Support for the routinization hypothesis has also been found when focusing on job polarization in specific countries.[13]

When comparing our findings with those presented above, we do have similar patterns regarding those performing non-routine tasks. Our results show that the share of employment in abstract tasks has experienced a sharp increase between 1996 and 2018, relative to manual. The evolution of abstract tasks is relatively similar between sectors in the first period, whereas employment in abstract tasks increases more in the service sector between 2011 and 2018. Figure 9 (p. 25) shows that employment among female workers holding abstract tasks accelerates faster than male workers in the second period. This could be related to initiatives from the Norwegian government in turns of decreasing the gender gap. In the second period, women represented 66% of the employment share holding abstract tasks as their comparative advantage, in contrast to 49% in the first period.

[12] Acemoglu and Autor (2011), Cortes (2016), Goos and Manning (2007), Sebastian (2018).

[13] Fonseca et al. (2018), Sebastian (2018), Goos and Manning (2007).

It is also conceivable that the constant increase of employment share in abstract tasks could be correlated to the educational level among participants in the survey. In the first period (1996-2010), 34% of the participants fall in the higher education category, i.e., having a university degree or a Ph.D. In our data, we find that between 1996 and 2018, the number of participants with higher education increased by 15%. When controlling for shocks in educational levels, the results still show an increase in employment holding abstract tasks, substantiating the findings in the main analysis.

Subsequently, given the more aggregated occupational codes in STYRK-88, the second period encompasses more occupations than the first. As many of these have the highest intensity of abstract tasks, this could also explain the steady increase in this category (Table 2 and 3 on p. 15-16).

There could be various reasons why our findings regarding employment in routine tasks contradict those found in studies of other countries. In the next paragraphs, we will attempt to distinguish between some different explanations. We discuss probable data-driven explanations and then reasons that might be specific to the Norwegian context.

6.1 Data-issues: Specification of tasks

As the information on the participants is collected through survey interviews, our data could, as other studies using LFS data, be subject to measurement error and response bias. Also, in the complex procedure of constructing the data used, we could have introduced additional inaccuracies. Another possible explanation is that information on occupational tasks is derived using the O*NET database, which is based on task composition in jobs in the U.S. It would be naive to assume that the task composition in the same occupations across the two countries is the same. Nonetheless, given the lack of information on occupational tasks in Norway, O*NET is the best source available.

One final data-driven concern, could be that our results are driven by our choice to classify tasks into four categories, rather than the three-way classification used in Autor (2013), Cortes (2016), Goos and Manning (2007) and Sebastian (2018).

To exclude these explanations, we perform an additional regression in which we combine the two routine tasks, to see whether the results are driven by our choice of classifying routine tasks separately. Additionally, we proceed by using a classification of tasks based on broad occupational groups, with similarities to the method presented by Acemoglu and Autor (2011), instead of using information derived from the O*NET database. The results are presented in Table A9 and A10 in the appendix.

6.1.1 Three-way classification

In order to see whether the chosen classification of tasks, i.e., keeping routine cognitive and routine manual separate, best represent the employment share trends in Norway, we run an additional regression in which we combine the two routine tasks.

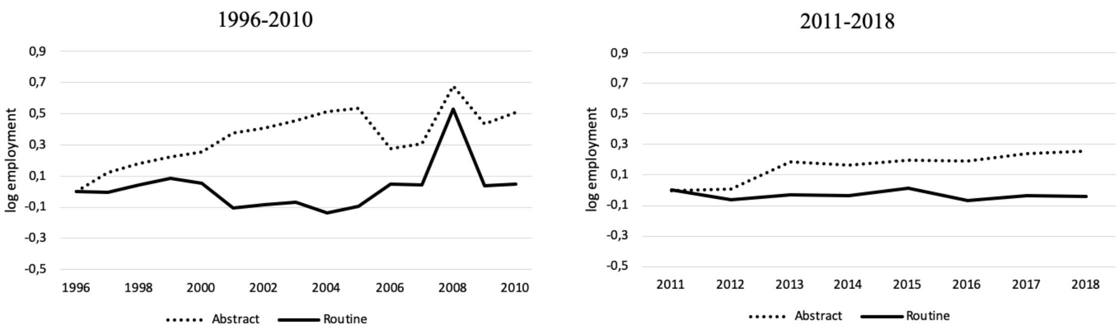

Figure 13: The estimates displayed are for the interaction term between initial task and time dummies for the economy as a whole, using the three-way classification of tasks (abstract, routine and manual). The model contains fixed effects for cells.

When combining the two routine tasks, the trend in employment holding routine tasks do increase less in the first period, compared to the original model. In the second period, the trend is overall similar to the trend in employment holding routine manual tasks in the main model. As the main model do show a small decrease in employment holding routine manual tasks, but a more stable trend in routine cognitive tasks, we believe the three-way classification provide wrongful information about employment share trends in routine tasks in Norway.

6.1.2 Broad occupational groups

As there could be differences between task composition in jobs in Norway and the U.S, we also estimate the model using broad occupational groups as the basis for task classification. The groups are: (1) Technical and professional, (2) Managerial and health professionals, (3) Office clerks, (4) Sales, ticket clerks and other services, (5) Operators, (6) Agricultural, forestry and fishing, (7) Personal and protective services, and (8) Routine operators. Groups (1)-(2) are classified as abstract, (3) and (4) as routine cognitive, (5), (6) and (7) as manual, and (8) as routine manual.[14]

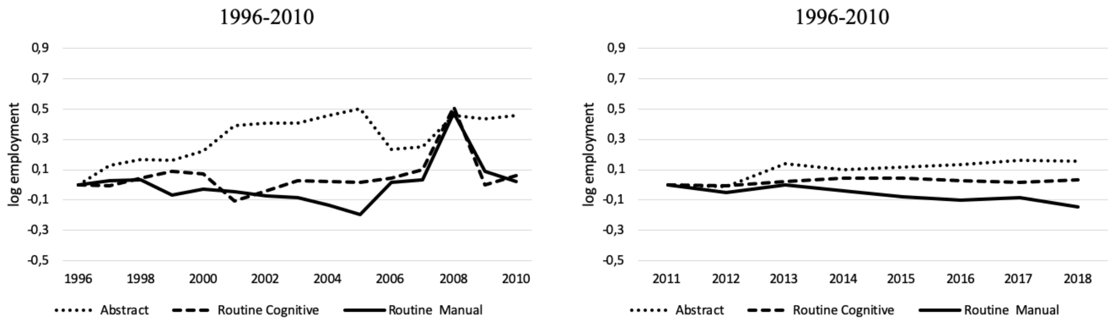

Figure 14: The estimates displayed are for the interaction term between initial task and time dummies for the economy as a whole. The task classification is based on broad occupational groups. The model contains fixed effects for cells.

The results are not substantially different from those obtained in the original model, but it does show a stronger decrease in employment shares holding routine manual tasks in the second period. On the other hand, the trend in employment holding abstract tasks do not increase as much in the first period, compared to the original model. As previously mentioned, we believe the classification based on occupational titles could be subject to selection bias. As the trends follow similar pattern as the original model, we are confident that using information regarding occupational tasks from the O*NET database is valid, in addition to limiting possible biases arising from selection bias.

[14]See table A1 & A2 in appendix.

6.2 Importance of the petroleum sector

The Norwegian labour market is highly dependent on the petroleum industry, both directly and through employment in industries producing goods and services used in the production of oil and gas (Brasch, Hungnes & Strøm, 2018). In the last decades, the petroleum industry has been an important industry that drives for innovation, focusing on utilizing resources efficiently. While technological development has made the production process more efficient, our results indicate that demand for human capital performing routine manual tasks has not decreased as much as expected. In the manufacturing sector, 55% of the workers holding routine manual tasks in the first period work in occupations such as process - and machine operators, which are highly represented in the petroleum industry.

6.2.1 Excluding petroleum industries

Because of the petroleum industry's strong impact on the labour market, it could explain why our findings, to some extent, contradicts the trends found in studies of other countries. For this reason, we do an additional check excluding the industries directly linked to oil.[15] In the modified model, the regression and cells are defined in the same way as the original model.

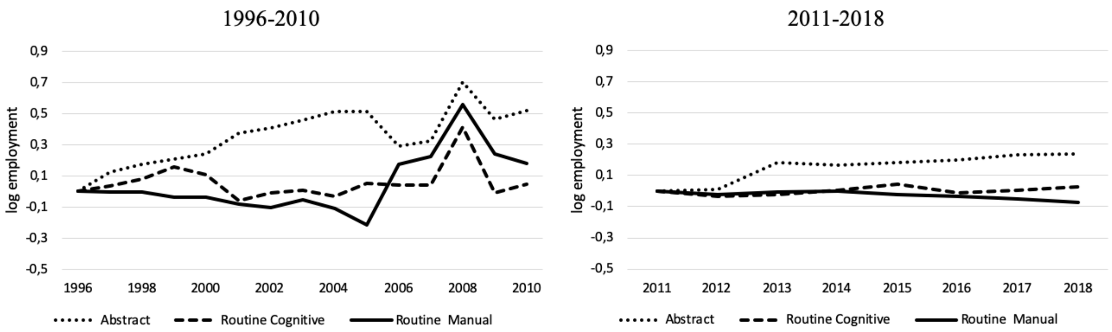

Figure 15: The estimates displayed are for the interaction term between initial task and time dummies for the economy as a whole, now excluding industries directly connected to the petroleum sector. The model contains fixed effects for cells.

[15] When creating the industry groups listed on p. 11, we exclude the two-digit industry codes 11. Extraction of crude petroleum and natural gas, service activities incidental to oil and gas extraction excluding surveying and 23. Manufacture of coke, refined petroleum products and nuclear fuel (1996-2002) and 06. Extraction of crude petroleum and natural gas, 09. Mining support services, and 19. Manufacture of coke and refined petroleum products (2008-2018).

The patterns in figure 15 are also similar to those in the original model, looking at the economy as a whole. This indicates that the exclusion of industries directly linked to the petroleum industry does not change the overall outcome. However, we see a relation between the changes in the oil price and the employment trends, which we believe substantiates the high dependency of the petroleum industry by other industries, as reported by Statistics Norway (2016a).

In the years following 2002, the petroleum industry experienced an increase in demand for oil, which in turn increased the demand by the petroleum industry for goods and services produced by other industries. Looking at the changes between sectors (figure 8 p.24), the employment share increased substantially in both between 2005 and 2008. These trends show that workers performing routine manual tasks were in higher demand compared to manual workers, in the time before the financial crisis. Not surprisingly, in the years after the drop in the price of oil, we see a decline in the employment share performing routine manual tasks, especially in the manufacturing sector. Between the first and the second period, this employment share decreased by 22%.

6.3 Do trade unions play a role?

In studies exploring wage patterns along with employment patterns, many scholars address the implication of trade unions.[16] Even though we do not look at wages, it is interesting to discuss how trade unions in Norway could explain the employment share patterns found in our analysis. Because of Norway's high unionization rate (49%) compared to countries such as the U.S (10%), U.K. (23%), and Portugal (15%)[17], we believe this could be a possible mechanism explaining the weak evidence found supporting the routinization hypothesis.

Our data do not provide information on trade union members, so in order to explore whether trade unions have an impact, we rely on the information published by Statistics Norway. We use their data on how many lost working days and work conflicts there have been based on trade union members in specific industries in each year since 1998 (Statbank Norway, n.d.). Identifying highly contentious industries

[16] Fölster (2018), Cortes (2016), Acemoglu and Autor (2011), Asplund et al. (2011).

[17] See figure 3 in section 4.2 for information on unionization rates in Denmark, Sweden, Finland, Spain and Germany.

over time can give us an indication of workers "strength" in different industries.

Using the data presented by Statistics Norway, we find that the industries construction, transportation and storage, hotels and restaurant, education, and health- and social services have the highest average of lost working days and work conflicts. We proceed by modifying the original model, now excluding workers within these industries.

6.3.1 Excluding unionized industries

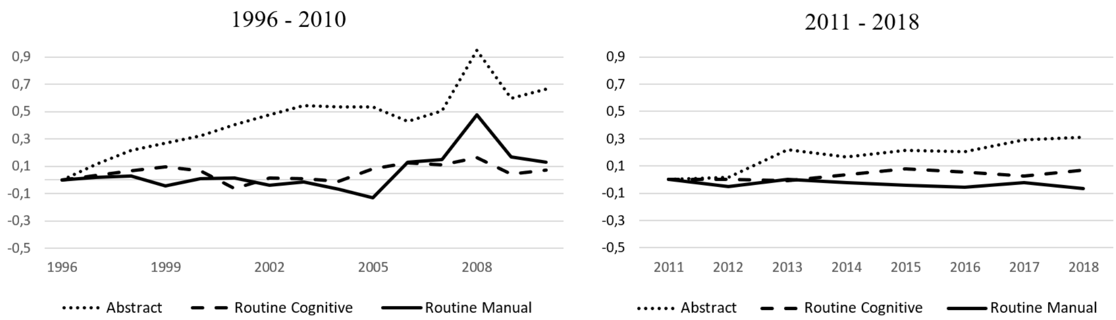

Figure 16: The estimates displayed are for the interaction term between initial task and time dummies for the economy as a whole, now excluding industries assumed to be highly unionized

The trends in figure 16 follow, to some extent, similar patterns as the main model. However, we do see a weaker increase in employment shares in both routine cognitive and routine manual tasks in the first period. Additionally, the results show a more consistent decrease in employment holding routine manual tasks as their comparative advantage throughout the whole second period. The industries education and health-and social services encompass many occupations with high intensity of abstract tasks. We see that, when excluding these industries, the trend in employment holding abstract tasks increase more in both periods, compared to the original model. The results show that omitting highly unionized industries do provide more persuasive evidence supporting the routinization hypothesis, compared to the original model, which substantiate our assumption of unionization affecting the observed patterns.

It is worth mentioning that as our data do not include information on trade union members, the method used might not capture the actual effect trade unions have on the labour market. The industries considered as highly unionized encompass many occupations with high intensity of routine tasks, such as customer service clerks, personal service workers and stationary plant and machine operators. When excluding these from our data, we lose a significant amount of the observations in routine tasks, which is likely to affect the results.

6.4 Service sector and gender-specifics

In the service sector, occupations with high intensity of routine manual tasks are related to service elementary occupations, such as cleaners, hairdressers, cooks, and building and housekeepers supervisors. These occupations conduct tasks that are typically hard to substitute by machines, as they require some manual dexterity. Also, it could be argued that high-income levels in Norway have led to an increase in demand for goods and services typically provided by occupations with high intensity of routine manual tasks, explaining the almost non-existing decrease for employment in routine manual tasks in the service sector.

Putting aside the boom between 2005 and 2008, the trend in employment holding routine cognitive tasks is relatively stable throughout both periods. We believe this could be explained by the impact of the service sector, which holds 70% of the workforce in Norway. Compared to the manufacturing sector, the share of workers performing routine cognitive tasks is more than twice as large in the service sector, being employed in occupations such as customer service, sales and clerical jobs. Even though we do not analyze gender differences between sectors, we believe the observed patterns between genders could explain why routine cognitive tasks are relatively stable in both the service and manufacturing sector.

The observed trends in routine cognitive tasks (fig.9, p.25) could indicate a task shift between genders, switching from female workers to male workers. In the first period, we see a small increase in the employment share of female workers holding routine cognitive tasks, whereas the second period shows a decrease. It is likely to believe that initiatives related to increasing female participation in the labour market, as well as evening out the gender distribution in typically male - or female-dominated occupations, have in fact affected the employment distribution between genders. As the share of male workers holding routine cognitive tasks increase between 2011 and 2018, while the share of female workers decreases, it might suggest that female workers have changed their comparative advantage. In the second period, the share of female workers holding abstract tasks has increased by 17%, which might indicate a shift from occupations with high intensity of routine cognitive tasks, to occupations with high intensity of abstract tasks.

6.5 Summary and steps ahead

In the previous sections, we have discussed possible explanations for the observed trends in our analysis. We have looked at Norwegian-specific implications, such as high dependence of oil, highly unionized labour market and the implications of a large service sector. The additional regressions, excluding the petroleum industry and unionized industries, do show more robust evidence supporting the routinization hypothesis but does not necessarily pin down the cause for the observed patterns in the primary analysis.

Even though we do not observe the same trends in routine tasks in Norway, it does not necessarily mean that implementation of new technology has not occurred. It is plausible that cooperation between government, firms, and unions, have weakened the decrease by re-educating employees, enabling continued employment in an automated workplace. In our analysis, occupations are assigned the task with the highest intensity at the beginning of each period, limiting our possibility to observe switching patterns between tasks in occupations. As most jobs encompass a variety of tasks, re-education of employees could likely shift their responsibilities to other tasks. We believe these Norwegian-specifies explanations emphasize that we also have to take other considerations into account when exploring employment trends within tasks, including cyclical variations in the economy.

The objective of this thesis was to describe whether the routinization hypothesis fitted the Norwegian context. Across a battery of checks, we have consistently found that this has occurred in the first decade and towards the end of the second period. We leave it to future work to investigate the possible causes of such reversion and a full explanation of these patterns.

7 Conclusion

The aim of this thesis has been to analyze the implications of technology on the labour force distribution within a given occupational task. In doing so, we have attempted to provide evidence supporting the routinization hypothesis in the case of Norway in time between 1996-2018. We have analyzed the trends in employment shares holding abstract, routine cognitive and routine manual tasks as their comparative advantage at the beginning of each period (1996 or 2011).

Even though our findings show that the labour distribution is sensitive to shocks in the economy, we do find some evidence supporting the routinization hypothesis. Our results show a steady increase in employment holding abstract tasks, providing evidence supporting that non-routine tasks are harder to automate than routine tasks. Looking at the economy as a whole, the trend for routine manual tasks are somewhat in line with the hypothesis, where we do see a small but steady decrease in the second period. These findings are more profound in the manufacturing sector, but not substantially different between genders. We are unable to provide evidence for the routinization hypothesis in regards to routine cognitive tasks, as the employment share trend is relatively stable in both periods.

Our contribution to the field of study provides new information in the case of Norway. To our knowledge, the task-based method has not been used when analyzing the impact of technology on tasks performed by workers in this country. We believe this thesis could provide the government and policymakers in Norway with information on what kind of jobs and skills that will be in demand in the future.

In future research, it would be important to understand what drives the specific behaviour of the Norwegian labour market, and the changes we have uncovered. In particular, it would be interesting to analyze more closely the implications of a more unionized labour market on employment share trends. Finally, the use of longitudinal data would allow understanding of switching patterns between tasks. These future venues of investigation would enrich our understanding of the relationship between jobs and technology.

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9 Appendix

Table A1: Broad occupational groups 1996 - 2010

Abstract	Routine Cog.	Manual	Routine Man.
1. Technical and Professional	**3. Office Clerks**	**5. Operators**	**8. Routine Operators**
21 Physical, mathematical and engineering science professionals	41 Office clerks	71 Stone and building trades workers	73 Precision, handicraft, print, and related trade workers
11+24+25 Other professionals	34 Other associate professionals	72 Metal, machinery and related trades workers	74 Other craft and related trades workers
23 Teaching professionals		83 Drivers and mobile-plant operators	81 Process operators
31 Engineering science associate professionals		93 Laborers in construction and manufacturing	82 Machine operators
33 Teaching associate professionals			
2. Managerial and health professionals	**4. Sales, ticket clerks and other services**	**6. Agricultural, forestry and fishing**	
12+13 Small enterprises and corporate managers	42 Customer service clerks	61 Agriculture professionals	
22 Biology and health professionals	52 Models, salespersons and demonstrators	62 Forestry occupations	
32 Biology and health associate professionals	91 Service elementary occupations	63 Fish farmers etc.	
		64 Fishery workers and hunters	
		92 Agriculture associate professionals	
		7. Personal and protective services	
		51 Personal and protective service workers	

Note: The table display STYRK-88 occupational codes and titles, divided into 8 broad occupational groups, based on similarities with the method presented by Acemoglu and Autor (2011).

Table A2: Broad occupational groups 2011 - 2018

Abstract	Routine Cog.	Manual	Routine Man.
1. Technical and Professional	**3. Office Clerks**	**5. Operators**	**8. Routine Operators**
11 Chief executives, senior officials and legislators	33 Business and administration associate professionals	71 Building and related trades workers, excluding electricians	73 Handicraft and printing workers
21 Science and engineering professionals	41 General and keyboard clerks	72 Metal, machinery and related trades workers	74 Electrical and electronics trades workers
23 Teaching professionals	43 Numerical and material recording clerks	83 Drivers and mobile-plant operators	75 Food processing, woodworking, garment and other craft and related trades workers
24 Business and administration professionals	44 Other clerical support workers	93 Labourers in mining, construction, manufacturing and transport	81 Stationary plant and machine operators 25+26 Other professionals
		82 Assemblers	
31+34 Other associate professionals			
35 Information and communications technicians			
2. Managerial and health professionals	**4. Sales, ticket clerks and other services**	**6. Agricultural, forestry and fishing**	
12 Administrative and commercial managers	42 Customer service clerks	61 Market-oriented skilled agricultural workers	
13 Production and specialised services managers	52 Sales workers	62 Market-oriented skilled forestry, fishery and hunting workers	
14 Hospitality, retail and other services managers	91 Cleaners and helpers	92 Agricultural, forestry and fishery labourers	
22 Health professionals	94 Food preparation assistants		
32 Health associate professionals	96 Refuse workers and other elementary workers		
		7. Personal and protective services	
		51 Personal service workers	
		53 Personal care workers	
		54 Protective services workers	

Note: The table display STYRK-08 occupational codes and titles, divided into 8 broad occupational groups, based on similarities with the method presented by Acemoglu and Autor (2011).

Table A3: Division of industry groups between sectors

	Manufacturing sector		Service sector
1.	Agriculture, forestry and fishing	4.	Wholesale and retail trade, transportation and storage, accommodation and food service activities
2.	Manufacturing, mining and quarrying, and other industries	5.	Information and communication
3.	Construction	6.	Financial and insurance activities
		7.	Real estate activities
		8.	Professional, scientific, technical, administration and support service activities
		9.	Public administration, defence, education, human health and social work activities
		10.	Other services

Note: The division of industry groups between sectors is done by aggregating two-digit industry codes into broader groups. This is done based on the classification of Eurostat (n.d.)

Table A4: Employment share changes 1996-2010

			Employment share			% △ 1996-2010		
STYRK-88	**Occupational title**	**Task**	**2011**	**All**	**Manufacturing**	**Service**	**Female**	**Male**
Technical and professional								
21	Physical, mathematical and engineering science professionals	Abstracts	3.0	1.00	0.95	0.98	0.72	1.36
11+24+25	Other professionals	Abstract	3.7	3.13	0.71	3.78	4.28	2.35
23	Teaching professionals	Abstract	2.2	0.09	0.02	-0.15	0.38	-0.14
31	Engineering science associate professionals	Manual	5.6	1.06	2.82	0.44	0.48	1.91
33	Teaching associate professionals	Abstract	4.4	0.59	-0.08	0.33	1.30	-0.27
Managerial and health professionals								
12+13	Small enterprises and corporate managers	Abstract	9.8	-2.06	-0.61	-2.93	0.89	-3.50
22	Biology and health professionals	Abstract	1.7	0.61	0.00	0.66	0.94	0.27
32	Biology and health associate professionals	Abstract	2.7	0.86	-0.25	1.02	1.12	0.30
Office clerks								
41	Office clerks	R.Cog	9.6	2.49	0.62	2.50	3.65	1.42
34	Other associate professionals	Abstract	8.1	-2.48	-0.60	-3.61	-6.70	-0.52
Personal and protective services								
51	Personal and protective services workers	Manual	9.2	0.49	-0.19	-0.25	-0.59	0.29
Sales, ticket clerks and other services								
42	Customer services clerks	R.Cog	1.4	-0.37	-0.15	-0.58	-1.15	-0.05
52	Models, salespersons and demonstrators	R.Cog	4.6	0.95	0.88	0.51	-0.16	-0.16
91	Service elementary occupations	R.Man	2.1	-0.06	0.14	-0.23	-0.93	0.28
Routine operators								
73	Precision, handicraft, print and related trade workers	R.Man	0.7	-0.13	-0.21	-0.04	-0.17	-0.10
74	Other craft and related trades workers	R.Man	2.0	-1.11	-2.33	-0.29	-0.90	-1.17
81	Process operators	R.Man	2.1	-0.40	-0.19	-0.02	-0.04	-0.44
82	Machine operators	R.Man	3.9	-1.33	-1.85	-0.38	-1.20	-1.35
Operators								
71	Stone and building trade workers	Manual	5.4	0.21	3.53	-0.03	-0.08	0.97
72	Metal, machinery and related trades workers	Manual	7.3	-0.86	1.39	-0.88	-0.14	-0.53
83	Drivers and mobile-plant operators	Manual	4.7	0.10	1.28	-0.40	-0.02	0.66
93	Labourers in construction and manufacturing	Manual	1.4	-0.79	-1.42	-0.40	-0.81	-0.74
Agricultural, forestry and fishing								
61	Agriculture professionals	Manual	3.2	-1.57	-3.61	-0.04	-0.75	-1.90
62	Forestry occupations	Manual	0.2	-0.11	-0.24	0.00	-0.01	-0.15
63	Fish farmers	Manual	0.2	-0.06	-0.04	-0.02	-0.06	-0.04
64	Fishery workers and hunters	Manual	0.7	-0.28	-0.63	0.01	-0.05	-0.37
92	Agriculture associate professionals	Manual	0.0	0.02	0.05	0.01	-0.01	0.04

Note: The table display STYRK-88 occupational codes and titles, as well as the assigned task. Column four shows the employment share in 1996, and column five to nine shows the percentage changes in the employment share in each occupation in the economy as a whole, within sectors and genders in the time period 1996-2010.

Table A5: Employment share changes 2011-2018

			Employment			% △		
			share			2011-2018		
STYRK-08	**Occupational title**	**Task**	**2011**	**All**	**Manufacturing**	**Service**	**Female**	**Male**
Technical and professional								
11	Chief exectuvies, senior officials and legislators	Abstract	1,01	0,33	0,15	0,40	0,75	0,09
21	Science and engineering professionals	Abstract	2,10	0,91	1,86	0,59	0,73	1,07
23	Teaching professionals	Abstract	7,04	0,24	0,17	0,03	0,71	-0,44
24	Business and administration professionals	Abstract	5,78	0,40	-0,30	0,56	1,21	-0,24
25+26	Other professionals	Abstract	4,84	1,43	0,52	1,64	1,01	1,72
31+34	Other associate professionals	Abstract	7,22	0,29	0,77	0,20	0,74	0,21
35	Information and communations technicians	R.Cog	1,06	-0,21	-0,01	-0,30	0,17	-0,40
Managerial and health professionals								
12	Administrative and commercial managers	Abstract	2,39	1,05	0,78	1,13	1,35	0,86
13	Production and specialised services managers	Abstract	3,72	0,30	1,72	-0,18	0,01	0,59
14	Hospitality, retail and other services managers	Abstract	1,71	0,88	0,21	1,08	1,35	0,59
22	Health professionals	Abstract	5,16	0,37	0,12	0,30	0,15	0,21
32	Health associate professionals	Abstract	1,28	0,35	0,61	0,24	0,36	0,26
Office clerks								
33	Business and administration associate professionals	Abstract	8,82	-0,54	-0,60	-0,69	-0,54	-0,66
41	General and keyboard clerks	R.Cog	1,83	-0,24	-0,23	-0,26	-1,04	0,14
43	Numerical and material recording clerks	R.Cog	3,82	-0,90	-0,33	-1,12	-1,49	-0,54
44	Other clerical support workers	R.Cog	0,49	-0,29	-0,04	-0,41	-0,50	-0,17
Personal and protective services								
51	Personal service workers	R.Man	3,34	0,02	0,21	-0,14	-0,54	0,34
53	Personal care workers	Manual	4,84	0,15	0,01	0,03	-0,68	0,28
54	Protective services workers	Abstract	0,79	-0,10	-0,07	-0,13	-0,07	-0,10
Sales, ticket clerks and other services								
42	Customer services clerks	R.Cog	0,97	-0,19	-0,08	-0,25	-0,56	0,00
52	Sales workers	R.Cog	3,93	-0,59	-0,30	-0,81	-1,37	-0,16
91	Cleaners and helpers	R.Man	1,39	-0,14	0,06	-0,25	-0,69	0,14
94	Food preparation assistants	R.Man	0,22	-0,05	-0,04	-0,06	-0,14	0,00
96	Refuse workers and other elementary workers	Manual	0,45	-0,18	-0,12	-0,19	-0,06	-0,24
Routine operators								
73	Handicraft and printing workers	R.Man	0,48	-0,27	-0,66	-0,11	-0,21	-0,31
74	Electrical and electronics trades workers	Manual	3,01	-0,23	0,34	-0,25	0,11	-0,25
75	Food processing, woodworking, garment and other craft and related trades workers	R.Man	0,58	0,02	0,02	0,05	-0,03	0,06
81	Stationary plant and machine operators	R.Man	3,09	-0,82	-2,37	0,00	-0,55	-0,91
82	Assemblers	R.Man	0,39	-0,29	-0,95	-0,02	-0,25	-0,31
Operators								
71	Building and related trades workers, excluding electricians	Manual	5,03	0,16	1,77	-0,08	0,18	0,49
72	Metal, machinery and related trades workers	Manual	3,93	-0,44	-0,85	-0,16	0,19	-0,60
83	Drivers and mobile plant operators	Manual	5,37	-0,97	-0,84	-0,95	-0,04	-1,34
93	Labourers in mining, construction, manufacturing and transport	Manual	0,47	0,04	0,36	-0,07	-0,03	0,10
Agriculture, forestry and fishing								
61	Market-oriented skilled agricultural workers	Manual	1,79	-0,39	-1,48	0,16	-0,15	-0,48
62	Market-oriented skilled forestry, fishery and hunting workers	Manual	0,61	-0,10	-0,32	0,04	-0,04	-0,10
92	Agricultural, forestry and fishery labourers	Manual	0,04	-0,02	-0,08	0,01	-0,06	0,00

Note: The table display STYRK-08 occupational codes and titles, as well as the assigned task. Column four shows the employment share in 2011, and column five to nine shows the percentage changes in the employment share in each occupation in the economy as a whole, within sectors and genders in the time period 2011-2018.

Table A6: Regression period 1996 - 2018

	Economy			Manufacturing			Service		
	Abstract	**R. Cognitive**	**R. Manual**	**Abstract**	**R. Cognitive**	**R. Manual**	**Abstract**	**R. Cognitive**	**R. Manual**
Period 1									
1997	0.119*	0.0298	-0.00176	0.0471	-0.0556	-0.0465	0.215*	0.0824	0.00475
	(0.0555)	(0.0580)	(0.0623)	(0.0935)	(0.115)	(0.0998)	(0.0842)	(0.0715)	(0.0799)
1998	0.174**	0.0862	-0.00691	0.0424	0.120	-0.111	0.313***	0.117	0.0285
	(0.0553)	(0.0572)	(0.0612)	(0.0928)	(0.108)	(0.100)	(0.0817)	(0.0704)	(0.0774
1999	0.209***	0.162**	-0.0478	0.0978	0.144	-0.155	0.326***	0.198**	-0.00529
	(0.0551)	(0.0574)	(0.0626)	(0.0923)	(0.106)	(0.103)	(0.0828)	(0.0716)	(0.0787)
2000	0.243***	0.111*	-0.0281	0.218*	0.0612	-0.115	0.297***	0.141*	0.00750
	(0.0556)	(0.0562)	(0.0630)	(0.0971)	(0.115)	(0.107)	(0.0804)	(0.0684)	(0.0780)
2001	0.372***	-0.0604	-0.0773	0.440***	-0.174	-0.221*	0.437***	0.00570	-0.0294
	(0.0554)	(0.0560)	(0.0633)	(0.0948)	(0.112)	(0.108)	(0.0817)	(0.0682)	(0.0779)
2002	0.400***	-0.0160	-0.107	0.499***	-0.143	-0.313**	0.423***	0.0346	-0.0250
	(0.0548)	(0.0553)	(0.0627)	(0.0963)	(0.113)	(0.110)	(0.0802)	(0.0674)	(0.0762)
2003	0.452***	0.00858	-0.0579	0.558***	-0.0976	-0.290**	0.421***	0.0294	0.0461
	(0.0555)	(0.0564)	(0.0619)	(0.0915)	(0.110)	(0.107)	(0.0811)	(0.0690)	(0.0761)
2004	0.506***	-0.0470	-0.100	0.499***	-0.0718	-0.318**	0.537***	-0.0360	-0.00482
	(0.0564)	(0.0577)	(0.0638)	(0.0951)	(0.117)	(0.112)	(0.0840)	(0.0695)	(0.0778)
2005	0.512***	0.0499	-0.201**	0.519***	0.0669	-0.454***	0.548***	0.0532	-0.0956
	(0.0560)	(0.0568)	(0.0643)	(0.0966)	(0.109)	(0.111)	(0.0817)	(0.0687)	(0.0790)
2006	0.289***	0.0301	0.167**	0.252**	-0.0874	-0.104	0.248**	0.0213	0.307***
	(0.0540)	(0.0532)	(0.0594)	(0.0932)	(0.108)	(0.107)	(0.0794)	(0.0640)	(0.0713)
2007	0.328***	0.0280	0.223***	0.280**	-0.140	0.0548	0.259***	0.0276	0.331***
	(0.0540)	(0.0529)	(0.0597)	(0.0922)	(0.110)	(0.108)	(0.0785)	(0.0629)	(0.0715)
2008	0.694***	0.409***	0.548***	0.461***	0.195	0.320**	0.593***	0.354***	0.763***
	(0.0610)	(0.0613)	(0.0651)	(0.100)	(0.122)	(0.116)	(0.0862)	(0.0727)	(0.0787)
2009	0.460***	-0.00766	0.251***	0.293**	-0.00513	0.000226	0.470***	-0.0395	0.392***
	(0.0533)	(0.0515)	(0.0581)	(0.0904)	(0.100)	(0.101)	(0.0776)	(0.0627)	(0.0711)
2010	0.525***	0.0463	0.196***	0.316***	0.142	-0.129	0.542***	-0.0134	0.369***
	(0.0536)	(0.0518)	(0.0591)	(0.0916)	(0.104)	(0.107)	(0.0774)	(0.0624)	(0.0706)
Constant			1.798***			1.933***			1.742***
			(0.0141)			(0.0238)			(0.0173)
N			37802			11184			26618
R^2			0.659			0.707			0.641
Period 2									
2012	0.0132	-0.0301	-0.0190	0.0518	-0.0609	-0.0515	0.00669	-0.0173	-0.00729
	(0.0579)	(0.0507)	(0.0538)	(0.0903)	(0.110)	(0.0995)	(0.0928)	(0.0589)	(0.0654)
2013	0.189***	-0.0121	0.00141	0.176*	-0.00265	-0.0292	0.251**	0.000265	0.0220
	(0.0566)	(0.0503)	(0.0537)	(0.0848)	(0.101)	(0.0991)	(0.0944)	(0.0592)	(0.0652)
2014	0.169**	0.0179	-0.000490	0.172*	-0.00411	-0.0170	0.229*	0.0417	0.00806
	(0.0579)	(0.0511)	(0.0545)	(0.0873)	(0.105)	(0.102)	(0.0958)	(0.0603)	(0.0655)
2015	0.190***	0.0467	-0.00863	0.159	-0.0611	-0.0423	0.267**	0.0953	0.0216
	(0.0571)	(0.0502)	(0.0536)	(0.0881)	(0.105)	(0.101)	(0.0923)	(0.0587)	(0.0644)
2016	0.191**	-0.0179	-0.0345	0.0710	0.0446	-0.212*	0.272**	-0.0359	0.0508
	(0.0571)	(0.0502)	(0.0546)	(0.0876)	(0.0989)	(0.0978)	(0.0933)	(0.0599)	(0.0666)
2017	0.228***	0.00333	-0.0536	0.171	0.0458	-0.208*	0.293**	-0.00274	0.0189
	(0.0597)	(0.0505)	(0.0546)	(0.0894)	(0.102)	(0.0981)	(0.0954)	(0.0594)	(0.0664)
2018	0.238***	0.0311	-0.0811	0.217*	-0.0497	-0.157	0.250**	0.0548	-0.0450
	(0.0594)	(0.0506)	(0.0553)	(0.0900)	(0.107)	(0.103)	(0.0946)	(0.0590)	(0.0663)
Constant			1.638***			1.649***			1.634***
			(0.0129)			(0.0229)			(0.0155)
N			22881			6494			16387
R^2			0.658			0.688			0.647

Note: The dependent variable is log employment per cell. The coefficients presented are from the interaction term between employment share per task and time dummies. Manual is the omitted variable. The model contains fixed effects for cells and year dummies. Robust standard errors are displayed in parentheses
($^{***}p < 0.01$, $^{**}p < 0.05$ $^{*}p < 0.1$)

Table A7: Regression period 1996 - 2018. By gender

	Female			Male		
	Abstract	**R. Cognitive**	**R. Manual**	**Abstract**	**R. Cognitive**	**R. Manual**
Period 1						
1997	0.254**	0.0558	0.102	0.0298	0.0674	-0.0778
	(0.0922)	(0.0946)	(0.0877)	(0.0692)	(0.105)	(0.0881)
1998	0.210*	0.193*	0.0116	0.145*	-0.0880	-0.0316
	(0.0888)	(0.0930)	(0.0854)	(0.0712)	(0.111)	(0.0874)
1999	0.261**	0.265**	-0.0802	0.169*	0.0263	-0.0150
	(0.0872)	(0.0920)	(0.0864)	(0.0711)	(0.114)	(0.0899)
2000	0.272**	0.166	-0.0221	0.221**	0.00365	-0.0362
	(0.0879)	(0.0902)	(0.0858)	(0.0719)	(0.108)	(0.0919)
2001	0.314***	0.0119	-0.0940	0.404****	-0.205	-0.0731
	(0.0879)	(0.0909)	(0.0879)	(0.0714)	(0.106)	(0.0903)
2002	0.430***	0.0539	-0.145	0.376***	-0.123	-0.0714
	(0.0871)	(0.0892)	(0.0860)	(0.0706)	(0.104)	(0.0910)
2003	0.424***	0.149	-0.0520	0.460***	-0.218*	-0.0777
	(0.0859)	(0.0880)	(0.0835)	(0.0724)	(0.111)	(0.0908)
2004	0.507***	0.0808	-0.0184	0.502***	-0.314**	-0.192*
	(0.0898)	(0.0905)	(0.0862)	(0.0723)	(0.113)	(0.0933)
2005	0.502***	0.230**	-0.109	0.518***	-0.235*	-0.300**
	(0.0868)	(0.0889)	(0.0889)	(0.0730)	(0.114)	(0.0923)
2006	0.434***	0.0809	0.115	0.193**	-0.00943	0.242**
	(0.0833)	(0.0828)	(0.0806)	(0.0703)	(0.105)	(0.0865)
2007	0.503***	0.00129	0.345***	0.226**	0.0744	0.123
	(0.0840)	(0.0823)	(0.0793)	(0.0702)	(0.102)	(0.0890)
2008	0.758***	0.569***	0.587***	0.647***	0.398***	0.545***
	(0.0894)	(0.0932)	(0.0882)	(0.0827)	(0.112)	(0.0949)
2009	0.588***	0.0123	0.209**	0.371***	-0.103	0.307***
	(0.0824)	(0.0813)	(0.0781)	(0.0696)	(0.0990)	(0.0858)
2010	0.644***	0.0916	0.206**	0.445***	-0.0491	0.197*
	(0.0818)	(0.0803)	(0.0788)	(0.0704)	(0.0991)	(0.0882)
Constant			1.618***			1.927***
			(0.0223)			(0.0181)
N			15743			22059
R^2			0.635			0.670
Period 2						
2012	0.0590	-0.0798	-0.0218	-0.0187	-0.0168	-0.0125
	(0.0866)	(0.0712)	(0.0754)	(0.0777)	(0.0840)	(0.0779)
2013	0.205*	-0.0266	-0.0114	0.177*	0.00562	0.0135
	(0.0852)	(0.0707)	(0.0749)	(0.0760)	(0.0829)	(0.0776)
2014	0.222**	0.0566	-0.00166	0.127	-0.00127	-0.00427
	(0.0861)	(0.0710)	(0.0753)	(0.0779)	(0.0850)	(0.0792)
2015	0.225**	0.0473	-0.0330	0.161*	0.0387	0.0197
	(0.0854)	(0.0704)	(0.0748)	(0.0768)	(0.0817)	(0.0777)
2016	0.164	-0.0609	-0.0783	0.206**	0.0147	0.000770
	(0.0854)	(0.0711)	(0.0750)	(0.0790)	(0.0816)	(0.0797)
2017	0.245**	-0.0763	-0.0794	0.208*	0.0268	-0.0259
	(0.0862)	(0.0701)	(0.0760)	(0.0813)	(0.0833)	(0.0786)
2018	0.203*	-0.0812	-0.105	0.250**	0.0722	-0.0609
	(0.0882)	(0.0695)	(0.0761)	(0.0799)	(0.0857)	(0.0809)
Constant			1.477***			1.760***
			(0.0197)			(0.0171)
N			9865			13016
R^2			0.643			0.662

Note: The dependent variable is log employment per cell by gender. The coefficients presented are from the interaction term between employment share per task and time dummies. Manual is the omitted variable. The model contains fixed effects for cells and year dummies. Robust standard errors are displayed in parentheses (***$p < 0.01$, **$p < 0.05$ *$p < 0.1$)

Table A8: Regression period 1996 - 2018. Robustness checks

	Temporarily Absent			Year x Educ			Year x Industry		
	Abstract	**R. Cog**	**R. Man**	**Abstract**	**R.Cog**	**R. Man**	**Abstract**	**R.Cog**	**R. Man**
Period 1									
1997	0.133*	0.0493	-0.0446	0.0515	0.0392	0.0309	0.130	0.0363	0.00351
	(0.0578)	(0.0603)	(0.0649)	(0.0674)	(0.0589)	(0.0680)	(0.0677)	(0.0650)	(0.0741)
1998	0.185**	0.0881	-0.00854	0.0709	0.104	0.0414	0.201**	0.112	0.0103
	(0.0576)	(0.0598)	(0.0640)	(0.0665)	(0.0580)	(0.0669)	(0.0678)	(0.0630)	(0.0721)
1999	0.211***	0.165**	-0.0919	0.152*	0.175**	-0.00601	0.228***	0.181**	-0.0403
	(0.0571)	(0.0597)	(0.0657)	(0.0663)	(0.0583)	(0.0681)	(0.0681)	(0.0628)	(0.0727)
2000	0.260***	0.123*	-0.0478	0.135*	0.127*	0.0391	0.257***	0.133*	-0.00476
	(0.0575)	(0.0585)	(0.0653)	(0.0664)	(0.0568)	(0.0688)	(0.0682)	(0.0636)	(0.0724)
2001	0.356***	-0.0629	-0.112	0.191**	-0.0362	0.0207	0.421***	0.00313	-0.109
	(0.0574)	(0.0586)	(0.0655)	(0.0656)	(0.0567)	(0.0689)	(0.0684)	(0.0627)	(0.0732)
2002	0.365***	0.0134	-0.145*	0.263***	0.00537	-0.0569	0.451***	0.0495	-0.0982
	(0.0569)	(0.0586)	(0.0654)	(0.0650)	(0.0561)	(0.0686)	(0.0674)	(0.0615)	(0.0722)
2003	0.462***	-0.00282	-0.116	0.282***	0.0295	0.0134	0.523***	0.0839	-0.0115
	(0.0577)	(0.0585)	(0.0656)	(0.0672)	(0.0573)	(0.0671)	(0.0670)	(0.0627)	(0.0701)
2004	0.510***	-0.0290	-0.121	0.284***	-0.0155	0.00349	0.532***	-0.0135	-0.0827
	(0.0577)	(0.0598)	(0.0658)	(0.0675)	(0.0588)	(0.0697)	(0.0691)	(0.0634)	0.0728)
2005	0.531***	0.0448	-0.230***	0.292***	0.0652	-0.0638	0.552***	0.101	-0.182*
	(0.0584)	0.0595)	(0.0664)	(0.0669)	(0.0573)	(0.0691)	(0.0678)	(0.0620)	(0.0734)
2006	0.319***	0.0560	0.178**	0.320***	0.0606	0.0687	0.266***	0.0167	0.247***
	(0.0559)	(0.0553)	(0.0616)	(0.0641)	(0.0538)	(0.0647)	(0.0660)	(0.0586)	(0.0666)
2007	0.344***	0.0367	0.199**	0.332***	0.0630	0.114	0.253***	0.00836	0.286***
	(0.0559)	(0.0553)	(0.0613)	(0.0641)	(0.0536)	(0.0647)	(0.0662)	(0.0584)	(0.0671)
2008	0.780***	0.442***	0.580***	0.836***	0.420***	0.423***	0.288***	0.136*	0.433***
	(0.0634)	(0.0639)	(0.0681)	(0.0699)	(0.0622)	(0.0707)	(0.0714)	(0.0636)	(0.0708)
2009	0.491***	0.00776	0.229***	0.461***	0.0113	0.170**	0.406***	0.0552	0.265***
	(0.0552)	(0.0543)	(0.0599)	(0.0615)	(0.0522)	(0.0635)	(0.0640)	(0.0569)	(0.0659)
2010	0.533***	0.0271	0.183**	0.489***	0.0700	0.146*	0.493***	0.121*	0.227***
	(0.0554)	(0.0544)	(0.0607)	(0.0627)	(0.0526)	(0.0648)	(0.0639)	(0.0572)	(0.0656)
Constant			2.015***			1.797***			1.792***
			(0.0146)			(0.0143)			(0.0138)
N			38605			37802			37802
R^2			0.651			0.664			0.671
Period 2									
2012	0.0125	-0.0528	0.0427	0.0511	-0.0445	-0.0436	0.0462	-0.0162	0.0150
	(0.0551)	(0.0538)	(0.0567)	(0.0715)	(0.0526)	(0.0564)	(0.0690)	(0.0563)	(0.0654)
2013	0.139*	-0.0356	0.0625	0.160*	0.00821	0.0244	0.192**	-0.0268	0.0220
	(0.0548)	(0.0531)	(0.0567)	(0.0696)	(0.0519)	(0.0568)	(0.0676)	(0.0550)	(0.0642)
2014	0.177**	0.00600	0.0503	0.136	0.0321	0.0121	0.204**	-0.00283	-0.0107
	(0.0547)	(0.0538)	(0.0574)	(0.0707)	(0.0528)	(0.0576)	(0.0698)	(0.0560)	(0.0650)
2015	0.243***	0.0187	0.0232	0.156*	0.0601	0.00751	0.197**	0.0224	0.0114
	(0.0547)	(0.0533)	(0.0569)	(0.0684)	(0.0523)	(0.0560)	(0.0693)	(0.0553)	(0.0650)
2016	0.249***	-0.0423	0.0145	0.103	0.00867	0.0152	0.182**	-0.0187	-0.0158
	(0.0557)	(0.0534)	(0.0576)	(0.0700)	(0.0521)	(0.0572)	(0.0692)	(0.0554)	(0.0665)
2017	0.287***	-0.0134	-0.0360	0.166*	0.0185	-0.0159	0.209**	0.0255	-0.0772
	(0.0558)	(0.0531)	(0.0576)	(0.0725)	(0.0524)	(0.0577)	(0.0699)	(0.0555)	(0.0657)
2018	0.252***	0.0115	-0.0174	0.150*	0.0421	-0.0350	0.178*	0.0332	-0.147*
	(0.0560)	(0.0528)	(0.0578)	(0.0722)	(0.0526)	(0.0585)	(0.0696)	(0.0564)	(0.0663)
Constant			1.877***			1.637***			1.638***
			(0.0136)			(0.0129)			(0.0129)
N			23480			22881			22881
R^2			0.651			0.659			0.659

Note: The dependent variable for all regressions is log employment per cell. The first columns shows the estimated coefficients from the interaction term between employment share per task and time dummies, when participants who are temporarily absent is included. The second column includes an additional fixed effect controlling for changes in education over time. The last columns include an additional fixed effect controlling for changes in industry groups over time. Manual is the omitted variable. The model contains fixed effects for cells and year dummies. Robust standard errors are displayed in parentheses (***$p < 0.01$, **$p < 0.05$ *$p < 0.1$).

Table A9: Possible mechanisms: Excluding oil and unionized industries

	Excluding oil			**unions**		
	Abstract	**R. Cognitive**	**R. Manual**	**Abstract**	**R.Cognitive**	**R. Manual**
Period 1						
1997	0.123*	0.0363	-0.00610	0.115	0.0352	0.0199
	(0.0558)	(0.0585)	(0.0626)	0.115	0.0352	(0.0612)
1998	0.172**	0.0769	-0.00262	0.215***	0.0681	0.0273
	(0.0555)	(0.0577)	(0.0614)	(0.0583)	(0.0564)	(0.0600)
1999	0.205***	0.157**	-0.0399	0.268***	0.0964	-0.0432
	(0.0553)	(0.0579)	(0.0624)	(0.0583)	(0.0566)	(0.0617)
2000	0.241***	0.107	-0.0392	0.320***	0.0681	0.00807
	(0.0559)	(0.0566)	(0.0631)	(0.0601)	(0.0564)	(0.0630)
2001	0.372***	-0.0569	-0.0794	0.404***	-0.0635	0.0155
	(0.0557)	(0.0563)	(0.0631)	(0.0594)	(0.0561)	(0.0630)
2002	0.405***	-0.0109	-0.104	0.476***	0.0125	-0.0371
	(0.0550)	(0.0556)	(0.0627)	(0.0602)	(0.0565)	(0.0629)
2003	0.457***	0.00692	-0.0524	0.545***	0.00705	-0.0146
	(0.0557)	(0.0569)	(0.0619)	(0.0598)	(0.0566)	(0.0618)
2004	0.514***	-0.0300	-0.109	0.535***	-0.0111	-0.0663
	(0.0567)	(0.0582)	(0.0641)	(0.0608)	(0.0570)	(0.0631)
2005	0.514***	0.0518	-0.214***	0.533***	0.0787	-0.129*
	(0.0561)	(0.0572)	(0.0641)	(0.0607)	(0.0569)	(0.0642)
2006	0.288***	0.0394	0.172**	0.428***	0.124*	0.127*
	(0.0541)	(0.0534)	(0.0592)	(0.0574)	(0.0531)	(0.0587)
2007	0.325***	0.0414	0.221***	0.505***	0.110*	0.147*
	(0.0539)	(0.0529)	(0.0598)	(0.0579)	(0.0533)	(0.0587)
2008	0.703***	0.414***	0.559***	0.947***	0.164*	0.477***
	(0.0610)	(0.0616)	(0.0650)	(0.0673)	(0.0669)	(0.0686)
2009	0.460***	-0.00700	0.242***	0.597***	0.0436	0.170*
	(0.0535)	(0.0518)	(0.0582)	(0.0571)	(0.0526)	(0.0576)
2010	0.517***	0.0465	0.181**	0.663***	0.0715	0.129*
	(0.0538)	(0.0523)	(0.0592)	(0.0569)	(0.0520)	(0.0581)
Constant			1.791***			1.623***
			(0.0141)			(0.0145)
N			37591			32303
R^2			0.658			0.609
Period 2						
2012	0.0128	-0.0352	-0.0228	0.0152	0.00324	-0.0525
	(0.0577)	(0.0508)	(0.0537)	(0.0657)	(0.0506)	(0.0539)
2013	0.181**	-0.0219	-0.00634	0.218***	-0.00716	0.0000284
	(0.0567)	(0.0505)	(0.0537)	(0.0638)	(0.0501)	(0.0543)
2014	0.169**	0.00518	0.000768	0.165*	0.0382	-0.0208
	(0.0579)	(0.0511)	(0.0543)	(0.0652)	(0.0503)	(0.0551)
2015	0.181**	0.0453	-0.0217	0.214***	0.0781	-0.0419
	(0.0571)	(0.0503)	(0.0535)	(0.0644)	(0.0500)	(0.0538)
2016	0.198***	-0.0122	-0.0319	0.203**	0.0577	-0.0545
	(0.0582)	(0.0503)	(0.0547)	(0.0652)	(0.0504)	(0.0551)
2017	0.234***	0.00492	-0.0518	0.291***	0.0275	-0.0228
	(0.0597)	(0.0507)	(0.0548)	(0.0671)	(0.0508)	(0.0547)
2018	0.238***	0.0291	-0.0708	0.310***	0.0686	-0.0677
	(0.0593)	(0.0506)	(0.0552)	(0.0664)	(0.0511)	(0.0552)
Constant			1.621***			1.445***
			(0.0130)			(0.0135)
N			22723			19503
R^2			0.654			0.569

Note: The dependent variable is log employment per cell. The coefficients presented are from the interaction term between employment share per task and time dummies. Manual is the omitted variable. The model contains fixed effects for cells and year dummies. The first columns show the estimated coefficients, when excluding petroleum industries. The last columns show estimated coefficients when excluding industries assumed to be highly unionized. Robust standard errors are displayed in parentheses (***$p < 0.01$, **$p < 0.05$ *$p < 0.1$).

Table A10: Possible mechanisms: 3-way task, Broad occupational groups

	3-way classification		Broad occ. Groups		
	Abstract	**Routine**	**Abstract**	**R. Cognitive**	**R. Manual**
Period 1					
1997	0.122*	-0.00522	0.126*	-0.00602	0.0249
	(0.0552)	(0.0538)	(0.0534)	(0.0553)	(0.0685)
1998	0.181***	0.0430	0.168**	0.0457	0.0353
	(0.0548)	(0.0535)	(0.0523)	(0.0547)	(0.0661)
1999	0.223***	0.0848	0.164**	0.0902	-0.0662
	(0.0546)	(0.0539)	(0.0524)	(0.0546)	(0.0679)
2000	0.254***	0.0542	0.223***	0.0744	-0.0261
	(0.0552)	(0.0531)	(0.0529)	(0.0550)	(0.0689)
2001	0.377***	-0.104	0.389***	-0.105	-0.0435
	(0.0548)	(0.0534)	(0.0526)	(0.0553)	(0.0689)
2002	0.410***	-0.0844	0.407***	-0.0419	-0.0705
	(0.0543)	(0.0525)	(0.0525)	(0.0537)	(0.0688)
2003	0.458***	-0.0700	0.408***	0.0296	-0.0846
	(0.0550)	(0.0532)	(0.0524)	(0.0542)	(0.0673)
2004	0.513***	-0.136*	0.459***	0.0221	-0.136
	(0.0558)	(0.0538)	(0.0530)	(0.0558)	(0.0696)
2005	0.534***	-0.0958	0.500***	0.0173	-0.196**
	(0.0555)	(0.0534)	(0.0523)	(0.0553)	(0.0691)
2006	0.274***	0.0478	0.232***	0.0435	0.0176
	(0.0537)	(0.0504)	(0.0504)	(0.0523)	(0.0659)
2007	0.305***	0.0406	0.252***	0.0974	0.0356
	(0.0539)	(0.0501)	(0.0504)	(0.0518)	(0.0664)
2008	0.677***	0.527***	0.459***	0.516***	0.474***
	(0.0607)	(0.0597)	(0.0569)	(0.0632)	(0.0731)
2009	0.435***	0.0360	0.437***	-0.00292	0.0905
	(0.0529)	(0.0495)	(0.0494)	(0.0512)	(0.0634)
2010	0.507***	0.0502	0.456***	0.0590	0.0219
	(0.0532)	(0.0497)	(0.0500)	(0.0515)	(0.0663)
Constant		1.797***			1.797***
		(0.0141)			(0.0141)
N		37802			37802
R^2		0.658			0.658
Period 2					
2012	0.00942	-0.0625	-0.0144	-0.00384	-0.0524
	(0.0566)	(0.0452)	(0.0503)	(0.0456)	(0.0612)
2013	0.185***	-0.0311	0.139**	0.0235	0.000425
	(0.0556)	(0.0453)	(0.0497)	(0.0452)	(0.0609)
2014	0.166**	-0.0369	0.102*	0.0458	-0.0395
	(0.0568)	(0.0463)	(0.0505)	(0.0464)	(0.0622)
2015	0.195***	0.0131	0.117*	0.0465	-0.0793
	(0.0561)	(0.0451)	(0.0499)	(0.0453)	(0.0618)
2016	0.191***	-0.0653	0.135**	0.0276	-0.103
	(0.0571)	(0.0458)	(0.0505)	(0.0456)	(0.0610)
2017	0.238***	-0.0350	0.160**	0.0189	-0.0855
	(0.0586)	(0.0458)	(0.0510)	(0.0457)	(0.0602)
2018	0.254***	-0.0413	0.155**	0.0332	-0.147*
	(0.0583)	(0.0461)	(0.0512)	(0.0460)	(0.0632)
Constant		1.638***			1.638***
		(0.0129)			(0.0129)
N		22881			22881
R^2		0.658			0.658

Note: The dependent variable is log employment per cell. The coefficients presented are from the interaction term between employment share per task and time dummies. Manual is the omitted variable. The model contains fixed effects for cells and year dummies. The first columns show the estimated coefficients, when combining routine cognitive and routine manual tasks. The last columns show estimated coefficients when using broad occupational groups as task classification. Robust standard errors are displayed in parentheses (***$p < 0.01$, **$p < 0.05$ *$p < 0.1$).

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