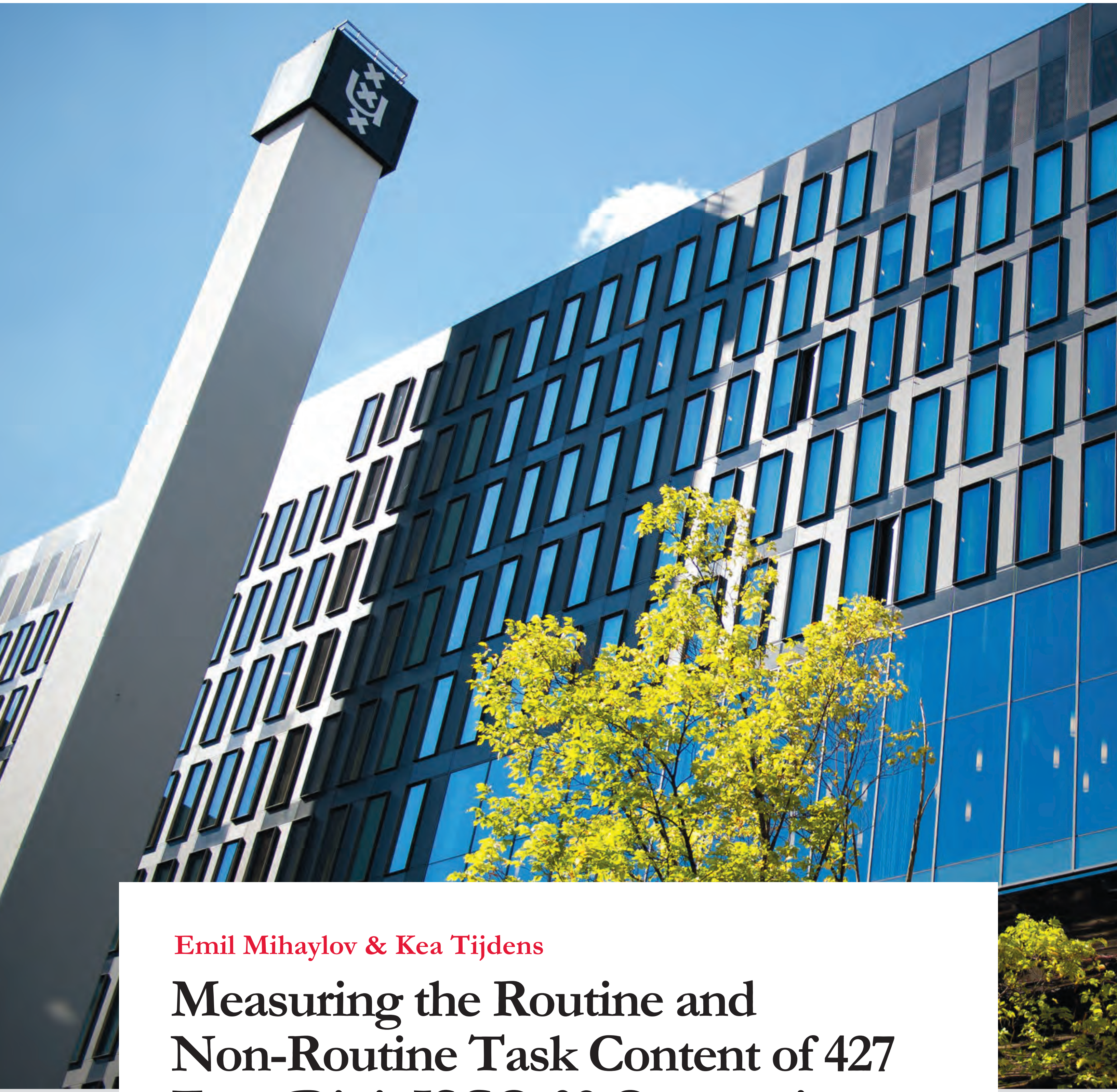
UNIVERSITY OF AMSTERDAM

AIAS-HSI



Emil Mihaylov & Kea Tijdens

Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations

AIAS-HSI Working Paper Series

WP 8 - May 2019

June 2019

Contact: e.s.mihaylov@vu.nl
General contact: aias-hsi@uva.nl
Bibliographical information:
E. Mihaylov & K. Tijdens (2019). Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations, *AIAS-HSI Working Paper 8*

This paper can be downloaded from our website http://hsi.uva.nl/ under the section: Publications/AIAS-HSI Working Papers Series.
ISSN online: 2590-0145

Measuring the Routine and Non-Routine Task Content of 427 Four-Digit ISCO-08 Occupations

Emil Mihaylov

VU Amsterdam and Tinbergen Institute

Kea Tijdens

AIAS-HSI, University of Amsterdam

Table of contents

Abstract

This paper develops new measures of the task content of occupations that are based on the International Standard Classification of Occupations 2008 (ISCO-08). Using a detailed set of 3,264 occupation-specific tasks, we construct five measures of non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks for 427 four-digit occupations. To generate these measures, first we assign each of the 3,264 tasks to one or more of the five task categories. The decision to classify tasks as routine or non-routine, and as cognitive or manual, depends on whether the tasks can be replaced by computer-controlled technology and whether the performance of the tasks requires cognitive or manual skills. We judge the automation potential of tasks on a case-by-case basis and classify tasks to one or more of the five task categories. Because the classification of 3,264 tasks can be prone to errors, we devote substantial attention to the possibility of misclassifying tasks. We discuss three particular types of task misclassifications and provide examples of tasks that could be potentially misclassified.

In line with the previous literature, we find that non-routine analytic and interactive tasks are most prevalent in the work of Managers and Professionals, routine cognitive tasks are mainly concentrated in the work of Clerical Support Workers, and routine and non-routine manual tasks are most common in the work of Plant and Machine Operators and Assemblers and Elementary Occupations, respectively. We compare the newly developed task measures with three previous studies (Acemoglu and Autor, 2011; Dengler, Matthes and Paulus, 2014; Frey and Osborne, 2017) and demonstrate that our measures are moderately to strongly positively correlated with the previous papers' indexes. Based on our task content measures, we provide a back of the envelop estimation of the number of occupations that might be at risk of automation. We find that approximately 16 percent of the 427 ISCO-08 occupations fall into the so-called high risk of automation category – they contain 70 percent or more routine tasks. The 16 percent of automatable occupations correspond roughly to 11 percent of total employment in the Netherlands.

JEL Classification: J21, J24, J62, J82, O33

Keywords: Technological change, Computerization, Occupations, Routine and non-routine tasks, International Standard Classification of Occupations 2008 (ISCO-08)

1 Introduction

To study the effects of computerization on the labor market, back in 2003 Autor, Levy and Murnane proposed a tractable model that helps explain what it is that computers do at the workplace, and how they interact with human labor. On the basis of this model is the notion that computers are biased towards replacing labor in performing routine tasks that can be described with programmed rules, and complementing labor in performing non-routine tasks that require analytic and interactive skills that cannot be described with programmed rules. An implication of the model is that computers (and technologies in general) have differential effects on workers across occupations, and these effects depend on the tasks content of occupations. The seminal paper of Autor, Levy and Murnane (2003) has laid the foundation of a new and rapidly growing strand of literature studying the impacts of computerization on the labor market. Their model, which is often labeled as the task-based approach, has proven to be a valuable tool for analyzing various labor market outcomes such as employment and wage polarization (Autor and Dorn, 2013; Goos and Manning, 2007; Goos, Manning and Salomons, 2014), wage inequality (Autor, Katz and Kearney, 2008) and task specialization (Basso, Peri and Rahman, 2017).

One crucial element in the task-based approach literature is the measurement of routine and non-routine tasks in occupations. To measure these tasks, researchers generally rely on a handful of occupational and survey-based data sources such as the Dictionary of Occupational Titles (DOT), the Occupational Information Network (O*NET) and the German Qualification and Career Surveys (BIBB/BAuA and BIBB/IAB). Even though useful, all these sources have their limitations – for example, the information in the DOT has not been updated since 1991, which means that it reflects the occupational and workplace requirements back in 1991, O*NET contains “numerous potential task scales, and it is rarely obvious which measure (if any) best represents a given task construct” (Acemoglu and Autor, 2011, p. 1078), and the German surveys were not originally intended to measure routine and non-routine tasks (Rohrbach-Schmidt and Tiemann, 2013).

The goal of the current paper is to develop new measures of the task content of occupations that are based on the International Standard Classification of Occupations 2008 (ISCO-08). Using information on 3,264 occupation-specific tasks, we construct five measures of non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks for 427 four-digit occupations. To generate these measures we proceed as follows. First, we assign each of the 3,264 tasks to one of the five routine clusters – non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual. The decision to classify tasks to a particular cluster depends on whether the tasks can be replaced by computer technology (routine versus non-routine tasks), and whether the performance of the tasks requires cognitive or manual skills. Second, we estimate the shares of the five task categories for each of the 427 four-digit occupations.

Our routine indexes have a number of advantages as compared to existing measures. First, to create the indexes we employ the whole set of 3,264 occupation-specific tasks provided by ISCO-08, and in this way we work around the issue of selectively choosing from too many potential task scales, as discussed by Acemoglu and Autor (2011). Second, our task measures are based on ISCO-08, which is an international classification system that is used by many countries worldwide (including the EU member states). O*NET and DOT, on the other side, use the US SOC occupational classification system, which has a different coding and hierarchical structure. This essentially means that routine measures that are based on O*NET and DOT cannot be directly applied to countries outside the US, without using a crosswalk between the SOC and the classification system of the foreign country in question. Our routine indexes, on the contrary, can be directly linked to many European data sources[1] and can be used to explore the impact of computerization on the labor markets in Europe. Third, the majority of existing task measures (e.g. Autor, Levy and Murnane, 2003, Acemoglu and Autor, 2011, Spitz-Oener, 2006) are constructed on the basis of a limited set of commonplace variables (variables that are not specific to any occupation), while our indexes are developed on the basis of occupation-specific data, which enables us to capture the routine content of occupations more precisely. One exception is the paper of Dengler, Matthes and Paulus (2014) who employ a set of occupation-specific requirements to create task content measures for 334 German occupations. However, the latter measures are specific to German occupations and are also aggregated at the level of three-digit occupations. Last but not least, to our knowledge, this is the first study to simultaneously compare the newly developed task measures with three previous studies (Acemoglu and Autor, 2011; Frey and Osborne, 2017 and Dengler, Matthes and Paulus, 2014) and analyze the similarities and differences between the four studies' indexes.

The rest of the paper is organized as follows. Chapter 2 provides an overview of occupational and survey-based data sources that are commonly used to create task content measures. It shows examples of how researchers utilize the databases to generate task indexes. Chapter 3 presents the International Standard Classification of Occupations 2008, which is our data source. Chapter 4 describes the classification process in which we assign 3,264 occupation-specific tasks into five task categories – non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual. The chapter extensively discusses the possibility of misclassifying tasks and the potential implications of such misclassifications. Chapter 5 outlines the empirical methodology for calculating the five task measures. The empirical results are presented in Chapter 6. In line with expectations, we find that analytic and interactive tasks are most prevalent in the work of Managers and Professionals, routine

[1] In 2009 the European Commission issued a recommendation to the European Union member states to "develop, produce and disseminate statistics […] using the International Standard Classification of Occupations of 2008" (European Commission, 2009, p. 31). Today, ISCO-08 is the standard classification used in the European Labor Force Survey.

cognitive tasks are typically performed by Clerical Support Workers, and routine manual and non-routine tasks are largely concentrated in the work of Plant and Machine Operators and Assemblers and Elementary Occupations, respectively. In Chapter 7 we compare our routine indexes with Acemoglu and Autor (2011), Frey and Osborne (2017) and Dengler, Matthes and Paulus (2014). To this end, we convert their indexes to four-digit ISCO-08 occupations. In Chapter 8, inspired by Frey and Osborne (2017), we provide a back of the envelope estimation of the number of occupations that might be at risk of automation. We find that approximately 16 percent of the 427 ISCO-08 occupations are comprised of 70 percent or more routine tasks, and therefore they fall into the high risk of automation category, as defined by Frey and Osborne (2017). Finally, Chapter 9 concludes and provides a discussion of the strengths and limitation of the present analysis.

2 Literature review

This chapter provides a brief overview of five data sources that are commonly used by researchers to extract information about the routine content of occupations. The chapter describes each data source in turn and gives examples of how researchers utilize the data sources to create task indexes. The focus here is thus on the databases and the task indexes (the way they are created), and not so much on the results and conclusions of the discussed papers. Later, in Chapter 7 we compare our task indexes with three of the papers reviewed in this chapter[2], and provide an in-depth discussion of the similarities and differences between the different studies' indexes.

2.1 The Dictionary of Occupational Titles (DOT)

The Dictionary of Occupational Titles (DOT) and its successor, the Occupational Information Network (O*NET), are the two primary data sources when it comes to occupational information. The DOT was developed in the 1930's by the US Employment Service – its first edition was published in 1939, and since then the database has been updated four times, with the last update in 1991 (Autor, Levy and Murnane, 2003). The DOT provides occupation-specific information on more than 12,000 detailed occupational tiles, which are evaluated by occupational analysts "along 44 objective and subjective dimensions, including training times, physical demands and required worker aptitudes, temperaments, and interests" (Autor, Levy and Murnane, 2003, p. 1293)[3].

In the context of the task-based approach, Autor, Levy and Murnane (2003) were the first to demonstrate the usefulness of the database to create routine task measures for occupations. Using data from the Fourth Edition (1977) and the Revised Fourth Edition

[2] We compare our indexes with Acemoglu and Autor (2011), Frey and Osborne (2017) and Dengler, Matthes and Paulus (2014).

[3] Additional information about the Dictionary of Occupational Titles can be obtained from the following online sources - https://occupationalinfo.org/ and http://www.govtusa.com/dot/

(1991) of the DOT, Autor, Levy and Murnane construct five variables measuring non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks. To this end, the authors select a set of five relevant DOT variables, which are thought to approximate the five task categories. To capture non-routine analytic tasks, they select the DOT variable GED-MATH. GED-MATH stands for General Educational Development in Mathematics, and measures the level of quantitative requirements necessary for satisfactory job performance. High levels of GED-MATH are associated with high quantitative requirements and serve as a proxy for non-routine analytic tasks. Non-routine interactive tasks are approximated by the DOT variable DCP, which stands for Direction, Control, and Planning of Activities. DCP is defined as the "adaptability to accepting responsibility for the direction, control, or planning of an activity" (p. 1323). Analogously to GED-MATH, high scores for DCP are associated with high intensity of using interactive and communication tasks. Routine tasks are approximated by two variables, STS and FINGDEX. The first variable stands for Set Limits, Tolerances, or Standards and measures the adaptability to work situations requiring setting of limits, tolerances or standards. STS is meant to capture routine cognitive tasks. The second variable stands for Finger Dexterity, which is defined as the ability to move fingers and manipulate small objects with fingers, and measures routine manual tasks. Finally, non-routine manual tasks are captured by the variable EYEHAND, which measures the ability to coordinately move hand and foot in accordance with visual stimuli.

The seminal paper of Autor, Levy and Murnane (2003) has resulted in a revived interest in the DOT database and the widespread use of the five routine measures in empirical research. The five indexes, as developed by Autor, Levy and Murnane, have been used among others to study employment and wage polarization (Autor and Dorn, 2013; Goos and Manning, 2007; Goos, Manning and Salomons, 2014), wage inequality (Autor, Katz and Kearney, 2008), task specialization (Peri and Sparber, 2008), etc.

A major drawback of DOT, and consequently of the five routine indexes, is that the database is no longer updated. The last edition of DOT dates back to 1991, which means that the DOT ratings reflect the occupational and workplace requirements back in 1991, and not those at present. This limitation is overcome by the Occupational Information Network (O*NET).

2.2 The Occupational Information Network (O*NET)

In 1998 the US Department of Labor replaced the DOT database by O*NET, and since then O*NET has been the US primary source of occupational information. O*NET is a comprehensive online database, which provides ratings and descriptive information for hundreds of standardized and occupation-specific variables for more than 900 US occupations (see O*NET OnLine)[4]. The information in the database is organized around six

[4] The database can be accessed at https://www.onetcenter.org/overview.html (last accessed in November 2018).

domains and includes worker characteristics, worker requirements, experience requirements, occupational requirements, workforce characteristics, and occupation-specific information. For each occupation, the database provides a rich set of variables related to these domains. Furthermore, the database is updated every quarter, which assures that the information in the database reflects the latest occupational and workplace requirements.

Similarly to its predecessor, the DOT, O*NET has been widely used by researchers to construct measures of occupational routine task intensity. To our knowledge, Acemoglu and Autor (2011) and Goos, Manning and Salomons (2010) were among the pioneers who utilized the O*NET database to create such measures. Based on data from the 14.0 Release of O*NET, Acemoglu and Autor develop five measures of non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks. To create these measures, they utilize a set of sixteen O*NET variables, including eight work activity, six work context and two work ability variables. They construct the measure of non-routine analytic tasks as a sum of the importance scales of three variables - Analyzing Data or Information, Thinking Creatively, and Interpreting the Meaning of Information for Others. Analytic tasks are assumed to be positively related to these variables, and therefore the importance ratings of these variables are used as a proxy for non-routine analytic tasks. The interactive task measure is constructed again as a sum of the importance scales of three variables - Establishing and Maintaining Interpersonal Relationships, Guiding, Directing, and Motivating Subordinates, and Coaching and Developing Others. The importance ratings of these variables are expected to capture the importance of interactive tasks in occupations. Routine cognitive tasks are defined as a sum of the importance scales of three variables – Importance of Repeating Same Tasks, Importance of Being Exact or Accurate, and Structured v. Unstructured work (reverse). The routine cognitive index is positively related to the importance of repeating the same tasks, the importance of being exact and accurate, and to the extent of performing structured work. The index measuring routine manual tasks is defined as a sum of the importance ratings of three variables - Pace Determined by Speed of Equipment, Controlling Machines and Processes, and Spend Time Making Repetitive Motions. Finally, the non-routine manual tasks are constructed on the basis of four variables - Operating Vehicles, Mechanized Devices, or Equipment, Spend Time Using Your Hands to Handle, Control, or Feel Objects, Tools, or Controls, Manual Dexterity, and Spatial Orientation. Again, the non-routine manual task measure is computed as a sum of the importance ratings of these four variables. The five routine indexes developed by Acemoglu and Autor (2011) are used among others by Autor and Handel (2013).

As Acemoglu and Autor (2011) point out, a drawback of both databases, the DOT and O*NET, is that they contain “numerous potential task scales, and it is rarely obvious which measure (if any) best represents a given task construct” (Acemoglu and Autor, 2011, p. 1078). The “O*NET’s large set of loosely defined and weakly differentiated scales present challenges for researchers” (Acemoglu and Autor, 2011, p. 1079) and leaves room for researchers' discretion which scales to "pick and choose among the plethora of scales available" (Autor, 2013, p. 15).

The abundance of scales and the absence of a standard agreed-upon definition of the five task measures have led to a countless number of tasks operationalizations. A Google search on keywords like "O*NET, routine, non-routine tasks" shows that there are nearly as many different tasks operationalizations based on O*NET data, as there are papers. Different studies choose different sets of O*NET variables to approximate for the same five task categories. In that sense, the task indexes of Acemoglu and Autor are just one example of how researchers utilize the O*NET database to construct routine intensity measures[5].

Another paper that utilizes O*NET data, albeit in a different fashion, and is worth mentioning here because of its innovative approach, is Frey and Osborne (2017). The paper of Frey and Osborne (2017) is probably one of the most cited and debated works studying the impact of computerization on the labor market. Using a novelty approach, the paper estimates the probability of computerization of 702 US occupations, and ranks occupations accordingly. The novelty of their approach is that (i) it is forward-looking, in the sense that the paper describes technological developments that are yet to be implemented on a broader scale, and assesses the impact of these developments on the labor market, and (ii) computerization is no longer confined to routine tasks only, as is the case in canonical model of Autor, Levy and Murnane, but it spreads to every domain of routine and non-routine tasks alike.

To estimate the probability of computerization the authors proceed as follows. During a workshop held at the Oxford University Engineering Sciences Department, Frey and Osborne, together with a group of machine learning experts, assessed the possibility of automation of 70 O*NET occupations, and subjectively hand-labeled them as either automatable or non-automatable. The 70 occupations are evaluated based on the occupation-specific tasks descriptions provided by O*NET. Eyeballing the tasks descriptions, the researchers assign each occupation a value of 1 (automatable) or 0 (non-automatable), whereas as automatable are considered only those occupations whose full list of tasks are thought to be potentially automatable, conditional upon the availability of state-of-the-art technology and big data. This exercise provides the authors with what they call a "training dataset" for their algorithm. In a second step, Frey and Osborne select a set of nine commonplace O*NET variables, which, in their opinion, represent bottlenecks to computerizations and are therefore informative about the potential of occupations to be computerized. The selected nine variables are related to perception and manipulation,

[5] Goos, Manning and Salomons (2010), for example, identify 96 O*NET variables and based on them develop three measures of abstract, routine and service tasks. However, in the published version of their paper (Goos, Manning and Salomons, 2014), they replaced the three indexes by a single routine-intensity measure based on Autor, Levy and Murnane (2003).

creative intelligence and social intelligence[6]. Equipped with a "training dataset" consisting of 70 occupations hand-labeled as either automatable or non-automatable, and a set of nine commonplace variables, Frey and Osborne allow their algorithm to learn about the features of automatable and non-automatable jobs, and make predictions for the rest of occupations that are not included in the "training dataset". The trained algorithm eventually estimates the probability of computerization of 702 occupations as a function of the nine O*NET variables. Frey and Osborne's approach combines both subjective judgment (hand-labeling of occupations as automatable or non-automatable) and objective evaluation of the automation potential of occupations.

2.3 BERUFENET – German Occupational Database

BERUFENET[7] is an occupational online database that is comparable to the US databases DOT and O*NET. BERUFENET is provided by the German Federal Employment Agency and contains detailed up-to-date information on all occupations known in Germany (Dengler, Matthes and Paulus, 2014). The database covers more than 4,200 single occupations (Janser, 2018)[8], which are coded at the eight-digit level according to the German Classification of Occupations 2010. For each occupation BERUFENET provides descriptions of the required training, knowledge, skills, and other professional and personal requirements that are necessary to perform the work in that occupation. The information in BERUFENET is primary used by career counselors and job placement officials for the purposes of career guidance and job placement (Janser, 2018).

Dengler, Matthes and Paulus (2014) is the first study, to our knowledge, to operationalize the occupational descriptions in BERUFENET in the context of the task-based approach. Using information from three subsequent years (2011, 2012 and 2013), the authors construct five task indexes measuring the shares of non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks in occupations. To create the measures, Dengler, Matthes and Paulus utilize an extensive set of core requirements that are reported for each occupation. There are about 6,500 core requirements in the year 2011 and 6,700 in 2013, and these requirements are linked to about 3,900 single occupations. The authors classify each of the 6,700 core requirements to one or more of the five routine groups. The five task indexes are calculated by dividing the number of core requirements in each task category by the total number of tasks requirements in a given occupation. The five indexes are consequently aggregated from the eight-digit level (about 3,900 occupations) to the two and three-digit level, which results in 334 three-digit occupations when coded to the German Classification of Occupations in

[6] The nine variables are Finger Dexterity, Manual Dexterity, Cramped Work Space, Originality, Fine Arts, Social Perceptiveness, Negotiation, Persuasion, and Assisting and Caring for Others.

[7] https://berufenet.arbeitsagentur.de/

[8] The number of occupations in BERUFENET increased from 3,926 in 2012 to 4,251 in 2016 (see Janser, 2018, Table 5, p. 31).

1988, and 144 three-digit occupations when coded to the German Classification of Occupations in 2010.

The five indexes of Dengler, Matthes and Paulus serve as an alternative to the task measures developed by Autor, Levy and Murnane (2003) for the US, and reflect the German task content of occupations. The main difference between the routine indexes of Autor, Levy and Murnane, and Acemoglu and Autor, from one side, and those of Dengler, Matthes and Paulus, from the other side, is that the indexes in the latter paper are based on a set of thousands of occupation-specific core requirements, while the indexes in the first two papers are based on a set of five and sixteen, respectively, commonplace variables[9]. In that sense, the paper of Dengler, Matthes and Paulus is close in spirit to the present paper, because both studies employ occupation-specific data to create routine measures.

An advantage of Dengler, Matthes and Paulus' approach, as compared to Autor, Levy and Murnane (2003) and Acemoglu and Autor (2011), is that it employs the whole set of occupation-specific requirements and in this way it works around the challenge of choosing from too many potential task scales, as discussed by Acemoglu and Autor (2011). On the other side, however, the categorization of over 6,700 task requirements into five task types brings another challenge, and this is classification consistency.

2.4 The BIBB/IAB and BIBB/BAuA Employment Surveys

The German Employment Surveys, also referred to as the Qualification and Career Surveys, are a collection of six repeated cross-section surveys conducted in Germany in the years 1979, 1985/86, 1991/92, 1998/99, 2005/06 and 2012 (see Rohrbach-Schmidt, 2009; Rohrbach-Schmidt and Hall, 2013). The surveys target the labor force population in Germany and are held among 20,000 to 35,000 (in different waves) randomly selected individuals. What is unique about these surveys, as compared to other labor force surveys, is that they collect information on, among others, the activities which individuals perform in their jobs. Respondents are asked to indicate whether and how often certain work activities (such as producing goods, purchasing, nursing, cleaning, transporting) occur in their job[10]. The

[9] By commonplace variables we mean here variables which are measured and provide ratings for all occupations in a uniform way. Commonplace variables are the opposite of occupation-specific variables, which provide information that is specific for a given occupation (e.g. "preparing side dishes").

[10] The 2012 wave of the BIBB/BAuA Employment Survey includes the following list of work activities - "Manufacturing, producing goods and commodities", "Measuring, testing, quality control", "Monitoring, control of machines, plants, technical processes", "Repairing, refurbishing", "Purchasing, procuring, selling", "Transporting, storing, shipping", "Advertising, marketing, public relations", "Organizing, planning and preparing work processes", "Developing, researching, constructing", "Training, Instructing, teaching, educating", "Gathering information, investigating, documenting", "Providing advice and information", "Entertaining, accommodating, preparing food", "Nursing, caring, healing", "Protecting, guarding, patrolling, directing traffic", "Working with

number of activities varies between 121 in the 1979 wave of the survey, and 20 in the last wave of the survey in 2012. Furthermore, the surveys provide detailed information about respondents' education, qualifications, employment history, and workplace characteristics.

In the context of the task-based approach, Spitz-Oener (2006) was the first to operationalize the work activity items included in the surveys. Using data from the first four editions of the survey, Spitz-Oener constructs five task content measures for each worker in the surveys, and employs these measures to examine how the task content of occupations has changed in West Germany between 1979 and 1999, and how these changes have been affected by technology. To this end, she distinguishes between five routine categories, as defined by Autor, Levy and Murnane (2003), and assigns the surveyed work activities to one of these categories. Spitz-Oener classifies as non-routine analytic tasks, activities such as "researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, and using and interpreting rules" (p. 243). To the group of non-routine interactive tasks, she assigns activities such as "negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel" (p. 243). As routine cognitive tasks, Spitz-Oener classifies activities such as "calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature" (p. 243). Finally, the groups of routine manual and non-routine manual tasks include, respectively, activities such as "operating or controlling machines and equipping machines" and "repairing or renovating houses/apartments/machines/vehicles, restoring art/monuments, and serving or accommodating" (p. 243).

Based on the above classification, Spitz-Oener calculates five task intensity scores for each worker in the surveys. The five scores are computed by dividing the number of work activities in each routine category performed by worker *i* by the total number of work activities in each of the five routine categories.

The operationalization of the work activities items in the surveys by Spitz-Oener has opened up new research avenues for studying the demand for tasks and skills at individual level using German survey task data. This has given the literature in this field a new boost and has resulted in many subsequent papers utilizing the German Employment Surveys to study, among many others, wage inequality (Dustmann, Ludsteck and Schonberg, 2009; Antonczyk et al 2009), occupational mobility and wages (Gathmann and Schonberg, 2010) and other related topics.

2.5 Survey of Adult Skills (PIAAC)

computers", "Using the Internet or editing e-mails", "Cleaning, removing waste, recycling" (Rohrbach-Schmidt and Hall, 2013, p. 26).

The Survey of Adult Skills (PIAAC) is a large scale multi-country survey carried out in over 40 countries worldwide. The survey is an initiative of the Organization of Economic Co-operation and Development and is conducted as part of the Programme for the International Assessment of Adult Competencies[11]. The survey has two main elements – a direct assessment module and a background questionnaire. The direct assessment module assesses the competences of respondents in the domains literacy, numeracy and problem solving in technology rich environments. The background questionnaire collects standard information on the background characteristics of respondents, educational attainment, participation in learning activities, labor force status and job characteristics (OECD, 2016). The background questionnaire contains furthermore detailed information about the activities which respondents perform at work[12] and in everyday life.

One advantage of PIAAC over the German Employment Surveys, and other comparable single-country surveys, is that PIAAC collects data for a large number of countries in a synchronized way, which makes cross-country analyses and comparisons possible. The multi-country element, in combination with the available information on work activities, makes PIAAC a valuable data source.

Similar to O*NET, the PIAAC data have been used by researchers in many different ways to construct routine intensity measures. One example is Marcolin, Miroudot and Squicciarini (2016). Based on PIAAC data the authors construct an index measuring the routine content of occupations for 20 OECD countries. The routine index is calculated as a linear function of four PIAAC variables measuring the frequency of planning own activities, the frequency of organizing own work, the extent of choosing or changing the sequence of own tasks, and the extent of choosing or changing the way of doing own work. The composite index increases in its four components (low frequency and low extent are coded to take on high values), and is highest for Elementary Occupations and lowest for high-skilled occupations such as Managers and Professionals. One limitation of Marcolin, Miroudot and Squicciarini's (2016) routine measure is that it is based on four ad-hoc variables. The index is furthermore negatively correlated with the skill-level of occupations, which may suggest that it does not purely measures the routine content of occupations, but may partially captures the skill-level of occupations as well.

[11] The PIAAC survey can be accessed at http://www.oecd.org/skills/piaac/aboutpiaac.htm (accessed on December 7, 2018).

[12] Examples of work-related activities included in PIAAC are "instructing, training or teaching people, individually or in
groups", "making speeches or giving presentations in front of five or more people", "selling a product or selling a service", "advising people", "planning the activities of others", "persuading or influencing people", "read articles in professional journals or scholarly publications", "write reports", "fill in forms", etc. (see PIAAC, 2010, p. 79-91).

The five databases discussed in this chapter are the most widely used data sources in the task-based approach literature, containing information about the task content of occupations.

3 International Standard Classification of Occupations 2008

This chapter describes the International Standard Classification of Occupations 2008 (ISCO-08) on the basis of which we create five measures of the task content of occupations.

3.1 Structure and content of ISCO-08

The International Standard Classification of Occupations 2008 is a four-level hierarchical system for classifying jobs worldwide into 436 unit groups, 130 minor groups, 43 sub-major groups and 10 major groups (ILO, 2012a)[13]. Jobs are aggregated to unit groups based on the skill level and specialization required for performing these jobs. ISCO-08 distinguishes between four skill levels, depending on the tasks and duties that are carried out in jobs. Jobs with similar tasks are classified in the same unit group and one job is assigned to one unit group only. The 436 unit groups are commonly referred to as four-digit occupations, because they are designated by a four-digit code and a title. They represent the finest level of disaggregation available in ISCO-08.

Table 1 shows an example of the hierarchical structure of the group Managers. The occupations in this group are organized at four different levels of aggregation. Legislators (code 1111), Senior Government Officials (code 1112), Traditional Chiefs and Heads of Villages (code 1113) and Senior Officials and Special-Interest Organizations (code 1114) form the unit groups in the structure, and together they make up the minor group Legislators and Senior Officials (code 111). The two minor groups Legislators and Senior Officials (code 111) and Managing Directors and Chief Executives (code 112) aggregate to the sub-major group of Chief Executives, Senior Officials and Legislators (code 11).

The minor group Managing Directors and Chief Executives (code 112), on the other side, is made up of a single unit group, resulting in the same minor and unit groups. Finally, the four sub-major groups Chief Executives, Senior Officials and Legislators (code 11), Administrative and Commercial Managers (code 12), Production and Specialized Services Managers (code 13) and Hospitality, Retail and Other Services Managers (code 14) form the major group Managers (code 1), which is one of the 10 major groups in ISCO-08 and has the highest level of aggregation.

[13] The official ISCO-08 website can be accessed at http://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm (last accessed on February 23, 2017 at 13:05 p.m.).

Table 1: Example of the hierarchical structure of ISCO-08

1 MANAGERS	
11 Chief Executives, Senior Officials and Legislators	
111 Legislators and Senior Officials	
	1111 Legislators
	1112 Senior Government Officials
	1113 Traditional Chiefs and Heads of Villages
	1114 Senior Officials and Special-Interest Organizations
112 Managing Directors and Chief Executives	
	1120 Managing Directors and Chief Executives
12 Administrative and Commercial Managers	
13 Production and Specialized Services Managers	
14 Hospitality, Retail and Other Services Managers	

Source: ILO (2012a, p. 72).

The focus of the current analysis are the four-digit unit groups. For each unit group in the hierarchical structure, ISCO-08 provides a description of the tasks and duties associated with that group and gives examples of occupations that are assigned to the group. Table 2 shows an example for Legislators (code 1111). The unit group Legislators includes occupations such as City councilor, Government minister, Mayor, Member of Parliament, President, Secretary of state, Senator, State governor and other similar (in terms of skill level and specialization) occupations. Because the hierarchical structure goes down to the level of four-digit unit groups, there is no further information in ISCO-08 about the tasks and duties of city councilors, ministers, mayors, presidents, senators, etc. In that sense, the tasks of Legislators (listed in Table 2) are common for all occupations included in this unit group.

There are eight specific tasks associated with the work of Legislators and these include - presiding over legislative bodies, determining policies, making laws and rules, serving on administrative boards, investigating matters of concern to the public, attending community meetings, negotiating with other legislators and representatives of interest groups, and directing senior administrators and officials of government departments and agencies. The unit group tasks, as the ones listed in Table 2, are the main building blocks of this analysis – based on them we construct measures of the routine task content of occupations.

Table 2: Unit group Legislators – definition and tasks

1111 Legislators
Legislators determine, formulate and direct policies of national, state, regional or local governments and international governmental agencies, and make, ratify, amend or repeal laws, public rules and regulations. They include elected and non-elected members of parliaments, councils and governments.
Tasks:
▪ presiding over or participating in the proceedings of legislative bodies and administrative councils of national, state, regional or local governments or legislative assemblies ▪ determining, formulating and directing policies of national, state, regional or local governments ▪ making, ratifying, amending or repealing laws, public rules and regulations within a statutory or constitutional framework ▪ serving on government administrative boards or official committees ▪ investigating matters of concern to the public and promoting the interests of the constituencies which they represent ▪ attending community functions and meetings to provide service to the community, understand public opinion and provide information on government plans ▪ negotiating with other legislators and representatives of interest groups in order to reconcile differing interests, and to create policies and agreements ▪ as members of the government, directing senior administrators and officials of government departments and agencies in the interpretation and implementation of government policies
Examples of occupations classified in this unit group:
▪ City councilor; Government minister; Mayor; Member of parliament; President (government); Secretary of state; Senator; State governor

Source: ILO (2012b, p.5)

There are in total 3,264 tasks included in ISCO-08 and these are spread over 427 four-digit occupations. For five so-called 'not-elsewhere-classified' unit groups there are no tasks specified, because their tasks reflect a bulk of tasks in residual occupations[14]. There are no tasks specified also for three military occupational unit groups, because they perform specific military tasks or tasks similar to civilian occupations[15]. The remaining 427 occupations and the associated 3,264 tasks cover the whole range of four-digit occupations and form the basis of the current analysis. The number of tasks varies between 2 and 14 in different occupations with an average of 7.6. Craft and Related Workers Not Elsewhere Classified (code 7549) is the only occupation with 2 tasks, while Sign writers, Decorative

[14] The five occupations are Services Managers Not Elsewhere Classified (1439), Process Control Technicians Not Elsewhere Classified (3139), Sales Workers Not Elsewhere Classified (5249), Handicraft Workers Not Elsewhere Classified (7319) and Stationary Plant and Machine Operators Not Elsewhere Classified (8189).

[15] The three military occupations are Commissioned Armed Forces Officers (0110), Non-commissioned Armed Forces Officers (0210) and Armed Forces Occupations, Other Ranks (0310).

Painters, Engravers and Etchers (code 7316) and Handicraft Workers in Textile, Leather and Related Materials (code 7318) are the only two occupations with 14 tasks.

4 Classifying tasks into five routine categories

The 3,264 tasks are used to develop five measures of the routine task content of occupations. To construct these measures, first, we specify five routine domains and assign each occupational task to one or more of these domains.

4.1 Classification principles

Similar to Spitz-Oener (2006) we distinguish between non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks. In our classification of tasks we follow Spitz-Oener (2006) as closely as possible. One challenge of our approach, however, as compared to Spitz-Oener, is the large number of tasks. The 3,264 unit group tasks cover a wide variety of activities that goes far beyond the list of activities included in the classification of Spitz-Oener. To categorize tasks in a consistent way we adopted a three-step procedure to differentiate between the five task types.

In a first step we start by asking the question of whether a certain task can be automated and replaced by any kind of computer technology – e.g. a computer software, industrial production machinery, smart surveillance system, autonomous robotic equipment, etc. If the answer to this question is yes, then we categorize the activity as routine, and otherwise as non-routine. Examples of routine activities are preparing medicines, writing business correspondence, making hotel reservations, translating written works, sorting and filing documents, record keeping, compiling inventories, preparing bills and invoices, sorting mail, counting and packing produce, machine operation, etc. These and other similar activities can be accomplished by following explicit procedures on how to perform the work, and these procedures are readily programmable. As the programmability of tasks can change over time, similar to Dengler, Matthes and Paulus (2014), we judge this question against the current state of technology and what is feasible today. Driving, for example, is a programmable task which is likely to be replaced by autonomous self-driving cars in the near future, however, currently this task is exclusively done by humans, and therefore we classify driving as non-routine. In that sense, according to our definition non-routine tasks are those tasks that cannot be replaced by machines at present – e.g. housekeeping, hair-styling, entertaining, analyzing, designing, teaching, dancing, driving a truck, operating a crane, performing a surgery, etc.

In a second step we proceed by asking whether the task in question requires cognitive or manual skills. Depending on the answer we categorize tasks as routine cognitive and routine manual, and non-routine cognitive and non-routine manual, respectively. The group of routine cognitive tasks covers activities such as - record keeping, formatting correspondence, entering data into databases, ordering stores, preparing tax returns, maintaining databases, dealing with incoming calls and messages, arranging appointments and property transfers, making hotel reservations, translating written works, filing documents, compiling inventories, counting and recording money, changing money and other similar cognitive activities that can be accomplished by following a set of well-defined programmable rules and procedures. Tasks are classified as routine manual when they involve activities such as operating industrial machinery and equipment, fabricating standardized products (e.g. carpets, cigars, mattresses, clothes, bread, sausages), assembling prefabricated parts and components, sorting and storing produce, sorting mail, mixing ingredients, operating automatic car-wash facilities, etc. The group of non-routine manual tasks includes activities such as building, repairing, cleaning, hair-styling, patrolling, directing traffic, dancing, performing acrobatics and tricks of illusion, crafts (making jewelry from precious metals, baskets from rattan, handmade confectionary), driving, flying aircraft, navigating vessels, painting, etc. Non-routine manual tasks are bad candidates for automation, because they require situational, visional and other specific skills that cannot be easily described (yet) with programmed rules and procedures.

Finally, the non-routine cognitive tasks are subdivided into non-routine analytic and non-routine interactive, depending on whether analytic or interactive skills are required for the competent performance of the task. We classify tasks as non-routine analytic when they involve activities such as researching, analyzing, evaluating, planning, developing, designing, establishing, investing, overseeing, managing, examining patients, performing surgery and other similar activities that require non-programmable analytic skills. As non-routine interactive we classify tasks such as advising, organizing, teaching, supervising, coordinating, negotiating, directing, leading, liaising, entertaining, acting, singing, promoting, marketing, pleading in courts of law, preaching, representing, recruiting employees, reading news on radio and television, commanding vessels and other similar activities that require interactive and communication skills.

Following the above procedure, we classify the 3,264 tasks into one or more routine domains. Table 3 illustrates the assignment of tasks to the five categories.

Table 3: Assignment of tasks to five routine categories

Task groups	Work activities
NRA	Researching, analyzing, evaluating, forecasting, developing, designing, determining, studying, overseeing, planning, managing, investing, monitoring and controlling (firms' strategies, policies, operations), examining patients, providing medical treatment and care (including surgery and dentistry treatments), prescribing medications and assistive devices, reading and interpreting (data, information, technical drawings), using advanced software, drawing up agreements, creating (art, designs, music), applying knowledge, establishing (objectives, budgets, rules, procedures, standards), reviewing (programs, policies, work of subordinates), administering (programs, medications, anesthetics, medical diagnostic tests), evaluating staff, taking photographs to illustrate stories
NRI	Advising, consulting, recommending, organizing, teaching, training, supervising, coordinating, negotiating, directing, leading, liaising, collaborating, entertaining, acting, singing, playing musical instruments, promoting, marketing, purchasing, buying, selling, pleading in courts of law, preaching, conducting religious services, interviewing, obtaining information, interpreting simultaneously from one language into another, establishing contacts, representing individuals or organizations, recruitment, reading news on radio and television, commanding vessels
RC	Controlling balance sheets, preparing bills and receiving payments, operating cash registers, operating systems and networks (including operating computerized control systems from a central control room), operating laboratory and office computer equipment, testing, inspection and quality control, making hotel reservations, reading work orders, recording and processing information, reviewing records and documents for accuracy and completeness, scanning, photocopying and faxing documents, secretarial works, storing records and documents, keeping records, proofreading documents, filing, taking inventory, ordering materials and supplies, using standard accounting software, calculating (totals, averages, interest, brokerage charges, payable duties, dimensions), verifying accuracy of data, documents and records, correcting data, discarding inferior products, installing computer software and hardware, translating written works from one language into another, signing documents and contracts, compiling inventories, documents and records, approving or rejecting loan applications, maintaining databases, records and journal subscriptions, writing business correspondence, preparing medicines, sorting documents for filing, counting and recording money, changing money from one currency to another, dealing with incoming calls and messages, arranging appointments, arranging property transfers, formatting correspondence, entering data into databases, ordering stores, preparing tax returns
RM	Setting up, monitoring and operating stationary machinery and equipment (such as metal processing, chemical, photographic, rubber, plastic, paper, food, textile, fur, leather, wood and other industrial machinery and equipment, including drilling equipment in mines), controlling process start-up and shut-down, making standardized products (carpets, cigars, mattresses, tools, clothes, utensils, bread, sausages), assembling prefabricated parts and components, sorting and storing produce, sorting mail, filling and labeling containers, knitting garments, mixing (ingredients, chemicals, foodstuffs), processing of agricultural produce, cleaning and sorting and packing fish and seafood, cutting (fabric, insulation material, metal pieces), operating automatic car-wash facilities

Table 3: (continued)

Task groups	Work activities
NRM	Making involving craft and handwork (making jewelry from precious metals, musical instruments from wood and leather, baskets from rattan, handmade confectionary, carpentry, making articles according to individual requirements), patternmaking, operating non-stationary machines and mobile equipment (cranes, lifting trucks, excavating machines, machines for digging trenches, machines for hammering piles into ground, ski-lifts), driving, flying aircraft, navigating vessels, painting (buildings, objects, free-hand designs), restoring paintings and art objects, cooking, serving food, welcoming guests and clients, taking orders for food and drinks, cleaning, hair styling, patrolling, security checks, guarding, protecting, directing traffic, dancing, performing acrobatics, performing tricks of illusion, sports (conducting sports, training and participating in sporting events), posing and modeling work, repairing (machines, buildings, equipment, clothes), caring for elderly or small children, performing therapeutic procedures (applying manual technics), providing personal care and assistance (including limited in scope medical care with a manual focus, or care following treatment plans established by health professionals), administering manual treatments (such as massage therapy and first aid), building care-takers, installing machinery and equipment (manual focus), sorting tools and materials used by other workers, growing animals and plants (cultivating pastures, preparing soils, sowing, planting, tending and harvesting field crops, raising, feeding and tending animals), slaughtering animals

Note: NRA, NRI, RC, RM and NRM stand for non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks, respectively.

Classification of tasks containing multiple activities

For the purposes of our classification, ideally, each task should be narrowly specified and cover only one activity. In reality, however, there are some tasks in ISCO-08 that are broadly specified and contain several activities at the same time. This has implications for our classification, because different activities within a given task could be related to different routine domains. Consider for example the task “designing, installing, maintaining, servicing and repairing electric and hydraulic passenger and freight lifts, escalators, moving walkways and other lift equipment” (ILO, 2012b, p. 465)[16]. The workers performing this task engage into several distinct activities, ranging from designing to servicing and repairing. To reflect on the variety of activities included in this and other similar tasks, differently from Spitz-Oener, we allow single tasks to be classified into more than one routine group. In the above

[16] Unless otherwise stated, all quotes of tasks and occupational descriptions are from ILO (2012b). In order not to overload the text with this reference, from now on we will include only the page numbers after the quotes, without referring to ILO (2012b).

example, we classify the task as non-routine analytic (designing) and non-routine manual (installing, maintaining, servicing, repairing) at the same time[17].

Approximately 13 percent of the tasks in our data (that is 419 tasks) include activities associated with more than one task type. The biggest share of these tasks (254 tasks) is classified simultaneously as non-routine analytic and non-routine interactive. Tasks such as “planning, supervising and coordinating”, “planning, developing and organizing”, “developing and coordinating”, “conducting research and advising”, “advising on and designing” contain both analytic (planning, designing, developing, conducting research) and interactive elements (coordinating, supervising, organizing, advising), and are therefore classified as non-routine analytic and non-routine interactive. Unsurprisingly, most of these tasks are found in the occupations of Managers and Professionals.

In the second and third place are the groups of tasks which are simultaneously classified as non-routine interactive and routine cognitive (39 tasks), and non-routine analytic and routine cognitive (32 tasks), respectively. Examples of such tasks are “preparing tax returns, advising on taxation problems and contesting disputed claims before tax officials” (p.129), “maintaining production archives and negotiating royalties” (p.178), “ordering ships’ stores, recruiting crew as required and maintaining records of operations” (p.211) and “planning and developing recipes and menus, estimating food and labour costs, and ordering food supplies” (p.281). These tasks involve analytic (planning, developing, estimating costs), interactive (advising, contesting, negotiating, recruiting) and routine cognitive activities (preparing tax returns, maintaining archives, ordering stores, maintaining records) and are assigned simultaneously to two routine categories, respectively. These results might suggest that analytic and interactive activities are often bundled together in one task. They are also frequently bundled with routine cognitive activities in one task.

The rest of the 419 tasks that are simultaneously classified into two groups is distributed as follows - 24 tasks are assigned to the categories non-routine interactive and non-routine manual, 23 to the categories non-routine analytic and non-routine manual, 22 to the categories routine manual and non-routine manual, 17 to the categories routine cognitive and non-routine manual, 6 to the categories routine cognitive and routine manual, 1 to the categories non-routine analytic and routine manual, and 1 to the categories non-routine interactive and routine manual.

[17] Dengler, Matthes and Paulus (2014) apply a similar approach, where single occupational requirements are assigned to more than one routine group – for example, they assign the requirement “mountain forest (care, management)” to the non-routine manual and non-routine analytic groups. Antonczyk, Fitzenberger and Leuschner (2009), on the other side, categorize tasks to one routine group only - for example, they assign the task “transporting, stocking, posting” to the routine manual group, even though the task involves three separate activities, and transporting is generally considered as non-routine manual.

Tasks that contain multiple activities from the same routine category are assigned only once to that category. Consider for example the tasks "researching, designing, and developing", "studying, improving and developing" and "analysing, developing, interpreting and evaluating". Each of these tasks includes several analytic activities (such as researching, designing, developing), and therefore we classify the tasks as non-routine analytic. In doing so, we ignore how many analytic activities each task contains. We give equal weights to each task irrespective of whether the task in question involves many (e.g. researching, designing and developing) or few (e.g. researching) analytic activities.

In sum, we classify single tasks into multiple task groups when the tasks contain activities associated with different task groups. Tasks that contain several activities from a certain task type are treated in the same way as tasks containing only a single activity from this task type.

Classification of seemingly similar tasks

One challenge of our approach is related to the classification of similar activities that require different skills, or have different potential for automation. The large diversity of work activities and numerous work contexts where these activities take place makes it impossible to apply a one-size-fits-all categorization of tasks where "examining" is always considered as non-routine analytic, and "sorting" as routine manual. We consider and classify tasks on a case-by-case basis taking into account the whole work context, and not only single keywords like "examining" or "sorting". For our approach it is equally important what has been examined and what has been sorted, rather than focusing solely on keywords like "examining" or "sorting". This is a plausible strategy in our view, because not every examining task requires the same skill level, and not all sorting tasks are replaceable by machines.

For example, the task examining could have different meanings in different contexts and occupations. For Agricultural and Industrial Machinery Mechanics and Repairers, examining is a physical activity and involves "examining parts for defects such as breakage and excessive wear" (p. 445). For Optometrists and Ophthalmic Opticians, on the other side, examining is a complex analytical activity that involves "examining patients' eyes […] to assess ocular health and determine the nature and extent of vision problems and abnormalities" (p. 107). To reflect on the different complexity level and skills that are necessary to perform both examining tasks, we classify the first task as non-routine manual and the second as non-routine analytic. Moreover, examining is not necessarily a non-routine activity. For example, "examining logs and rough lumber to determine size, condition, quality and other characteristics to decide best lumber cuts to carry out, or operating automated equipment to convey logs through laser scanners which determine the most productive and profitable cutting patterns" (p. 524) is classified as routine manual, because, as the above task description suggest, the whole activity can be replaced by automated equipment and laser scanners which can decide on best lumber cuts. In this case examining is a programmable task.

Other examples of activities that are classified differently in different work contexts are the tasks sorting and machine operation. We classify sorting as routine manual when the task can be replaced by machines – e.g. mail sorting, produce sorting - and non-routine manual when sorting requires optical recognition, situational adaptability and other skills that cannot be automated using machines – e.g. "sorting […] tools, materials and supplies used by other mine workers" (p. 565). The same applies for the tasks involving machine operation. Machine operation is classified differently depending on the type of machines that are being operated and the possibility for machine operation to be automated. Here we distinguish between operating stationary, mobile and office machines and equipment and categorize them, respectively, as routine manual, non-routine manual and routine cognitive[18].

In sum, when assigning tasks to the five routine categories we judge on a case-by-case basis whether the tasks are replaceable by machines, and whether cognitive or manual skills are required for performing the tasks. This could lead in some cases to different categorization of seemingly similar activities such as "sorting produce" and "sorting […] tools, materials and supplies used by other mine workers" (p. 565).

4.2 Misclassification of tasks

The large variety of work activities and the subtle differences between some of the activities make our classification prone to errors. There are three potential types of errors that might occur. The first type would be present if we assign routine tasks to the wrong group of routine tasks – for example, assigning a "true" routine manual task to the group of routine cognitive tasks. The second type of error would be present if we classify non-routine tasks to the wrong group of non-routine tasks – for example, classifying a "true" non-routine analytic task to the groups of non-routine interactive or non-routine manual. And the third type of error would occur when we wrongly assign a routine task to one of the non-routine groups,

[18] Maintaining and controlling are yet another example of activities that are categorized differently depending on the context where the activities take place. For example, we assign the tasks "maintaining discipline and good working habits in the classroom" (2341-Primary School Teachers) to the group of non-routine interactive, "maintaining and repairing existing structures" (7111-House Builders) to the group of non-routine manual, and "maintaining journal subscriptions" (4411-Library Clerks) to the group of routine cognitive. Similarly, we classify as non-routine analytic tasks activities such as "controlling administrative operations such as budget planning, report preparations, and expenditure on supplies, equipment and services" (1342-Health Services Managers) and "controlling the preparation of production records and reports" (1321-Manufacturing Managers), and we classify as non-routine manual tasks activities such as "controlling access to establishments, monitoring and authorizing the entrance or departure of employees and visitors, checking identification and issuing security passes" (5414-Security Guards) and "controlling and extinguishing fires using manual and power equipment and firefighting chemicals" (5411-Firefighters). See ILO (2012b, p. 117, 414, 321, 34, 26, 380, 377).

and vice versa – for example, assigning a "true" routine cognitive task to the group of non-routine interactive.

The first type of classification error might be an issue especially for some of the tasks involving machine operation. Machine operation is generally considered as a routine manual task when stationary machines are involved (see Spitz-Oener, 2006; Autor, Levy and Murnane, 2003; Dengler, Matthes and Paulus, 2014). In our classification, however, we make a further distinction between direct machine operation or the operation of single machines, and indirect machine operation where several machines or processing units are operated through computer terminals located in central control rooms. We classify the tasks involving direct machine operation as routine manual[19], and the tasks involving indirect machine operation through control panels and computer terminals as routine cognitive[20]. The question here is whether such a differentiation is justified. If not, that would mean that we wrongly classify routine manual tasks as routine cognitive.

The division between direct and indirect machine operation is justified in our view, because the operation of machines from distance (through control panels and computer terminals in central control rooms) requires different types of skills. The typical manual skills that are characteristic for routine manual tasks, such as physical strength, finger dexterity, work pace set by the speed of machines, etc. are not present here. Analogously, the operation of computerized control panels requires cognitive skills that are not characteristic for routine manual tasks. A closer look at the occupations performing direct and indirect machine operation tasks shows a striking division – direct machine operation is mainly performed by occupations in sub-major group 81 Stationary Plant and Machine Operators, and the indirect machine operation is exclusively performed by occupations in minor group 313 Process

[19] Examples of tasks that we classify as routine manual are "operating and monitoring machines for tearing woollen rags into fibre" (8151-Fibre Preparing, Spinning and Winding Machine Operators), "operating and monitoring machines which mark patterns and cut shoe parts" (8156-Shoemaking and Related Machine Operators), "operating and monitoring papermaking and finishing process machinery and equipment to dry, calender, laminate, coat, slit, trim, wind or carry out other papermaking and finishing process steps" (8171-Pulp and Papermaking Plant Operators). See ILO (2012b, p. 512, 517, 523).

[20] Examples of tasks that we classify as routine cognitive are "coordinating and monitoring the operation of a particular aspect of metal processing production through control panels, computer terminals or other control systems, usually from a central control room" (3135-Metal Production Process Controllers), "operating electronic or computerized control panels from a central control room to monitor and optimize physical and chemical processes for several processing units" (3133-Chemical Processing Plant Controllers), "operating and monitoring computerized control systems, machinery and related equipment in wastewater treatment, sewage treatment, and liquid waste plants to regulate flow, treatment and disposal of sewage and wastes, and in water filtration and treatment plants to regulate the treatment and distribution of water for human consumption and for later disposal into natural water systems" (3132-Incinerator and Water Treatment Plant Operators). See ILO (2012b, p. 203, 201, 200).

Control Technicians. Considering also that both occupational groups require different skill levels[21], we believe it is plausible to assume that indirect machine operation is a cognitive type of task.

Of course, classification error of the first type is not limited to machine operation tasks only. There might be other routine tasks that are classified to the wrong routine group. At the end of this section we will discuss the actions we take to address classification error of this type.

The second type of classification error concerns non-routine tasks that are assigned to the wrong category of non-routine tasks. This type of error might be especially relevant for some of the health care tasks. The vast majority of tasks performed by medical doctors, paramedical practitioners, nurses, health care assistants and other health care personnel are classified as non-routine. At one extreme are the high-skill tasks performed by medical doctors and health professionals. These include activities such as examining patients, diagnosing diseases, treating patients, performing surgery, providing dental treatments, etc. These and other activities of this type require extensive medical knowledge and advanced analytic skills, and are therefore straightforward to classify. We classify them as non-routine analytic. At the other extreme are the low-skill tasks performed by health care assistants and health care support staff. These include activities such as providing personal and therapeutic care and support to patients, assisting patients with mobility, maintaining patients' environmental and personal hygiene, cleaning and sterilizing instruments and medical supplies, etc. These tasks are generally limited in complexity, require manual skills, and are also straightforward to classify. We classify them as non-routine manual[22]. The real

[21] The work of Process Control Technicians is associated with Skill Level 3 – "occupations at Skill Level 3 typically involve the performance of complex technical and practical tasks that require an extensive body of factual, technical and procedural knowledge in a specialized field" (ILO, 2012a, p. 13), while the work of Stationary Plant and Machine Operators is associated with Skill Level 2 – "occupations at Skill Level 2 typically involve the performance of tasks such as operating machinery and electronic equipment; driving vehicles; maintenance and repair of electrical and mechanical equipment; and manipulation, ordering and storage of information" (ILO, 2012a, p.12).

[22] Examples of health care tasks that we classify as non-routine manual are "preparing and handling medical instruments and supplies, including sterilizing instruments and disposing of contaminated supplies in accordance with safety procedures" (3256-Medical Assistants), "maintaining cleanliness of patient waiting and examination rooms" (3256-Medical Assistants), "setting up instrument trays, preparing materials, and assisting dentists or radiographers during procedures" (5329-Personal Care Workers in Health Services Not Elsewhere Classified), "providing care, support and treatment to patients and residents of medical, rehabilitative and residential care facilities according to treatment plans established by medical, nursing and other health professionals" (5321-Health Care Assistants), "assisting patients with personal and therapeutic care needs such as personal hygiene, feeding, dressing, physical mobility and exercise, communication, taking oral medications and changing dressings" (5321-Health Care Assistants), "positioning, lifting and turning patients and transporting them in wheelchairs or on movable beds" (5321-Health Care Assistants), "maintaining patients' environmental hygiene standards, such as cleaning patient rooms and changing bed linen" (5321-

challenge, however, are all tasks standing between the two extremes which involve some form of manual labor and at the same time have also an analytic component. These are the error-prone tasks that we are concerned about. Most of these tasks are found in the occupational group of Health Associate Professionals.

When classifying tasks for which a clear-cut assignment (to one of the non-routine groups) is not at hand, we examine whether manual or cognitive skills are predominantly required for the competent performance of the tasks. We classify tasks as non-routine manual when they require manual dexterity and the manual focus in performing the tasks outweighs the analytic component. For example, we consider as non-routine manual tasks activities such as providing massage and point therapy, administering acupuncture and ayurvedic treatments, setting fractured and dislocated bones using traditional methods of physical manipulation, administering electrical modality treatments[23]. We classify these and other similar activities as manual, because in the spectrum of non-routine tasks they stand closer to the manual type of tasks performed by health care assistants than to the analytic tasks performed by medical doctors. On the other hand, we consider as non-routine analytic those tasks that require analytic skills, and where the manual focus in performing the tasks is subordinate to the required analytic skills. Examples of activities that we classify as non-routine analytic are providing or assisting midwifery professionals with delivery care, assisting medical doctors and dentists during complex procedures, administering medications, giving injections[24]. In our view these activities stand closer to the analytic type of tasks performed by medical

---

Health Care Assistants) and “providing massage and other non-pharmacological pain relief measures, such as during pregnancy and labour’ (5321-Health Care Assistants). See ILO (2012b, p. 234, 374, 372).

[23] Examples of tasks that we classify as non-routine manual are “administering manual treatments such as massage therapy or pressure point therapy” (3255-Physiotherapy Technicians and Assistants), “administering electrical modality treatments, ultrasound and other physical therapies using specialized techniques and equipment” (3255-Physiotherapy Technicians and Assistants), “administering treatments such as acupuncture, ayurvedic, homeopathic and herbal medicine according to therapeutic care plans and procedures usually developed by a traditional medicine or other health professional” (3230-Traditional and Complementary Medicine Associate Professionals) and “providing care and treatment for physical injuries such as setting and healing fractured and dislocated bones using traditional methods of physical manipulation and herbal therapies” (3230-Traditional and Complementary Medicine Associate Professionals). See ILO (2012b, p. 233, 224).

[24] Examples of tasks that we classify as non-routine analytic are “providing delivery care, usually only in the absence of identified potential complications, or assisting medical doctors or midwifery professionals with delivery care” (3222-Midwifery Associate Professionals), “assisting dentists during complex dental procedures” (3251-Dental Assistants and Therapists), “assisting medical doctors and other health professionals to examine and treat patients, including measuring and recording vital signs, administering medications and performing routine clinical procedures such as giving injections and removing sutures” (3256-Medical Assistants). See ILO (2012b, p. 223, 229, 234).

professionals than to the manual tasks performed by health care assistants and support staff.

Misclassification of the second type, where non-routine tasks are wrongly classified, is not limited to the analytic and manual task types only. Interactive tasks are potentially at risk of misclassification too, especially in cases where the work activities are at the boundary edge between non-routine interactive and non-routine manual. This type of error could be relevant for some of the tasks of Child Care Workers and Teachers' Aids. For example, we classify as non-routine manual the tasks washing, dressing and feeding children, and as non-routine interactive the tasks entertaining children, managing children's behavior, disciplining children, learning children social skills, assisting children with their studies[25]. The differences between these activities might seem vague at first. However, we classify the first task (assisting children with washing, dressing and feeding) as non-routine manual, because the task is comparable to other caregiving tasks which are generally considered as non-routine manual. Furthermore, the task does not require any cognitive skills that are typical for interactive tasks such as teaching, educating, disciplining, influencing behavior, etc. On the other side, entertaining children by reading and storytelling, managing children's behavior, disciplining children and assisting children with learning social skills are all cognitive tasks targeting children's intellectual development and behavior, and therefore fit into the group of non-routine interactive tasks.

In that line of reasoning, we differentiate also between activities involving caring for animals and activities involving training animals to develop desired behavior for competition, entertainment or other purposes, and categorize them, respectively, as non-routine manual and non-routine interactive[26].

[25] We classify as non-routine manual the task "assisting children to wash, dress and feed themselves" (5311-Child Care Workers), and as non-routine interactive the tasks "playing games with children, or entertaining them by reading or storytelling" (5311-Child Care Workers), "managing children's behaviour and guiding their social development" (5311-Child Care Workers), "disciplining children and recommending or initiating other measures to control behaviour, such as caring for own clothing and picking up toys and books" (5311-Child Care Workers), "assisting children with intellectual, physical, behavioural and other learning difficulties with their studies" (5312-Teachers' Aides) and "assisting children individually to learn social skills" (5312-Teachers' Aides). See ILO (2012b, p. 369, 370).

[26] We classify as non-routine manual the tasks "bathing and feeding animals" (5164-Pet Groomers and Animal Care Workers), "grooming animals by performing tasks such as washing, brushing, clipping and trimming coats, cutting nails and cleaning ears" (5164-Pet Groomers and Animal Care Workers), "grooming, marking, clipping, trimming, drenching and/or castrating animals, and shearing coats to collect hair or wool" (6121-Livestock and Dairy Producers), "raising, feeding and tending animals" (6129-Animal Producers Not Elsewhere Classified), "grooming and marking animals and shearing coats to collect hair or wool" (6320-Subsistence Livestock Farmers), "feeding, watering and cleaning animals and keeping their quarters clean" (9212-Livestock Farm Labourers) and "grooming

Misclassification of the third type would occur when we wrongly classify "true" routine tasks to one of the non-routine groups, and vice versa. This type of classification error is arguably less common, as compared to the previous two types, because it is easier to distinguish between routine and non-routine tasks, rather than between different groups of routine and non-routine. Still, there are certain activities that are at risk of being misclassified. This concerns mainly activities that are commonly referred to as non-routine in the previous literature, but which are potentially (partly) replaceable by machines. Two such examples are the tasks "selling" and "buying". In accordance with the previous literature we classify both activities as non-routine interactive[27]. The question here is whether these tasks are indeed non-routine. Traditionally, selling involves face-to-face interactions between sellers and prospective buyers, in which buyers are informed about specific properties of goods and services and are provided with advice on product varieties, prices and selling conditions. During face-to-face contacts potential customers are convinced to make a purchase or to continue using an offered by the company service. From that perspective, selling is an interactive activity that requires interpersonal and communication skills necessary to inform, advise and persuade customers to buy products and services. On the other side, selling is a programmable task that can be partly automated. Think for example of self-service checkouts in stores, online shopping, vending machines in public places. In all these instances selling is replaced by machines, and could be considered as a routine task.

In reality both types of selling – performed by humans and machines – exist at the same time. Different types of products, markets and customers make selling to a different degree replaceable by machines. For some customers buying a new washing machine is a matter of going on the internet and ordering the product they want, while for others buying is a matter of going to the nearby store where they can receive information and advice, and buy the right product for them. The fact that identical products are simultaneously sold on the internet and in physical stores might suggest that activities like selling and buying are not entirely replaceable by machines. For this reason, in our categorization of tasks we consider selling and buying generally as non-routine interactive activities. Examples of selling tasks that we classify as non-routine interactive are selling technical equipment to businesses, soliciting orders and selling goods to retail, selling various kind of objects by auction, selling goods to customers, selling or bartering products at local markets, selling duty-free and other goods[28]. We assume that in all these and other similar cases selling involves

---

and feeding animals" (9332-Drivers of Animal-drawn Vehicles and Machinery). We classify as non-routine interactive the task "training animals to develop and maintain desired behaviors for competition, entertainment, obedience, security, riding and other activities" (5164-Pet Groomers and Animal Care Workers). See ILO (2012b, p. 347, 390, 393, 407, 558, 572).

[27] Autor, Levy and Murnane (2003, Table 1, p. 1286), Spitz-Oener (2006, Table 1, p. 243) and Antonczyk, Fitzenberger and Leuschner (2009, Table 5, p. 27) classify "selling" as non-routine interactive.

[28] The exact wording of the selling tasks is as follows: "soliciting orders and selling goods to retail, industrial, wholesale and other establishments" (2434-Information and Communications Technology

interpersonal contacts and requires communication skills. One may argue that selling duty-free goods is replaceable by machines and therefore routine, however, this task is performed by Stewards. We assume that buying duty-free and other products on-board of aircrafts and ships cannot be accomplished by other means than in person from the travel steward on duty, and therefore we classify the task as non-routine interactive.

The second group of tasks that might be subject to classification error of the third type are agricultural tasks. Agricultural tasks cover a wide variety of manual activities, some of which we classify as non-routine and others as routine. Similar to Autor, Levy and Murnane (2003)[29], we classify as non-routine manual tasks the activities involving preparing land for sowing, planting, cultivating, harvesting crops, picking fruits and vegetables, controlling weeds, pests and diseases, and as routine manual tasks the activities involving grading, sorting, bunching and packing produce into containers. Differently from Dengler, Matthes and Paulus (2014), we consider cultivation and harvesting as non-routine tasks, because in our view the performance of these tasks requires visual and situational capabilities (which crops to harvest, which fruits and vegetables to pick, and which to leave) that cannot be easily programmed. Moreover, tasks like cultivation and harvesting take place in open fields, which makes them fundamentally different than typical routine manual tasks that generally take place in closed and controlled factory environments.

Finally, misclassification might be an issue also for some of the assembling tasks. In our classification we distinguish between repetitive assembly on assembling lines and non-repetitive assembly and classify them, respectively, as routine and non-routine manual. Examples of routine assembling tasks are assembling prefabricated parts and components,

---

Sales Professionals), "selling technical equipment, supplies and related services to business establishments or individuals" (2434-Information and Communications Technology Sales Professionals), "soliciting orders and selling goods to retail, industrial, wholesale and other establishments" (3322-Commercial Sales Representatives), "selling equipment, supplies and related services to business establishments or individuals" (3322-Commercial Sales Representatives), "negotiating contracts on behalf of seller or buyer and explaining terms of sale and payment to client" (3339-Business Services Agents Not Elsewhere Classified), "selling by auction various kinds of property, cars, commodities, livestock, art, jewellery and other objects" (3339-Business Services Agents Not Elsewhere Classified), "selling or bartering some products at local markets" (6310-Subsistence Crop Farmers), "selling duty-free and other goods" (5111-Travel Attendants and Travel Stewards), "selling goods to customers and advising them on product use" (5221-Shopkeepers). We classify these and other selling tasks as non-routine interactive. See ILO (2012b, p. 141, 247, 255, 405, 329, 355).

[29] Autor, Levy and Murnane (2003) classify "attends to beef cattle on stock ranch" and "prunes and treats ornamental and shade trees" as non-routine, and "packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment" as routine manual (p. 1323). Dengler, Matthes and Paulus (2014) classify cultivation, farming and harvesting to the group of routine manual (Table 4, p. 16).

assembling, aligning and fastening units to subassemblies, assembling instruments and devices, fabricating and assembling thick cloth, canvas and similar materials, etc. These types of assembling tasks are performed according to strictly laid down procedures and are therefore good candidates for automation. On the other side, examples of non-routine assembling tasks are disassembling machinery to make repairs, reassembling engines after repairs, assembling dishes for service, assembling and dismantling mining equipment in mines, assembling carpet, tiles and other materials and laying them on floors according to design and other specifications, etc. These types of assembling tasks require visual recognition and adaptability to unforeseen situations and are therefore difficult to automate.

The distinction between routine and non-routine agricultural and assembling tasks is justified in our view, because different tasks require different skills and involve different activities, some of which are replaceable by technology and others are not.

5 Calculating routine task-intensities

To calculate routine task-intensities we largely follow the procedure of Antonczyk, Fitzenberger and Leuschner (2009), who compute routine indexes by dividing the number of tasks in each task category by the total number of tasks across all categories:

$$(1) \qquad AFLijt = \frac{\text{number of activities in category } j \text{ performed by worker i in cross section t}}{\text{total number of activities performed by worker i over all categories at time t}}$$

Where i, j and t stand for a worker, task category and year, respectively, and AFL indicates the five task indexes in their study.

We adapt Antonczyk, Fitzenberger and Leuschner's equation to take into account that (i) our data are at the occupational level, and (ii) about 13 percent of tasks in our data are assigned simultaneously into two routine groups. The latter means that for some occupations the number of task assignments can be larger than the total number of tasks[30]. To capture this, we replace the total number of tasks in the denominator of equation (1) with the total number of tasks assignments. In this way, the five routine measures will sum up to one for each occupation, and will show the relative importance of each task category for the 427 occupations.

We adjust equation (1) in the following way:

[30] For example, the occupation Legislators has 8 tasks and 2 of them are classified into 2 routine groups, resulting in 8 tasks and 10 tasks assignments.

(2) $$Tjk = \frac{\text{number of tasks in task category } j \text{ in occupation } k}{\text{total number of tasks assignments in occupation } k}$$

Where T is the task content, *j* indicates the five routine categories non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual, and *k* stands for each of the 427 four-digit occupations. The five T_{jk} indexes range between zero and one - whereas a score of zero indicates that there are no tasks classified in category j in occupation k, and a score of one means that all tasks of occupation k are classified into category j.

Consider for example two occupations with the same number of tasks and a different number of tasks assignments - Data Entry Clerks and Pawnbrokers and Money-lenders. Both occupations include 5 tasks each – all 5 tasks of Data Entry Clerks are classified as routine cognitive, whereas 4 of the tasks of Pawnbrokers and Money-lenders are classified as routine cognitive and 1 task is classified as routine cognitive and non-routine analytic at the same time. For Data Entry Clerks the routine cognitive score will be equal to 1 (5 routine cognitive tasks / 5 total task assignments), and for Pawnbrokers and Money-lenders the routine cognitive score will be .83 (5 routine cognitive tasks / 6 total task assignments) and the non-routine analytic score will be .16 (1 non-routine analytic task / 6 total task assignments). Even though both occupations include 5 routine cognitive out of 5 tasks, the share of routine cognitive tasks is different in both occupations, because the workers in the second occupation spend part of their time performing non-routine analytic tasks as well. The two scores reflect the different shares (importance) of routine cognitive tasks in both occupations. If we would replace the total number of task assignments with the total number of tasks in the denominator of (2), we would get the same routine cognitive scores. However, these scores would be less informative about the share (importance) of routine cognitive tasks in both occupations.

As discussed in the previous chapter, there are three types of classification error that potentially may occur. To address misclassification of the first and second type, where routine and non-routine tasks are classified into the wrong group of routine and non-routine tasks, respectively, in equation (2) we combine the five routine indexes into a single measure of routine task-intensity:

(3) $RTI_k = RC_k + RM_k – NRA_k – NRI_k – NRM_k$

Where RTI indicates routine task-intensity of occupation k, and RC, RM, NRA, NRI and NRM stand for the five task categories routine cognitive, routine manual, non-routine analytic, non-routine interactive and non-routine manual, respectively. RTI increases in the use of routine cognitive and manual tasks, and decreases in the use of non-routine analytic, interactive and manual tasks. Aggregation of this type is expected to reduce classification error of the first and second type, because the different routine and non-routine groups enter equation (3) with the same sign, respectively. It is unclear, though, whether and how aggregation would impact on classification error of the third type, where truly routine tasks are classified as non-routine and vice versa.

The RTI index ranges between 1 and -1, whereas 1 indicates that occupation k contains only routine tasks, and -1 indicates that occupation k contains only non-routine tasks.

The aggregated RTI serves as an additional measure showing the routine content of occupations, and is by no means a replacement of its five components. In the next chapter we present results for the six measures.

6 Results

This chapter presents the results. Section 6.1 describes the six task content measures and provides summary statistics related to them. Section 6.2 presents the top 15 occupations with the highest shares of non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks, respectively. Table B1 in the Appendix reports the six task content measures for each of the 427 four-digit occupations.

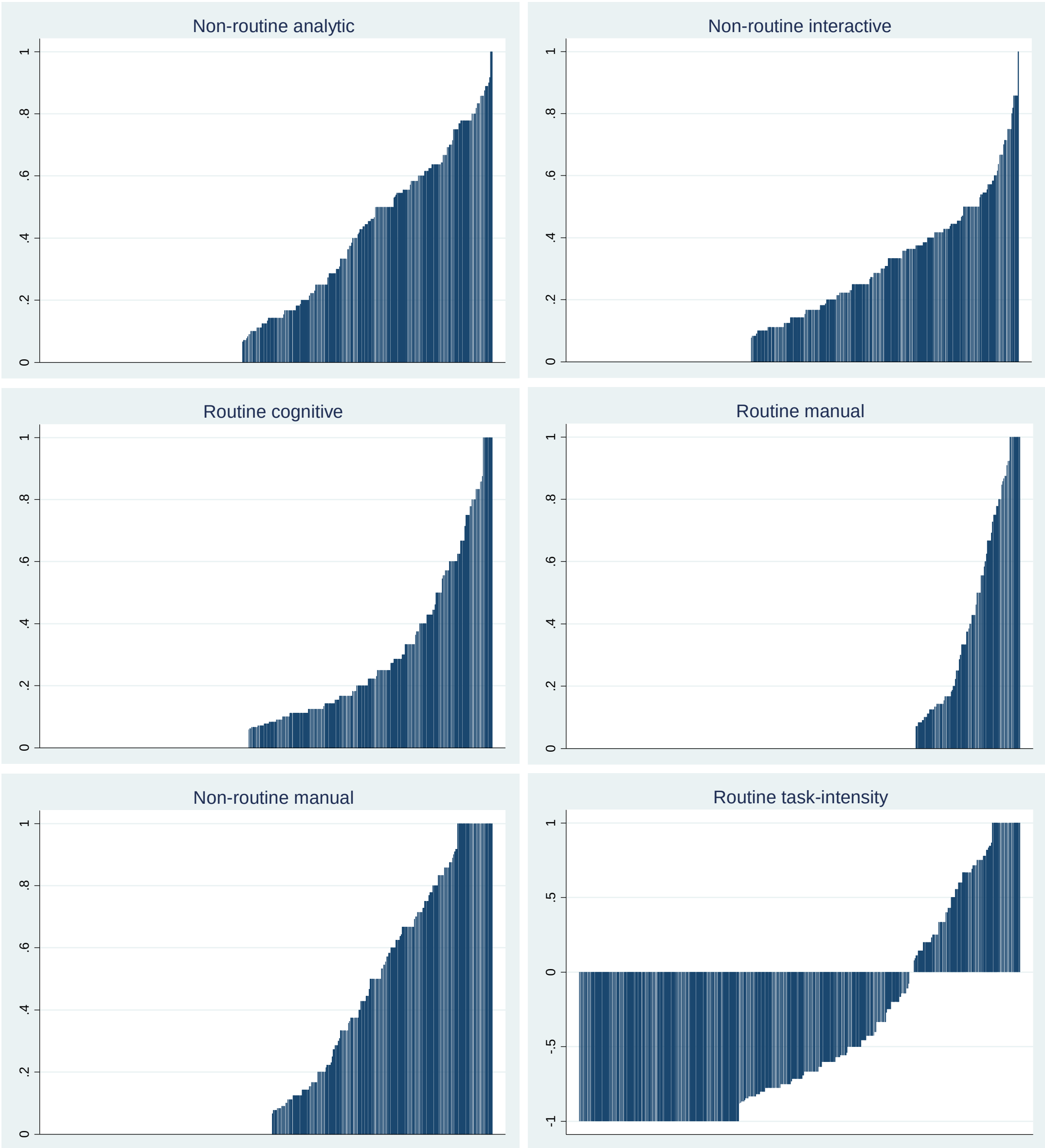
6.1 Distribution of tasks

Figure 1 depicts the global distributions of tasks across occupations - the x-axis plots the 427 occupations (each pile represents one occupation) and the y-axis shows the shares of the five task types per occupation. The y-axis ranges between zero and one, whereas a score of zero indicates that a given occupation does not contain any tasks from a particular task type, and a score of one means that all tasks of that occupation belong to one particular task type. The empty spaces on the left side of the x-axis depict thus the occupations with a zero score on non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks, respectively.

About 43 percent of the occupations (that is 184 occupations) have a zero score on analytic tasks, 39 percent (that is 167 occupations) have a zero score on interactive tasks, 44 percent (that is 190 occupations) have a zero score on routine cognitive tasks, 76 percent (that is 326 occupations) have a zero score on routine manual tasks, and 49 percent (that is 213 occupations) have a zero score on non-routine manual tasks. On the other side of the spectrum, the figure shows that there are occupations which are comprised entirely of tasks belonging to one task type. Two occupations have a score of one on analytic tasks, one occupation on interactive tasks, nine occupations on routine cognitive tasks, ten occupations on routine manual tasks, and 34 occupations on non-routine manual tasks.

Turning to the last panel in Figure 1, the graph illustrates that around 36 percent of the occupations (that is 155 occupations) have a routine task-intensity score of -1, and about 6 percent (that is 27 occupations) have a score of 1, which implies that these occupations contain non-routine and routine tasks only, respectively. Furthermore, the graph shows that the vast majority of occupations have a negative score on routine task-intensity, which indicates that the share of non-routine tasks outweighs the share of routine tasks in these occupations.

Figure 1: Distribution of tasks per four-digit occupation



Note: The figure is based on 427 occupations.

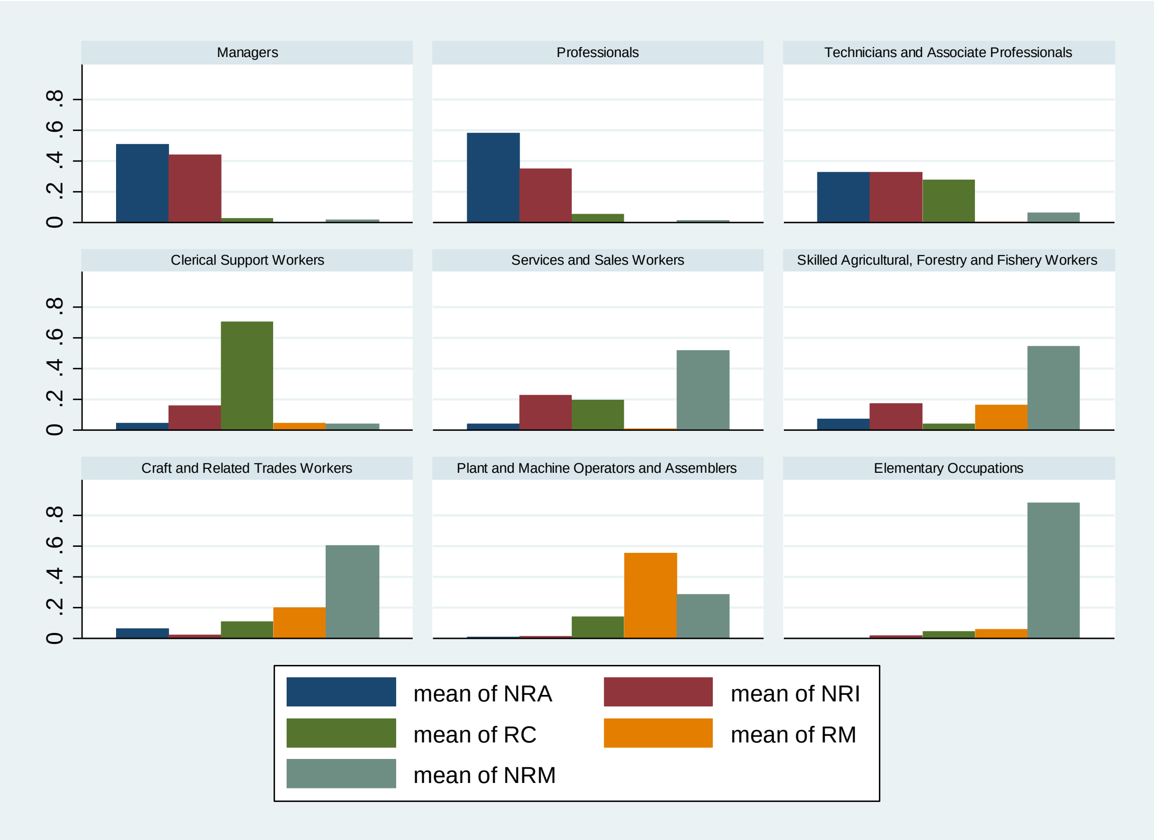
Figure 2 depicts the task composition of the nine major occupational groups[31]. The x-axis shows the five task categories, and the y-axis exhibits the shares of each category for the nine occupational groups. Looking at the first graph, the figure shows that the work of

[31] The major occupational groups are commonly referred to as one-digit occupations, because they are designated by a one-digit code and a name.

Managers is almost entirely comprised of non-routine analytic and interactive tasks – these two categories alone account for over 95 percent of the tasks performed by Managers. About 3 percent of the Managers' work consists of routine cognitive, and 2 percent of non-routine manual tasks[32]. For the group of Professionals, analytic tasks have an even higher importance as these tasks constitute nearly 60 percent of the tasks of Professionals, followed by interactive tasks which account for nearly 35 percent of the tasks. As we move further rightwards in the graph, the task composition changes in favor of routine cognitive tasks. The work of Technicians and Associate Professionals is comprised for over 30 percent of analytic and interactive tasks, and nearly 30 percent of routine cognitive tasks. The latter task category increases further in importance and reaches its highest share of over 70 percent in the group of Clerical Support Workers. The figure documents furthermore a prominent role for non-routine manual tasks in the groups of Service and Sales Workers, Skilled Agricultural, Forestry and Fishery Workers, Craft and Related Trades Workers and Elementary Occupations. Non-routine manual tasks represent the dominant task type in these occupations, and constitute nearly 90 percent of the tasks performed by Elementary Occupations. Finally, routine manual tasks are the dominant task category for the group of Plant and Machine Operators and Assemblers – these tasks constitute more than 55 percent of all tasks in the group. Non-routine manual tasks account for about 29 percent of the tasks of Plant and Machine Operators and Assemblers.

[32] There are only two occupations in the group of Managers with a non-zero score on non-routine manual tasks, and these are Traditional Chiefs and Heads of Villages (1113) and Restaurant Managers (1412).

Figure 2: Task composition of nine major occupations

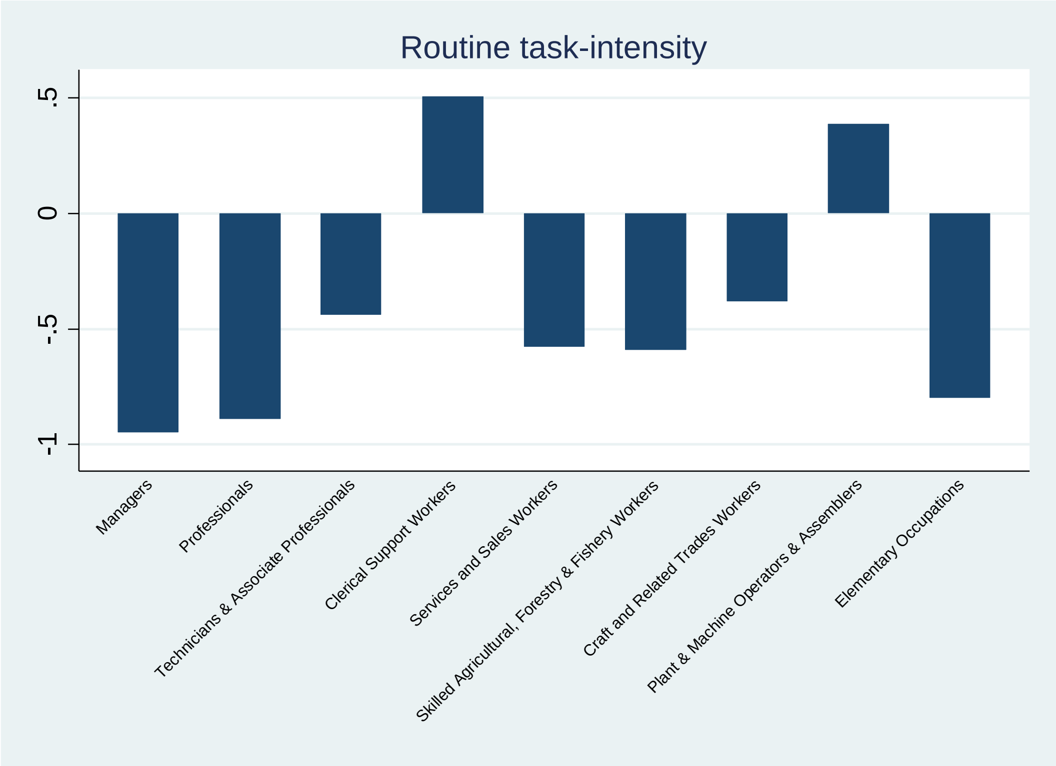


Note: NRA, NRI, RC, RM and NRM stand, respectively, for non-routine analytic, non-routine interactive, routine cognitive and non-routine manual tasks. The 427 four-digit occupations are aggregated to 9 one-digit occupations using employment weights - the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking). The employment weights are described in Appendix A. For comparison reasons, Figure A2 in Appendix A displays the un-weighted version of this graph. The figure is based on 427 occupations.

Figure 3 illustrates the composite routine task-intensity index for the nine major occupations. The RTI score ranges between 1 and -1, whereas a score of 1 (-1) indicates that an occupation is comprised entirely of routine (non-routine) tasks. The figure shows that the share of routine tasks is highest in the occupations Clerical Support Workers and Plant and Machine Operators and Assemblers. Analogously, the occupations Managers, Professionals and Elementary Occupations have the highest share of non-routine tasks among all occupations[33].

[33] It is worth noting that Elementary Occupations have the third lowest routine task-intensity index, after Managers and Professionals. This result confirms that routine intensity, as defined in this analysis, is a different metric than education or skill level. It measures solely the degree of replaceability of human labor by technology and does not say anything about the level of education or skills.

Figure 3: Routine task-intensity score of nine major occupations



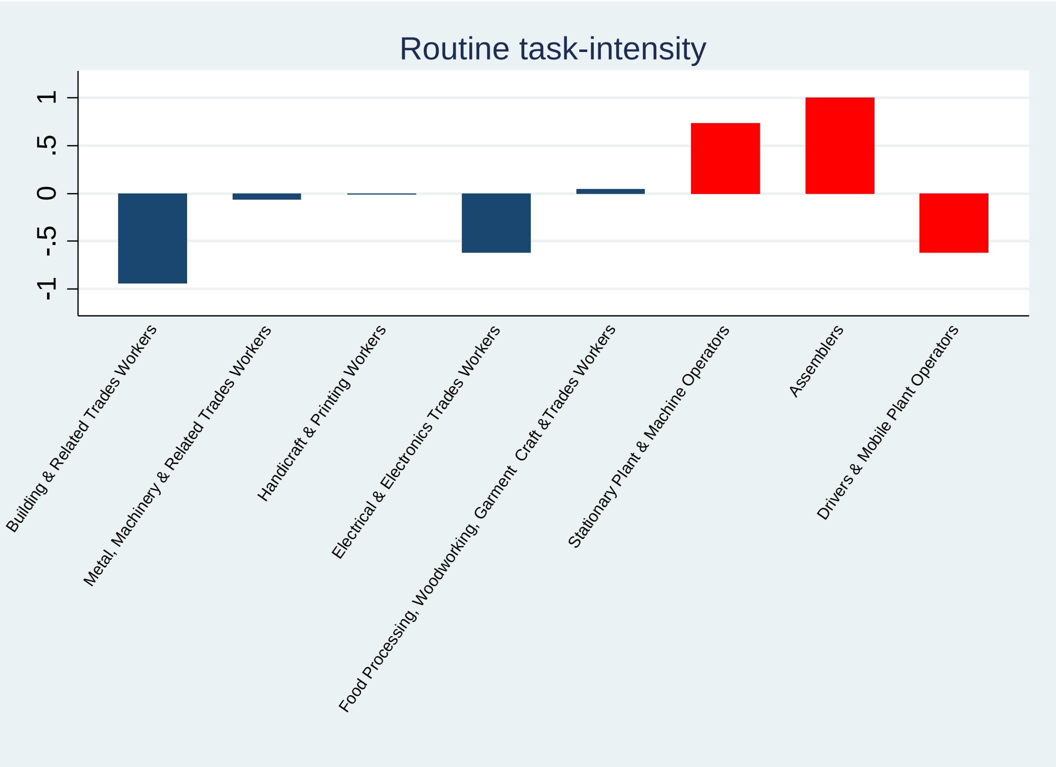
Note: The 427 four-digit occupations are aggregated to 9 one-digit occupations using employment weights - the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking). The employment weights are described in Appendix A. For comparison reasons, Figure A3 in the Appendix A displays the un-weighted version of this graph. The figure is based on 427 observations.

In sum, Figure 2 and 3 show that non-routine analytic and interactive tasks are predominantly performed by Managers, Professionals and Technicians and Associate Professionals, while routine cognitive tasks are typically performed by Clerical Support Workers. Routine manual tasks are largely found in the occupational group of Plant and Machine Operators and Assemblers, and non-routine manual tasks are the most common task type in the group of Elementary Occupations. Overall, these results are consistent with our expectations.

It is important to note that Figure 2 and 3 exhibit the task composition at the level of one-digit major occupations. The high aggregation level, however, could mask possible variations in routine task-intensity within these major groups. Table A1 in the Appendix shows indeed that task variation within the nine major groups can be substantial. Craft and Related Trades Workers and Plant and Machine Operators and Assemblers have the highest variation in routine task-intensity, as measured by the standard deviation coefficient, and Skilled Agricultural, Forestry and Fishery Workers and Managers have the lowest variation.

Figure 4 plots the routine intensity index for eight sub-major occupations, which form the two major groups with the highest RTI variation - Craft and Related Trades Workers and Plant and Machine Operators and Assemblers[34]. The first five bars in the graph (colored in blue) represent the group of Craft and Related Trades Workers, and last three bars (colored in red) represent the group of Plant and Machine Operators and Assemblers. As Figure 4 shows, the RTI index varies substantially within these two major groups.

Figure 4: Routine task-intensity score of eight sub-major occupations which form the major groups of Craft and Related Trades Workers and Plant and Machine Operators and Assemblers.



Note: The four-digit occupations are aggregated to two-digit occupations using employment weights - the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking). The employment weights are described in Appendix A. For comparison reasons, Figure A4 in Appendix A displays the un-weighted version of this graph.

Building and Related Trades Workers have the lowest RTI index within the group of Craft and Related Trades Workers. Around 94 percent of Building and Related Trades Workers' tasks

[34] We selected these two major groups as an example, because they have the highest within group variation in RTI (see Table A1 in the Appendix).

are classified as non-routine[35]. Food Processing and Other Craft and Related Trades Workers, on the other side, have the highest routine task-intensity within this group – their RTI score is just above zero (the exact score is .04). The differences in routine intensity are even more pronounced within the group of Plant and Machine Operators and Assemblers. Within this group, Stationary Plant and Machine Operators and Assemblers are estimated to have a high positive score on routine intensity, whereas Drivers and Mobile Plant Operators are found to have a negative score, which indicates that the work of the latter occupation is comprised mostly of non-routine tasks. Again, this is a logical result considering that we classify (stationary) machine operation and assembly as routine manual tasks, and driving and operation of mobile machines as non-routine manual tasks.

All in all, Figure 4 demonstrates that occupations with a comparable skill level (belonging to the same major group) can have different routine task-intensities, and aggregation can mask differences in routine intensity within occupational groups.

6.2 Routine task content of 427 four-digit occupations[36]

Appendix B reports the five routine indexes and the composite RTI index for 427 four-digit ISCO-08 occupations. Table 4 lists the top 15 occupations with the highest shares of NRA, NRI, RC, RM and NRM tasks, respectively. The first panel (NRA tasks) shows the 15 occupations with the highest scores on analytic tasks, the second panel (NRI tasks) shows the 15 occupations with the highest scores on interactive tasks, and so on. The table provides also the range of the 15 highest indexes in each task category. For example, the 15 occupations with the highest NRA scores have indexes ranging between .83 and 1, the 15 occupations with the highest NRI scores have indexes ranging between .7 and 1, and so on.

Turning to the first panel, the table shows that the highest analytic task content is found in occupations such as Manufacturing managers, Physicists and astronomers, Application programmers, Information technology trainers, Database designers and administrators, Economists, Authors and related writers, Visual artists, Chemists, Sociologists, anthropologists and related professionals, Air traffic safety electronics technicians, Meteorologists, Geologists and geophysicists, Physical and engineering science professionals not elsewhere classified and Telecommunications engineering technicians. Analytic tasks account for more than 83 percent of the tasks performed in these occupations. Two occupations (Physical and engineering and science technicians not elsewhere classified and

[35] This is a logical result when one considers that (the sub-major group of) Building and Related Trades Workers includes mainly non-routine manual occupations such as House Builders, Bricklayers and Related Workers, Stonemasons, Stone cutters, Splitters and Carvers, Concrete Placers, Concrete Finishers and Related Workers, Carpenters and Joiners, Building Structure Cleaners, Roofers, Floor Layers and Tile Setters, Plumbers and Pipe Fitters.

[36] The 427 four-digit occupations represent the most disaggregated level in ISCO-08 for which occupational and tasks descriptions are provided, and hence, routine task indexes can be calculated.

Telecommunications engineering technicians) have an NRA score of 1, which indicates that the work in these occupations is comprised entirely of analytic tasks.

The second panel lists the occupations with the highest interactive and communication task intensity. Occupations such as Legislators, Trade brokers, ICT sales professionals, Actors, Air traffic controllers, Commercial sales representatives, Social work associate professionals, Religious professionals, Insurance representatives, Driving instructors, etc. have the highest NRI score. Interactive tasks constitute 70 percent or more of the tasks in these occupations. Driving instructors is the only occupation with a 100 percent interactive task content, as indicated by the NRI score of 1[37].

The third panel shows the occupations with the highest routine cognitive task content. Routine cognitive tasks account for 83 percent or more of the tasks performed by Pawnbrokers and money-lenders, Contact centre information clerks, Stock clerks, Library clerks, Legal secretaries, Cashiers and ticket clerks, and 100 percent of the tasks performed by Clearing and forwarding agents, Secretaries, Typing and word processing operators, Data entry clerks, Bank tellers and related clerks, Accounting and bookkeeping clerks, Statistical, finance and insurance clerks, Payroll clerks and Filling and copying clerks. This panel includes 16 instead of 15 occupations, because the occupations with the 15^{th} and 16^{th} highest RC index have the same score.

The fourth panel reports the occupations with the highest shares of routine manual tasks. All occupations in this group have a score of .87 or higher on RM tasks, which indicates that routine manual tasks account for at least 87 percent of the tasks performed in these occupations. Among the occupations listed here are Metal finishing, plating and coating machine operators, Sewing machine operators, Fur and leather preparing machine operators, Bleaching, dyeing and fabric cleaning machine operators, Glass and ceramics plant operators, Print finishing and binding workers, Pelt dressers, tanners and fellmongers, Craft and related workers not elsewhere classified, Paper products machine operators, Fibre preparing, spinning and winding machine operators, Shoemaking and related machine operators, Textile, fur and leather products machine operators not elsewhere classified, Food and related products machine operators, Packing, bottling and labelling machine operators and Hand packers. The panel shows furthermore that ten of these occupations (starting from Print finishing and binding workers) have the highest possible score on routine manual tasks, which is 1.

[37] This result may seem contra-intuitive at first, however, it makes sense when one considers that the tasks of Driving Instructors include – “instructing students under actual driving conditions…”, “teaching road traffic regulations”, “teaching road craft and road safety”, “advising students when they are ready to undergo driving examination”, “advising on and teaching advanced driving techniques…” and “illustrating and explaining … driving techniques, using blackboard diagrams and audiovisual aids” (p. 348). All these tasks require communication and interaction skills and are typical examples of non-routine interactive tasks.

Table 4: Top 15 occupations with highest scores in the five task categories

Top 15 occupations intensive in …	
NRA tasks	
Manufacturing managers	NRA score = .83
Physicists and astronomers	
Applications programmers	
Information technology trainers	↓
Database designers and administrators	
Economists	
Authors and related writers	
Visual artists	.87
Chemists	
Sociologists, anthropologists and related professionals	
Air traffic safety electronics technicians	↓
Meteorologists	
Geologists and geophysicists	
Physical and engineering science technicians not elsewhere classified	1
Telecommunications engineering technicians	1
NRI tasks	
Legislators	NRI score = .7
Traditional chiefs and heads of villages	
Trade brokers	
Employment agents and contractors	
Information and communications technology sales professionals	↓
Actors	
Air traffic controllers	
Commercial sales representatives	.75
Social work associate professionals	
Religious professionals	
Community health workers	↓
Insurance representatives	
Conference and event planners	
Religious associate professionals	.85
Driving instructors	1
RC tasks	
Pawnbrokers and money-lenders	RC score = .83
Contact centre information clerks	
Stock clerks	
Library clerks	↓
Legal secretaries	
Personnel clerks	
Cashiers and ticket clerks	.87
Clearing and forwarding agents	1
Secretaries (general)	
Typists and word processing operators	
Data entry clerks	
Bank tellers and related clerks	
Accounting and bookkeeping clerks	
Statistical, finance and insurance clerks	
Payroll clerks	
Filing and copying clerks	1

Table 4: (continued)

Top 15 occupations intensive in …	
RM tasks	
Metal finishing, plating and coating machine operators	RM score = .87
Sewing machine operators	
Fur and leather preparing machine operators	
Bleaching, dyeing and fabric cleaning machine operators	↓
Glass and ceramics plant operators	
Print finishing and binding workers	1
Pelt dressers, tanners and fellmongers	
Craft and related workers not elsewhere classified	
Paper products machine operators	
Fibre preparing, spinning and winding machine operators	
Shoemaking and related machine operators	
Textile, fur and leather products machine operators not elsewhere classified	
Food and related products machine operators	
Packing, bottling and labelling machine operators	
Hand packers	1
NRM tasks	
Fashion and other models	NRM score = 1
Personal care workers in health services not elsewhere classified	
Police officers	
Security guards	
Protective services workers not elsewhere classified	
Bricklayers and related workers	
Concrete placers, concrete finishers and related workers	
Carpenters and joiners	
Building frame and related trades workers not elsewhere classified	
Floor layers and tile setters	
Plasterers	
Painters and related workers	
Spray painters and varnishers	
Building structure cleaners	
Handicraft workers in wood, basketry and related materials	
Mobile farm and forestry plant operators	
Earthmoving and related plant operators	
Crane, hoist and related plant operators	
Ships' deck crews and related workers	
Cleaners and helpers in offices, hotels and other establishments	
Hand launderers and pressers	
Vehicle cleaners	
Window cleaners	
Other cleaning workers	
Forestry labourers	
Mining and quarrying labourers	
Civil engineering labourers	
Building construction labourers	
Shelf fillers	
Kitchen helpers	
Garbage and recycling collectors	
Sweepers and related labourers	

Odd-job persons	
Water and firewood collectors	1

Note: The table shows the range of the 15 highest indexes in each task category. The 15 occupations with the highest NRA score have indexes ranging between .83 and 1. The 15 occupations with the highest NRI score have indexes ranging between .7 and 1, and so on. There are 34 occupations with a score of 1 on NRM tasks - therefore the NRM tasks panel includes 34 instead of 15 occupations with the highest scores. In order not to overload the table with numbers, we report only the range of the indexes. The complete list of routine indexes can be found in Table B1 in the Appendix.

Finally, the last panel in the table shows the occupations with the highest non-routine manual task intensity. There are 34 occupations where non-routine manual tasks are not only the dominant, but also the only task type, as indicated by the score of 1 on NRM tasks. Occupations such as Fashion and other models, Police officers, Security guards, Bricklayers and related workers, Carpenters and jointers, Plasterers, Building structure cleaners, Handicraft workers in wood, basketry and related materials, Crane, hoist and related plant operators, Forestry labourers, Shelf fillers, Kitchen helpers, Garbage and recycling collectors, Odd-job persons, etc. are comprised entirely of non-routine manual tasks.

All in all, these results are in line with expectations.

7 Comparing indexes with previous studies

In this chapter we compare our task indexes with three previous studies – Acemoglu and Autor (2011), Dengler, Matthes and Paulus (2014) and Frey and Osborne (2017). In Section 7.1-7.3 we compare our indexes with each of the three studies in turn, and in Section 7.4 we simultaneously compare all four papers' indexes (including the present study) and discuss the similarities and differences between them.

7.1 Routine indexes Acemoglu and Autor (2011)

To construct task indexes, Acemoglu and Autor (2011, AA afterwards)[38] employ release 14.0 of the O*NET database. In release 14.0 occupations are coded according to the O*NET-SOC 2009 taxonomy (the taxonomy contains 1,102 eight-digit occupations). AA aggregate the O*NET-SOC 2009 occupations to six-digit codes, which results in 801 occupations. Hence, our first task here is to convert the 801 occupations (for which AA construct task measures) to four-digit ISCO-08 codes. Unfortunately, there is no a direct crosswalk between O*NET-

[38] Acemoglu and Autor (2011) and AA are used interchangeably in the rest of the text.

SOC 2009 and ISCO-08, and we have to take several steps to bring AA's codes to ISCO-08 codes[39].

First, we start by converting AA's occupations and routine indexes to six-digit O*NET-SOC 2010 codes. To this end, we employ a crosswalk from O*NET-SOC 2009 to O*NET-SOC 2010[40]. Because this crosswalk links occupations at the eight-digit level, while the task measures of AA are aggregated at six-digit level, first we aggregate the codes in the crosswalk to the six-digit level and then we merge the crosswalk with AA's routine indexes. This step converts Acemoglu and Autor's occupation codes and the associated routine indexes to 6-digit O*NET-SOC 2010 codes. The O*NET-SOC 2010 taxonomy is based on SOC-2010, which means that now we can use a direct crossover between SOC-2010 and ISCO-08.

Second, we transform the six-digit O*NET-SOC 2010 codes to four-digit ISCO-08 codes using a crosswalk from SOC-2010 to ISCO-08, provided by the US Department of Labor[41]. In both conversions (to O*NET-SOC 2010 and ISCO-08) we weight the task indexes using labor supply weights (the weights are included in Acemoglu and Autor's file with task measures and reflect US employment per occupation in the years 2005, 2006 and 2007).

The use of two crosswalks and the aggregation of the task measures to four-digit occupations lead inevitably to some aggregation-related errors in the obtained results. However, to our knowledge, there is no shorter way of converting the task indexes of AA to ISCO occupations. With these limitations in mind we proceed further with the comparison of both data sets.

The original task measures of Acemoglu and Autor are standardized to have a mean of zero and a standard deviation of one, and differently than our measures, do not sum up to one for each occupation. In order to make both sets of indexes comparable, first we standardize all indexes (the converted indexes of Acemoglu and Autor and our indexes) to have a mean of zero and a standard deviation of one.

Table 5 shows the correlations between both sets of task measures. The five correlation coefficients on the diagonal have positive signs and magnitudes ranging from .41 to .70, which indicates a moderate to high positive relationship between both sets of measures. The highest correlation (.70) is documented for analytic tasks and the lowest (.41) for routine cognitive tasks. Routine manual, non-routine manual and non-routine interactive tasks take intermediary positions with correlation coefficients equal to .60, .55 and .48, respectively.

[39] For the purposes of this analysis, we downloaded the task indexes of Acemoglu and Autor ("onet-soc.dta") from David Autor's website (https://economics.mit.edu/faculty/dautor/data/acemoglu) on February 11, 2019 at 12.00 p.m.

[40] The crosswalk is freely accessible at https://www.onetcenter.org/taxonomy/2010/walk.html (last assessed on January 29, 2019).

[41] The crosswalk can be accessed at https://www.bls.gov/soc/soccrosswalks.htm (last assessed on January 29, 2019).

Overall, these results may suggest that both studies are in good agreement on the definition of analytic and routine manual tasks, and in moderate agreement on the definition of routine cognitive tasks. The high correlation for analytic tasks comes as no surprise, because analytic tasks are relatively easy to distinguish from other task types, and apparently both studies manage well to detect this type of tasks. What is puzzling, however, is the relatively low (as compared to other task groups) correlation coefficient for routine cognitive tasks. To found out what a possible cause of this relatively low correlation might be, we dig into the O*NET data used to construct the routine cognitive index of AA.

Acemoglu and Autor define routine cognitive tasks as a standardized sum of three O*NET variables - Importance of repeating the same tasks, Importance of being exact or accurate and Structured v. Unstructured work[42]. According to the O*NET Content Model, these three variables are meant to capture the "relative amounts of routine versus challenging work the worker will perform as part of this job" (O*NET Content Model)[43]. What is not evident from the above quote, however, is what the precise definition of routine is, and how it is related to cognitive tasks. The term routine here is likely to have a broader meaning than our definition of routine (i.e. work that can be replaced by computer-controlled technology), and in our opinion, the three variables are not specifically related to cognitive tasks. Take for example occupation "29-2021.00 - Dental Hygienists". On the question "How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?", 58 percent of respondents answer "extremely important" and 41 percent "very important"[44]. Considering the non-routine (i.e. non-programmable) nature of work of dental hygienists, it is counter-intuitive that 99 percent of respondents answer with extremely or very important[45]. The

---

[42] The three variables are constructed, respectively, from the answers of the following three questions – "How important is repeating the same physical activities (e.g., key entry) or mental activities (e.g., checking entries in a ledger) over and over, without stopping, to performing this job?)", "How important is being very exact or highly accurate in performing this job?" and "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals?" (See Online O*NET Work Content at https://www.onetonline.org/find/descriptor/browse/Work_Context/4.C.3/, last accessed February 14, 2019).

[43] See the O*NET Content Model -> Occupational Requirements -> Work Context -> Structural Job Characteristics -> Routine versus Challenging Work (https://www.onetcenter.org/content.html), last accessed on February 14, 2019.

[44] O*NET OnLine occupation report (https://www.onetonline.org/link/details/29-2021.00), accessed on February 14, 2019.

[45] Similar results are reported also for the occupation "37-2012.00 - Maids and Housekeeping Cleaners". On the question how important is repeating the same activities, 38% of respondents answer "extremely important", 17% "very important" and 37% "not important at all". Again, the majority of respondents (55%) answer with extremely or very important (see O*NET OnLine

same applies for the answers to the second question "How important is being very exact or highly accurate in performing this job?" Fifty-three percent of respondents answer with "extremely important" and 45 percent with "very important". A more mixed picture emerges from the responses to the third question "To what extent is this job structured for the worker, rather than allowing the worker to determine tasks, priorities, and goals? Nineteen percent say they have "a lot of freedom", 60 percent "some freedom" and 21 percent "limited freedom".

Table 5: Correlations between the task measures of Acemoglu and Autor and our task measures

		Acemoglu and Autor (2011) task measures				
		NRA	**NRI**	**RC**	**RM**	**NRM**
Own task measures	**NRA**	**.70**	.38	-.03	-.40	-.38
	NRI	.41	**.48**	-.26	-.57	-.49
	RC	-.14	-.18	**.41**	-.08	-.21
	RM	-.26	-.27	.13	**.60**	.36
	NRM	-.53	-.28	-.22	.37	**.55**

Note: The correlations are weighted by the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking), and are based on 426 four-digit ISCO-08 occupations. The occupation Community Health Workers could not be matched with Acemoglu and Autor's file and was dropped from the analysis. The figure is based on 426 occupations. The employment weights are described in Appendix A.

Taken together, these examples suggest to us that routine cognitive tasks are more broadly defined in Acemoglu and Autor than in our study (possibly capturing some none routine cognitive work elements as well), and this might partly explain the moderate correlation that we find for this type of tasks[46]. Both sets of task measures are further compared in Figure 5.

occupation report at https://www.onetonline.org/link/details/37-2012.00, accessed on February 14, 2019).

[46] Of course, an alternative explanation could be that our routine cognitive measure is poorly defined and this is what causes the moderate correlation. To look into this possibility, at the end of this chapter we simultaneously examine the correlations between all four studies' indexes (Acemoglu and Autor, 2011; Frey and Osborne, 2017; Dengler, Matthes and Paulus, 2014 and the present paper). The size of the correlation coefficients will give an idea of how strongly the different routine

Figure 5 depicts the five routine indexes of AA alongside our indexes for 9 one-digit occupations. AA's indexes are plotted on the left side and our indexes on the right side of the graphs. The ten indexes are standardized to have a mean of zero and an employment weighted standard deviation of one across the sample of 426 occupations. In terms of interpretation, a standard score of one indicates that a particular occupation has one standard deviation higher score than the average for a given task category, and a standard score of -1.5 indicates that it has 1.5 standard deviations lower score than the average. For instance, the occupation Managers has standard scores of roughly 1 for analytic tasks and roughly -1 for routine manual tasks – these results imply that Managers perform relatively more analytic tasks and less routine manual tasks, as compared to the mean.

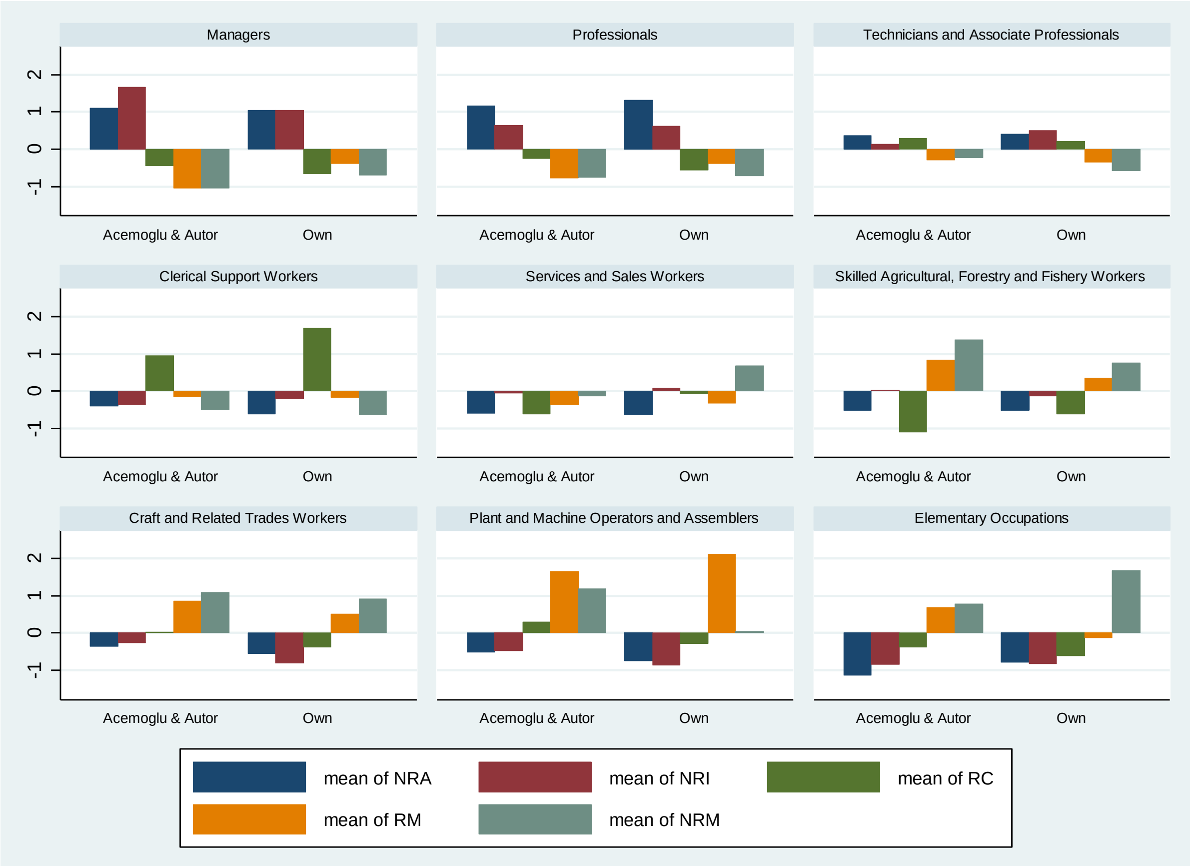
Largely, Figure 5 demonstrates that both sets of indexes exhibit similar patterns across occupations. At the level of tasks, the graph shows that non-routine analytic tasks are most prevalent in the work of Professionals and Managers, and least so in the work of Elementary Occupations (as indicated by the standardized scores for analytic tasks). Interactive tasks are most intensively performed by Managers and Professionals and to a lesser extent by Technicians and Associate Professionals. Routine cognitive tasks are the single most significant task category for Clerical Support Workers, while routine manual tasks are most common in the work of Plant and Machine Operators and Assemblers.

Regarding the differences, we find that non-routine manual tasks are most intensively used by workers in Elementary Occupations, Craft and Related Trades Workers, Skilled Agricultural, Forestry and Fishery Workers and Services and Sales Workers. Acemoglu and Autor's converted indexes, on the other side, illustrate that non-routine manual tasks are mainly concentrated in the work of Skilled Agricultural, Forestry and Fishery Workers, Plant and Machine Operators and Assemblers and Craft and Related Trades Workers – these three occupations have standardized scores that are roughly one standard deviation above the average.

All in all, the correlation matrix in Table 5 and the nine graphs in Figure 5 show that both sets of indexes exhibit strong similarities, in spite of the fact that both studies utilize different methodologies and datasets, and the indexes of Acemoglu and Autor are converted to ISCO-08 codes.

cognitive measures correlate with each others. If our routine cognitive measure is misspecified, then one would expect to find weak correlations with the other studies' indexes.

Figure 5: Task measures comparisons at the level of nine major occupational groups



Note: The graph depicts Acemoglu and Autor's five task measures alongside our five measures for 9 major one-digit occupations. The task indexes are standardized to have a mean of zero and a standard deviation of one (across the 426 occupations) and are aggregated to one-digit occupational level using employment weights – the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking). Each bar shows the mean standard deviation for a particular task measure and occupation. The graph is based on 426 observations (the occupation Community Health Workers could not be matched with Acemoglu and Autor's file and was dropped from the analysis). The employment weights are described in Appendix A.

7.2 Routine indexes Dengler, Matthes and Paulus (2014)

The present analysis is close in spirit to the study of Dengler, Matthes and Paulus (2014, DMP afterwards)[47] – both papers utilize detailed occupation-specific information to construct task intensity measures. DMP calculate task intensities for 334 three-digit occupations (based on the German Classification System in 1988) and 144 three-digit occupations (based on the German Classification System in 2010). In response to our request

[47] Dengler, Matthes and Paulus (2014) and DMP are used interchangeably in the rest of the text.

to provide us with their task indexes at a more disaggregated than the three-digit level, DMP converted their task measures to four-digit ISCO-08 occupations and provided us with the converted data[48]. The converted dataset contains 382 four-digit ISCO-08 occupations, which are ready to be merged with our task measures.

After merging both datasets, 377 occupations remain and form the basis for the comparison of both papers' indexes. The task measures take on values between 0 and 1, whereas a zero score indicates that a given occupation does not contain any tasks from a particular task type, and a score of one means that all tasks belong to a particular task type.

Table 6 shows the correlations between both sets of indexes. The correlation coefficients on the diagonal have positive sings and magnitudes between 0.51 and 0.74. The strongest correlation is reported for the pairs of non-routine manual, routine manual and non-routine analytic tasks, respectively - in these cases the correlation is 0.71 or higher. Routine cognitive tasks take an intermediary position with a correlation coefficient of 0.57, followed by the pair of non-routine interactive tasks, which have the lowest correlation among all tasks measures, even though the size of the correlation coefficient is still substantial (0.51).

Looking at the off-diagonal matrix elements, one surprising result is the negative, albeit small in size, correlation between DMP's interactive and our analytic tasks measures. This is surprising, because, as discussed already in the methodological chapter, analytic and interactive tasks are often bundled together in one occupation, and one would expect to find a (small) positive correlation between both measures[49]. Concerning the rest of the off-diagonal elements, we find that our non-routine analytic and interactive tasks are negatively correlated with DMP's routine cognitive, routine manual and non-routine manual tasks, respectively. Also, we find a small positive correlation for the pair of routine and non-routine manual tasks.

Overall, Table 6 shows that both papers' task measures exhibit strong similarities, as indicated by the high correlation coefficients on the diagonal of the correlation matrix.

[48] We are very grateful to Dr. Katharina Dengler for making the converted to ISCO-08 task measures available to us. For more information about their original three-digit task indexes please see Dengler, Matthes and Paulus (2014) and Dengler and Matthes (2018).

[49] As a reference, the correlation between Acemoglu and Autor's interactive and our analytic task measure is 0.38 (based on 426 occupations), and the correlation between our analytic and interactive measure is 0.21 (based on 427 occupations).

Table 6: Correlations between the task measures of Dengler, Matthes and Paulus (2014) and our task measures

		Dengler, Matthes and Paulus (2014) task indexes				
		NRA	**NRI**	**RC**	**RM**	**NRM**
Own task measures	**NRA**	**.71**	-.08	-.07	-.29	-.38
	NRI	.44	**.51**	-.22	-.36	-.35
	RC	-.15	.14	**.57**	-.17	-.28
	RM	-.32	-.25	-.08	**.73**	.04
	NRM	-.52	-.23	-.22	0.16	**.74**

Note: The correlations are weighted by the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking), and are based on 377 four-digit ISCO-08 occupations. The employment weights are described in Appendix A.

Figure 6 depicts the five indexes for nine major occupations. The indexes sum up to one for each occupation and show the relative importance of the five task types. The task indexes of Dengler, Matthes and Paulus are depicted on the left-hand side and our measures on the right-hand side of the graphs. Overall, the figure shows that according to both studies analytic tasks are the most important task category for the occupations Managers, Professionals and Technicians and Associate Professionals, while routine cognitive and manual tasks are most prevalent in the work of Clerical Support Workers and Plant and Machine Operators and Assemblers, respectively. Both studies' indexes find also that non-routine manual tasks are the dominant task category for Elementary Occupations, Services and Sales Workers and Skilled Agricultural, Forestry and Fishery Workers.

When it comes to the differences, there are several notable differences between both datasets. First, DMP's indexes show that the work of Managers and Technicians and Associate Professionals contains more routine cognitive than interactive tasks, and the work of Professionals contains roughly the same proportions of both task types. Oppositely, we find interactive tasks to have larger shares than routine cognitive tasks in all three occupations[50]. Second, we document a much larger share of routine cognitive tasks than

[50] Looking at the same three occupations, DMP estimate slightly larger shares of analytic tasks than we do, while we estimate much larger shares of interactive tasks than DMP. The latter result can be explained by the different classification of certain tasks in DMP and the present study – for example, DMP assign activities such as supervising, directing and leadership to the group of non-routine analytic tasks, while we assign the same activities to the group of interactive tasks. As a result, the

DMP for Clerical Support Workers, and a larger share of non-routine manual tasks for Elementary Occupations, Craft and Related Trades Workers and Services and Sales Workers.

Figure 6: Task measures comparisons at the level of nine major occupational groups

Note: The graph depicts Dengler, Matthes and Paulus' five task measures alongside our five measures for 9 major one-digit occupations. The task measures are aggregated from 377 four-digit to 9 one-digit occupations using employment weights – the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking). The five measures sum up to 1 for each occupation. The graph is based on 377 observations. The employment weights are described in Appendix A.

Taken together, the large correlation coefficients on the diagonal in Table 6 and the nine graphs in Figure 6 demonstrate that both sets of task indexes are largely comparable.

estimates of DMP show a 0 percent interactive task content for occupations such as Senior government officials and Aged care services managers, while our estimates show more than 50 percent interactive tasks content for these occupations. Also, Office supervisors are found to have about 2 percent interactive tasks according to DMP's measures, and about 55 percent according to our measures.

7.3 Probability of computerization Frey and Osborne (2017)

Frey and Osborne (2017, FO afterwards)[51] estimate the probability of computerization for 702 six-digit SOC-2010 occupations. In order to compare results, first, we downloaded the probability of computerization index from the appendix table of FO. Second, we converted the probability index to ISCO-08 occupations using a crosswalk between SOC-2010 and ISCO-08. To aggregate the index from six-digit SOC-2010 to four-digit ISCO-08 codes we used occupational employment weights from the Occupational Employment Survey (OES) in May 2017. The weights measure total US employment at the level of six-digit SOC-2010 occupations (excluding self-employment). Finally, we merged the converted probability of computerization index with our task measures, which resulted in 393 occupation matches based on ISCO-08.

Before proceeding further with the analysis of both papers' measures, it is essential to know what kind of information the measures are carrying. FO estimate the probability of computerization for 702 occupations – that is, the likelihood that occupations are being fully automated in the next decades. The estimated probability rests on the assumption that both routine and non-routine tasks can be replaced by computer-controlled equipment, conditional on the availability of big data. As such, the probability of computerization index does not say anything about the task content of occupations. Our task measures, on the other side, provide information about the intensity of using different types of routine and non-routine tasks by occupations. They do not further say anything about how likely it is for occupations to be computerized. The task content of occupations is thus a different measure than the probability of computerization. At the same time, both variables are not completely unrelated. From a theoretical point a view, all else equal, highly routine-intensive occupations will have higher chances of being computerized than non-routine intensive occupation (assuming that routine tasks are generally easier to computerize than non-routine tasks). Therefore, we expect to find a positive relationship between the routine task content and the probability of computerization of occupations.

Figure 7 plots the probability of computerization index (afterwards PCI) together with our RTI measure[52]. The converted to ISCO-08 PCI ranges between .0039 and .99 and RTI spreads between -1 and 1. For the purposes of Figure 7, we rescaled both indexes to take on values between 0 and 1, whereas a 0 score indicates that an occupation has a 0 probability of computerization and contains 0 percent routine tasks, respectively, while a score of 1 means a 100 percent probability of computerization and a 100 percent routine task content.

[51] Frey and Osborne (2017) and FO are used interchangeably in the rest of the text.

[52] We choose to compare RTI, instead of its five components NRA, NRI, RC, RM and NRM, because RTI combines information from the five measures in a single index, and this makes the comparison with Frey and Osborne' index more straightforward. At the end of this chapter, we present results showing the relationship between PCI and NRA, NRI, RC, RM and NRM.

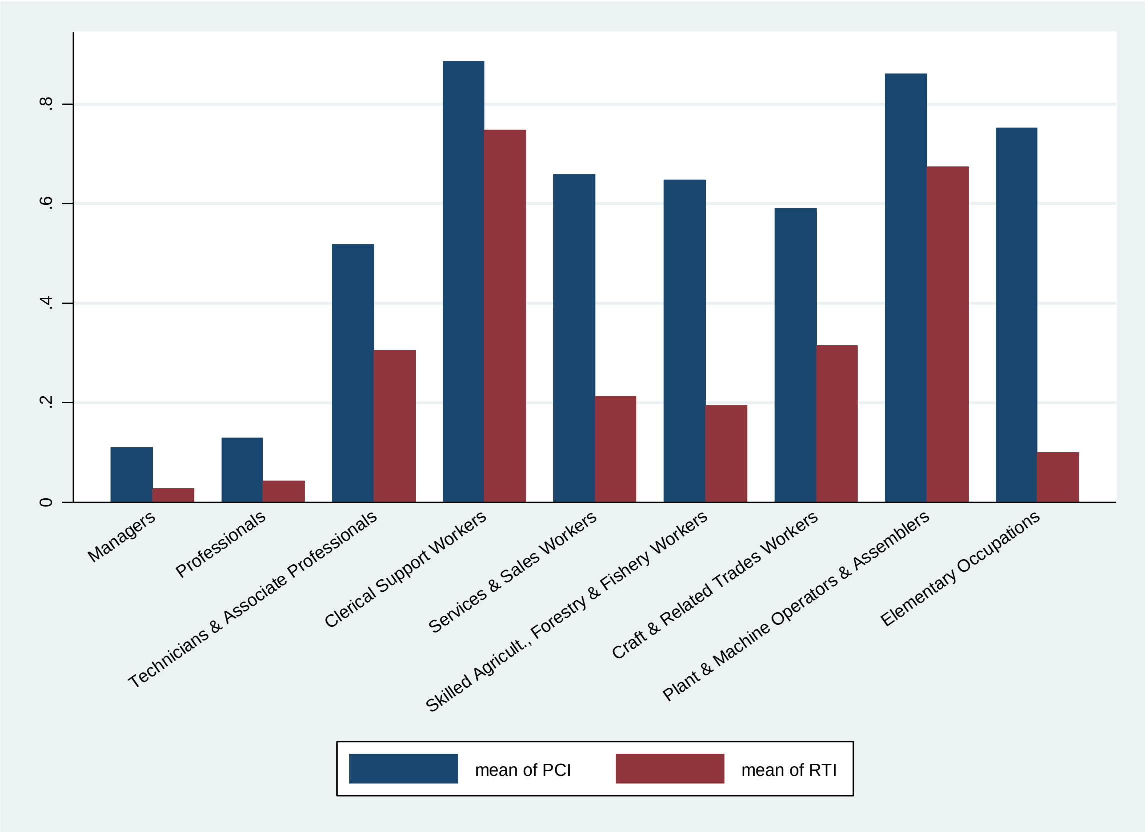
Overall, Figure 7 shows that PCI and RTI exhibit very similar patterns for the occupational groups Managers, Professionals, Clerical Support Workers and Plant and Machine Operators and Assemblers. The first two occupations are characterized by low routine task content and low probability of computerization, while the last two are found to have high routine intensity and high probability of computerization. For these four occupations CPI and RTI seem to go hand in hand. On the other side, the figure shows substantial differences between both indexes for Elementary Occupations, Services and Sales Workers and Skilled Agricultural, Forestry and Fishery Workers. Take for example the occupation Elementary Occupations which has the largest difference between PCI and RTI. This occupation has the third lowest routine task-intensity (approximately 10 percent of the tasks are classified as routine) and, at the same time, the third highest probability of computerization (as high as 75 percent) among all occupations. These results might suggest that routine tasks are not the driving force behind the high PCI index for Elementary Occupations. Similar results are documented also for Services and Sales Workers and Skilled Agricultural, Forestry and Fishery Workers, where routine tasks account for approximately 20 percent of the tasks in these occupations, while the probability of computerization is above 60 percent.

The large differences between PCI and RTI for services, agricultural and elementary occupations can be explained by the fact that Frey and Osborne assume that both routine and non-routine tasks can be computerized. This assumption results in estimating high probabilities of computerization for many occupations that we generally consider as non-computerizable, and thus non-routine. Typical non-routine occupations such as models, dental hygienists, housekeeping cleaners, personal care aids, manicurists and pedicurists, bartenders, waiters, barbers, repairers, roofers, tree pruners, hunters and trappers, nonfarm animal caretakers, carpet installers, highway maintenance workers, drivers, musical instrument repairers and tuners, fence erectors, cooks and many others are given implausibly high probabilities of computerization in Frey and Osborne[53]. This raises the question of whether PCI is not overestimated for this type of non-routine occupations. It is difficult to imagine how the work of dental hygienists, manicurists and pedicurists, barbers and other similar occupations could be computerized using computer-controlled technologies[54].

[53] The probabilities of computerization for these occupations (as reported in Frey and Osborne's appendix table on p. 269) are as follows: Cooks, restaurant (0.96), Manicurists and pedicurists (0.95), Waiters and waitresses (0.94), Fence erectors (0.92), Musical instrument repairers and tuners (0.91), Roofers (0.9), Bus drivers, school or special client (0.89), Rail car repairers (0.88), Carpet Installers (0.87), Highway maintenance workers (0.87), Nonfarm animal caretakers (0.82), Barbers (0.8), Bartenders (0.77), Tree trimmers and pruners (0.77), Hunters and trappers (0.77), Personal care aides (0.74), Maids and housekeeping cleaners (0.69), Dental hygienists (0.68).

[54] Of course, it can be equally true that our RTI is underestimated for these occupations, and this is what explains the large differences between PCI and RTI. To check this possibility, we take Autor and Dorn (2013) as a reference. Autor and Dorn compute routine task-intensities for US occupations and

Figure 7: Probability of computerization (PCI) and Routine task-intensity (RTI) by nine major occupations



Note: PCI and RTI are rescaled to have values between 0 and 1, and are weighted by the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking). The graph is based on 393 four-digit ISCO-08 occupations (34 occupations in our dataset could not be matched with Frey and Osborne's converted index and were dropped from the analysis). The correlation between PCI and RTI is 0.56 across the whole sample of 393 occupations. PCI is extracted from Frey and Osborne (2017) and converted to ISCO-08 occupations. The employment weights are described in Appendix A.

The second point that can be made regarding Frey and Osborne's PCI is that in several cases occupations with similar type of activities are estimated to have different probabilities of computerization. Bus driving, for example, has a very high PCI (0.89), while piloting an airplane has a very low PCI (0.18). Similarly, the occupation travel guides is estimated to have a very low probability of computerization (0.057) and the occupation tour guides and

---

find that the ten low-skilled occupations with the lowest routine task-intensity are bus drivers, taxi cab drivers and chauffeurs, waiters and waitresses, truck, delivery and tractor drivers, door-to-door/street sales, news vendors, carpenters, telecom and line installers and repairers, housekeepers, maids, butlers and cleaners, health and nursing aids and electricians (Appendix Table 2, p. 1593). These results provide suggestive evidence that our RTI is not underestimated for this type of occupations.

escorts is estimated to have a very high probability of computerization (0.91). Also, home health aides are estimated to have a low PCI (0.39) and personal care aides are estimated to have a high PCI (0.74). These results are surprising, because one would expect similar occupations to have similar PCIs. Also, one would expect the tasks of pilots (e.g. commercial pilots) to be easier to automate than the tasks of taxi or bus drivers[55].

In sum, PCI and RTI are positively correlated across the whole sample of 393 occupations (the correlation coefficient between both indexes is 0.56). The observed differences between PCI and RTI can be explained by the fact that (i) PCI and RTI are different variables measuring different things, and (ii) PCI rests on the assumption that computerization is no longer confined to routine tasks, but it is spreading to both routine and non-routine task domains. The latter assumption results in estimating a generally higher PCI than RTI at any level of routine task-intensity.

7.4 Bivariate correlations previous studies' indexes

Table 7 reports the correlations between the measures of Acemoglu and Autor (2011), Dengler, Matthes and Paulus (2014), Frey and Osborne (2017) and the present study. The coefficient values on the diagonals (in the highlighted squares) of the table show once again that our five measures exhibit strong positive correlations with both AA and DMP. The coefficients in Table 7 are slightly different than the ones in Table 5 and 6, because the calculations in Table 7 are based on a smaller number of observations (353 four-digit occupations were successfully matched across all four studies).

New to table 7 are the correlation matrices showing the bivariate correlations between the measures of AA, DMP and FO. Looking at the correlations between the task indexes of Acemoglu and Autor and Dengler, Matthes and Paulus, we see that the pairs of non-routine analytic, routine manual and non-routine manual tasks correlate strongly with each other – the estimated correlation coefficients for these groups are, respectively, .64, .65 and .52. Remarkably, the pair of interactive tasks exhibits a very weak correlation and has a coefficient value of just .13. Also, the pair of routine cognitive tasks shows a relatively low correlation, as compared to the rest of the indexes – the size of the correlation coefficient is around .36.

The bottom row in Table 7 shows the correlations between the probability of computerization index of Frey and Osborne and the five task measures. PCI is negatively correlated with analytic and interactive tasks and positively correlated with routine cognitive, routine manual and non-routine manual tasks, and these relationships are consistent across different studies. Also, the sizes of the estimated coefficients are largely

[55] The probabilities of computerization for pilots and drivers are as follows: Airline pilots, copilots, and flight engineers (0.18), Commercial pilots (0.55), Taxi drivers and chauffeurs (0.89) and Bus drivers, school or special client (0.89).

comparable across studies. One exception is the small size of the correlation between PCI and the interactive measure of Dengler, Matthes and Paulus – the correlation coefficient has a value of -.05, which is much weaker than the estimated correlations between PCI and the interactive indexes of Acemoglu and Autor and the present study, respectively, -.61 and -.49.

All in all, Table 7 shows that the task measures of Acemoglu and Autor, Dengler, Matthes and Paulus and the present paper correlate sufficiently with one another. One exception is the non-routine interactive measure of Dengler, Matthes and Paulus, which correlates weakly with both Acemoglu and Autor's interactive measure and Frey and Osborne's probability of computerization (interestingly, and perhaps surprisingly, we do not find a weak correlation between the interactive measures of DMP and the present study).

Table 7: Correlation matrix of the four studies' measures

		Own task measures					**Acemoglu and Autor**					**Dengler, Matthes and Paulus**				
		NRA	**NRI**	**RC**	**RM**	**NRM**	**NRA**	**NRI**	**RC**	**RM**	**NRM**	**NRA**	**NRI**	**RC**	**RM**	**NRM**
Own task measures	**NRA**	**1**														
	NRI	.23	**1**													
	RC	-.35	-.20	**1**												
	RM	-.27	-.31	-.12	**1**											
	NRM	-.47	-.44	-.35	-.07	**1**										
Acemoglu and Autor	**NRA**	**.69**	.47	-.17	-.27	-.54	**1**									
	NRI	.35	**.51**	-.21	-.28	-.26	.67	**1**								
	RC	-.10	-.28	**.45**	.15	-.21	-.05	-.25	**1**							
	RM	-.41	-.61	-.05	**.64**	.37	-.52	-.42	.31	**1**						
	NRM	-.38	-.52	-.19	.36	**.56**	-.42	-.26	.04	.77	**1**					
Dengler, Matthes, Paulus	**NRA**	**.72**	.47	-.15	-.33	-.54	**.64**	.39	-.14	-.57	-.55	**1**				
	NRI	-.06	**.51**	.13	-.26	-.23	.07	**.13**	-.05	-.39	-.39	.009	**1**			
	RC	-.05	-.21	**.57**	-.07	-.25	.009	-.05	**.36**	-.007	-.09	-.18	-.24	**1**		
	RM	-.28	-.36	-.19	**.73**	.17	-.29	-.26	.05	**.65**	.50	-.38	-.33	-.14	**1**	
	NRM	-.39	-.36	-.28	.03	**.76**	-.47	-.23	-.17	.35	**.52**	-.54	-.24	-.38	.004	**1**
Frey and Osbrone	**PCI**	**-.59**	**-.49**	**.47**	**.28**	**.20**	**-.63**	**-.61**	**.37**	**.42**	**.24**	**-.54**	**-.05**	**.23**	**.24**	**.19**

Note: The correlations are weighted by the number of employed individuals per occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking), and are based on 353 observations (353 occupations were successfully matched across all four studies). Unrounded coefficient values. The employment weights are described in Appendix A.

To get a better insight into the different interactive task measures (and possibly find an explanation for the low correlation between the interactive indexes of DMP and AA), Table 8 reports the top ten occupations with the largest bivariate differences in interactive tasks scores. The first panel compares the interactive measures of DMP and the present study and shows the ten occupations with the largest differences in interactive tasks scores. The second panel compares the interactive indexes of DMP and AA and the third panel compares the interactive indexes of AA and the present study.

To make the different interactive indexes comparable, in Table 8 we standardize them to have a mean of zero and an employment weighted standard deviation of one across the whole sample of 353 occupations. In terms of interpretation, a standard score of one indicates that the interactive score of a particular occupation falls one standard deviation above the average (which is set to zero). Generally, one would expect to find positive and higher than zero standard scores for occupations that are intensive in interactive tasks, and negative scores for occupations that are not intensively using interactive tasks.

Looking at the first panel (which compares DMP's and our interactive indexes), we see that DMP estimate relatively larger shares of interactive tasks than we do (as compared to the mean) for the occupations Transport conductors, Bookmakers, croupiers and related gaming workers, Fashion and other models, Hotel receptionists and Contact centre information clerks, while we estimate relatively larger shares of interactive tasks for the occupations Driving instructors, Police inspectors and detectives, Insurance representatives, Conference and event planners and Air traffic controllers. These differences are likely to arise from the different classification of certain tasks by both studies. Take for example the first group of occupations – we estimate low shares of interactive tasks and high shares of non-routine manual tasks for the occupations Transport conductors and Fashion and other models, and large share of routine cognitive tasks for the occupations Bookmakers, croupiers and related gaming workers, Hotel receptionists and Contact centre information clerks (see original task measures in Table B1 in the Appendix). We acknowledge that the work of transport conductors and models consists for the large part of interactions with others, but we do not consider these interactions as a cognitive type of interaction (like teaching, presenting, leading, organizing, advising), and therefore we classify them as non-routine manual (similar to other tasks involving non-cognitive interactions such as taking food orders, serving food, cutting hair etc.)[56]. Furthermore, it is interesting to note that also Acemoglu and Autor estimate a relatively low interactive task content (as indicated by the negative standard deviation coefficients) for Bookmakers, croupiers and related gaming workers, Hotel receptionists, Contact centre information clerks and Fashion and other models.

[56] According to ISCO-08 "transport conductors check and issue tickets and ensure the safety and comfort of passengers on trains, trams, buses and other public transport vehicles" (p.330) and "fashion and other models wear and display clothing and accessories and pose for photographs, film and video, advertising, still photography or for artistic creation" (p. 361).

On the other side, we estimate larger shares of interactive tasks than DMP for the occupations Driving instructors, Police inspectors and detectives, Insurance representatives, Conference and event planners and Air traffic controllers. We find interactive tasks to account for 57 percent or more of the tasks in these occupations (see original task indexes in Table B1 in the Appendix). Oppositely, DMP estimate a zero share of interactive tasks for Police inspectors and detectives and Air traffic controllers, and between 13 and 37 percent for Conference and event planners, Insurance representatives and Driving instructors (these percentages come from DMP's file with original task measures). It is hard to imagine, though, that the work of Police inspectors and detectives does not contain any interactive tasks – their tasks include many interactive activities such as "establishing contacts and sources of information", "interviewing witnesses and suspects", "establishing contacts and sources of information not readily available", "testifying in courts of law" (p. 266). The same applies to the work of Air traffic controllers.

Looking at the second panel, DMP estimate a relatively higher interactive task content (as indicated by the highly positive standardized scores) than Acemoglu and Autor for the occupations Bookmakers, croupiers and related gaming workers, Hotel receptionists, Contact centre information clerks, Debt collectors and related workers, Inquiry clerks and Fashion and other models, and a relatively lower interactive content for Office supervisors, Information and communications technology services managers, Health services managers and Training and staff development professionals. For the last group of occupations, DMP estimate the share of interactive tasks to be 3 percent or lower. Again, this result is surprising considering that the work activities performed by these occupations contain many interactive tasks[57].

Finally, the third panel compares the interactive scores of Acemoglu and Autor and the present study and shows the occupations with the largest differences. Acemoglu and Autor estimate larger shares of interactive tasks than we do (as compared to the mean) for the occupations Transport conductors, Electrical line installers and repairers, Railway brake, signal and switch operators, Bicycle and related repairers, Musical instrument makers and tuners, Ships' engineers and Information technology trainers, while we estimate larger shares of interactive tasks for Electronics engineers, Commercial sales representatives and Telecommunications engineers. There are two surprising elements that emerge from these results – first, occupations such as Transport conductors, Electrical line installers and repairers, Railway brake, signal and switch operators, Bicycle and related repairers and Musical instrument makers and tuners are estimated to have 1.59 or more standard

[57] For example, the work of Office supervisors consists of supervising and coordinating the activities of workers in Major Group 4: Clerical Support Workers, and as such it contains many non-routine interactive activities such as "coordinating … the work of clerks", "coordinating activities with other work units", "resolving work-related problems", "training and instructing employees", "assisting in recruitment, interviewing and selection of employees" (p. 257). As a reference, we find that 55 percent of the tasks of Office supervisors belong to the group of non-routine interactive tasks.

deviations higher interactive task scores than the mean (based on Acemoglu and Autor's estimates), and second, the occupation Information technology trainers is found to have about a quarter of a standard deviation lower interactive task score than the mean (based on our estimates).

The first result is surprising, because it suggests that the work of transport conductors, electrical line installers and repairers, railway switch operators, bicycle repairers and musical instrument makers and tuners is largely comprised by non-routine interactive tasks. This is however not the case – based on the occupational and tasks descriptions provided by ISCO-08, one would expect these occupations to be characterized mainly by non-routine manual tasks[58]. Likewise, the second result is also surprising, because it suggests that information technology trainers have a lower interactive task score than the average, while one would expect trainers to perform more interactive tasks than the average. When we consult ISCO-08, however, we see that this occupation is indeed comprised for the larger part of non-routine analytic tasks, and to a smaller extend by interactive tasks[59].

---

[58] According to the occupational descriptions in ISCO-08 "transport conductors check and issue tickets and ensure the safety and comfort of passengers on trains, trams, buses and other public transport vehicles" (p. 330), "electrical line installers and repairers install, repair and join electrical transmission and supply cables and related equipment" (p. 466), "railway brakers, signallers and shunters take charge of and safeguard railway freight trains during runs, control the movement of railway traffic by operating signals, switch rolling stock and make up trains in railway yards, make up trains for hauling in mines and control their movement" (p. 535), "bicycle and related repairers fit, maintain, service and repair the mechanical and related equipment of bicycles, rickshaws, baby carriages, wheelchairs and similar non-motorized transport equipment" (p. 446), "musical instrument makers and tuners make, assemble, repair, adjust and restore musical instruments and tune them to the required pitch with hand or power tools. They usually specialize in one type of instrument, such as stringed instruments, brass instruments, reed instruments, pianos or percussion instruments" (p. 450).

[59] The tasks of Information Technology Trainers include: "identifying the information technology training needs and requirements of individual users and organizations", "preparing and developing instructional training material and aids such as handbooks, visual aids, online tutorials, demonstration models and supporting training reference documentation", "designing, coordinating, scheduling and conducting training and development programmes that can be delivered in the form of individual and group instruction, and facilitating workshop meetings, demonstrations and conferences", "monitoring and performing ongoing evaluation and assessment of training quality and effectiveness, and reviewing and modifying training objectives, methods and course deliverables", "gathering, investigating and researching background materials to gain a full understanding of the subject matter and systems", "keeping up to date with new product version releases, advances in software and general information technology trends, writing end user products and materials such as user training, tutorial and instruction manuals, online help, and operating and maintenance instructions" (p. 125).

Table 8: Top ten occupations with the largest differences in interactive tasks scores

Occupations	DMP interactive measure	Own interactive measure
Transport conductors	1.913	-.466
Driving instructors	1.175	3.606
Police inspectors and detectives	-.789	1.667
Insurance representatives	.470	2.960
Bookmakers, croupiers and related gaming workers	2.703	-.013
Fashion and other models	1.830	-.918
Hotel receptionists	2.865	.086
Conference and event planners	-.093	2.960
Air traffic controllers	-.789	2.475
Contact centre information clerks	3.327	-.164
	DMP interactive measure	**AA interactive measure**
Office supervisors	-.666	2.377
Bookmakers, croupiers and related gaming workers	2.703	-.420
Hotel receptionists	2.865	-.259
Information & communications technology services managers	-.679	2.607
Health services managers	-.736	2.655
Training and staff development professionals	-.588	2.823
Contact centre information clerks	3.327	-.227
Debt collectors and related workers	3.140	-.689
Inquiry clerks	3.140	-.992
Fashion and other models	1.830	-2.468
	AA interactive measure	**Own interactive measure**
Transport conductors	2.023	-.466
Electrical line installers and repairers	1.596	-.918
Electronics engineers	-1.799	.726
Railway brake, signal and switch operators	1.646	-.918
Bicycle and related repairers	1.706	-.918
Musical instrument makers and tuners	1.724	-.918
Commercial sales representatives	-.221	2.475
Ships' engineers	2.088	-.918
Telecommunications engineers	-2.160	.891
Information technology trainers	2.823	-.272

Note: To aid comparison, the task measures are standardized to have a mean of zero and a standard deviation of one across the whole sample of 353 occupations. A standardized score of one indicates that the interactive score of a particular occupation falls one standard deviation above the mean (the mean of interactive tasks is set to zero across the 353 occupations). Generally, one would expect to find positive and higher than zero scores for occupations that are intensively using non-routine interactive tasks, and negative scores for occupations that are not intensively using interactive tasks. Un-rounded standardized values.

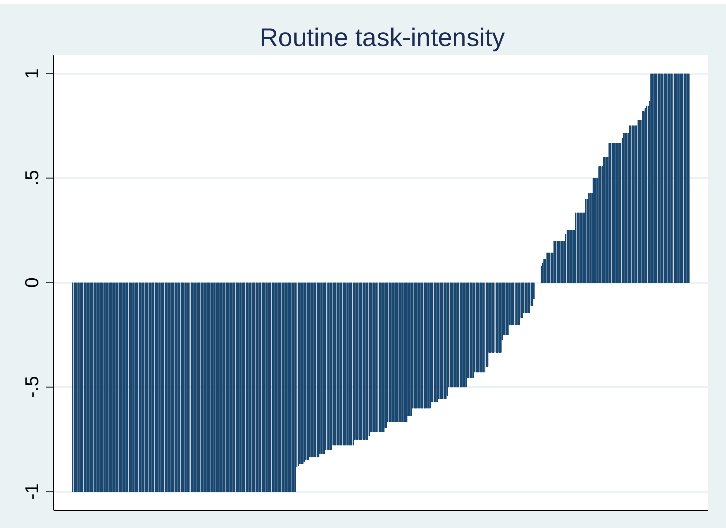
Overall, the presented results in Table 7 show that the five task measures correlate sufficiently with one another. The relatively low correlation between the interactive indexes of Acemoglu and Autor and DMP is likely to result from the slightly different definition of interactive tasks in both studies.

8 A note on the automatibility of occupations

So far we analyzed the 427 occupations in our sample only in terms of their task contents, without making any inferences about their potential to be automated. Based on the estimated shares of routine and non-routine tasks, however, we can say something about the potential of occupations to be replaced by technology. So let's look once again at our routine task-intensity index and see what it has to say, if anything, on that matter.

Figure 8 plots the RTI score of 427 occupations – the score ranges between -1 and 1, whereas a score of -1 indicates that all tasks of a given occupation are classified as non-routine and a score of 1 indicates the opposite. A first look at the graph shows that the lion share (about three-quarters) of occupations has a negative RTI score, a handful of occupations have a zero score, and about one-quarter of occupations have a positive RTI score. When we look at the occupations with scores 1 and -1, we see that only a tiny fraction of occupations has a score of 1, while there are more occupations with a score of -1 than with any positive score. So, what do these numbers say about the automation potential of occupations?

Figure 8: Routine task-intensity per four-digit occupation



Note: The figure is based on 427 occupations.

To draw inferences about the automation potential of occupations we consider several cut-offs with different shares of routine tasks. In Table 9 we divide the 427 occupations into six segments depending on the shares of routine tasks – we distinguish between occupations with no routine tasks, up to 30 percent routine tasks, less than 50 percent routine tasks, 50 percent or more routine tasks, 70 percent or more routine tasks and 100 percent routine tasks.

Columns (1)-(4) in Table 9 show that around 36 percent of the occupations contain no routine tasks, 74 percent contain less than 50 percent routine tasks, and only 16 percent of the occupations are comprised of 70 percent or more routine tasks. If we threshold at 70 percent and assume this to be the high risk category for automation, as most previous studies have done (e.g. Frey and Osborne, 2017, Arntz, Gregory and Zierahn, 2016), then we can say that about 16 percent of the occupations in our sample are in the high risk category and in theory could be automated. If and when this will happen, however, is a prediction that in our opinion cannot be made. As the last row in Table 9 witnesses, around 6 percent of the occupations are comprised entirely of routine tasks, and nevertheless these occupations are still there, which means that a high share of routine tasks is by no means a guarantee for automation.

Columns (5)-(6) show the number of employed individuals in the six routine segments in the Netherlands in 2017. The estimations are based on 412 occupations (due to the lack of employment data for 15 occupations) and cover over 95 percent of the total employment in the Netherlands in 2017[60]. The estimates show that over 60 percent of the workers in the Netherlands are employed in jobs with low routine task content (that is 30 percent or less), and 80 percent are employed in jobs with less than 50 percent routine content. Only 11 percent of the Dutch workers hold jobs in the high risk category, which is 70 percent or more routine task content. These results are in line with the OECD study by Arntz, Gregory and Zierahn (2016) who find that about 10 percent of the jobs in the Netherlands are at risk of automation.

[60] We are very grateful to Prof. Wendy Smits from Statistics Netherlands for providing us with employment data at the level of four-digit ISCO-08 occupations (CBS, EBB). One limitation of this dataset, however, is that it does not contain employment data for 15 of the 427 occupations in our sample, and therefore in columns (5)-(6) the sample is reduced to 412 occupations. In addition to the employment data provided by Prof. Smits, we have access to another dataset, which provides employment statistics for all 427 occupations for the Netherlands. However, these employment statistics are derived via a 1 to m crosswalk, which links one employment number to several ISCO-08 occupations, and we therefore consider these data as less suitable for the purposes of Table 9 (the trade-off here is between using crude employment data and including all 427 occupations, or using precise employment data and dropping 15 occupations). For a description of both employment datasets see Appendix A.

Table 9: Number of occupations in different RTI segments

Share of routine tasks	RTI score	# of occupations	% of occupations	Employment in the Netherlands (based on 412 occupations)	
				# of jobs	% of jobs
0%	-1	155	36.2%	3,262,870	39.8%
≤ 30%	-1 ÷ -0.6	246	57.6%	4,970,312	60.7%
< 50%	< 0	320	74.9%	6,515,874	79.6%
≥ 50%	0 ÷ 1	107	25%	1,666,309	20.3%
≥ 70%	0.4 ÷ 1	72	16.8%	927,490	11.3%
100%	1	27	6.3%	400,523	4.8%

Note: Columns (1)-(4) show the number of occupations in six segments of the RTI distribution - the numbers are based on the whole sample of 427 occupations. Columns (5)-(6) show the number of employed individuals per RTI segment in the Netherlands in 2017. Columns (5)-(6) are based on 412 occupations and 8,182,183 jobs, which account for 95.3% of the total employment (8,579,428) in the Netherlands in 2017. Un-rounded occupation and job shares.

Other studies that have attempted to estimate the number of jobs at risk of automation are Frey and Osborne (2017), Dengler and Matthes (2018), Nedelkoska and Quintini (2018) and Arntz, Gregory and Zierahn (2016). For US, Frey and Osborne (2017) estimate that around 47 percent of US jobs are at high risk of automation - these jobs have a 70 percent or higher probability of computerization and according to the authors could be automated relatively soon, “perhaps over the next decade or two” (p. 268). Dengler and Matthes (2018) estimate much lower automation potentials for Germany, where “only” 15 percent of the employees are at high risk of being replaced by automation. Similarly magnitudes are reported also by Nedelkoska and Quintini (2018) and Arntz, Gregory and Zierahn (2016). Nedelkoska and Quintini (2018) find that around 14 percent of the jobs in OECD countries are highly automatable (their probability of automation is over 70 percent) and 32 percent have a moderate probability of automation (between 50 and 70 percent). Arntz, Gregory and Zierahn (2016) estimate that on average approximately 9 percent of the jobs in OECD countries and the US, and 10 percent of the jobs in the Netherlands are at risk of automation (the automatability of these jobs is at least 70 percent).

Overall, the above discussion suggests that approximately 16 percent of the 427 ISCO-08 occupations and 11 percent of the jobs in the Netherlands fall into the so-called high risk of automation category.

9 Conclusions

This paper develops new measures of the task content of occupations that are based on the International Standard Classification of Occupations 2008. Using a detailed set of 3,264 occupation-specific task descriptions, we construct five indexes measuring non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks. We estimate the five measures for 427 four-digit occupations. To construct the indexes, first we assign each of the 3,426 tasks to five routine categories. The decision to classify tasks as routine or non-routine, and as cognitive or manual, depends on whether the tasks can be replaced by computer-controlled technology and whether the performance of the tasks requires cognitive or manual skills. We judge the automation potential of tasks on a case-by-case basis and classify tasks to one or more of the five routine categories. Because the classification of 3,264 tasks can be prone to errors, we devote substantial attention to the possibility of misclassifying tasks. We discuss three particular types of task misclassifications and provide examples of tasks that could be potentially misclassified.

We estimate the five routine indexes for 427 four-digit ISCO-08 occupations and report the results in Table B1 in the Appendix. In line with expectations and the previous literature, we find that non-routine analytic and interactive tasks are most prevalent in the work of Managers and Professionals, routine cognitive tasks are concentrated in the work of Clerical Support Workers, and routine and non-routine manual tasks are most common in the work of Plant and Machine Operators and Assemblers and Elementary Occupations, respectively. Furthermore, the paper demonstrates that there is a substantial variation in the five measures within occupational groups. The work of Assemblers, for example, has a much higher routine content than the work of Drivers and Mobile Plant Operators, even though both occupations are part of the same major occupational group.

In Chapter 7, we compare our task indexes with the measures of three previous studies – Acemoglu and Autor (2011), Dengler, Matthes and Paulus (2014) and Frey and Osborne (2017). To this end, first we convert the measures of these papers to four-digit ISCO-08 occupations. The comparisons show that our task indexes are strongly correlated with the measures of Dengler, Matthes and Paulus (2014), and moderately to strongly correlated with the indexes of Acemoglu and Autor (2011). Additionally, we simultaneously compare all four studies' indexes and extensively discuss the similarities and differences between the different measures.

At the end of the paper, inspired by Frey and Osborne (2017), we provide a back of the envelop estimation of the number of occupations that might be at risk of automation. We find that approximately 16 percent of the 427 occupations fall into the so-called high risk of automation group – they contain 70 percent or more routine tasks. When we look at the number of jobs that are associated with these occupations, we find that around 11 percent of the jobs in the Netherlands in 2017 are associated with these routine-intensive occupations.

Finally, it is fair to acknowledge that our classification of tasks is a reflection of our subjective judgment about which tasks are replaceable by technology, and which are not. A potential limitation of such an approach is that it could leave room for discretion when assigning tasks to different routine domains. An alternative to our approach would be to use a set of commonplace variables and generate the five task content measures based on them (similar to Autor, Levy and Murnane, 2003 and Spitz-Oener, 2006). This alternative approach, however, has its own limitations - as Acemoglu and Autor (2011) point out, it is rarely obvious which of the hundreds of available commonplace variables best represent a given task construct, and the choice of commonplace variables could be arbitrary. Moreover, classifications and rankings that are based on commonplace variables could provide results that are far from reasonable (see Blinder, 2009 for a discussion). For example, the study of Frey and Osborne (2017) estimates implausibly high probabilities of computerization for many typical non-routine occupations such as barbers, dental hygienists, personal care aids, maids, manicurists and pedicurists, waiters, carpet installers and others.

Acknowledgments

This work is part of the PhD research of Emil Mihaylov, which is financed by the Netherlands Organisation for Scientific Research (NWO) through the Mosaic program (grant number 017.008.004).

We would like to thank Frank den Butter and participants in the TASKS III conference in Nuremberg and AIAS lunch seminars for valuable comments and suggestions on an earlier version of this paper. We are also very grateful to Katharina Dengler, Britta Matthes and Wiebke Paulus for sharing their routine task indexes with us, and to Wendy Smits from Statistics Netherlands for providing us with employment data at the level of four-digit ISCO-08 occupations for the Netherlands.

References

Acemoglu, D., and D. Autor (2011), Skills, Tasks and Technologies: Implications for Employment and Earnings, in *Handbook of Labor Economics*, ed. Orley Ashenfelter and David Card, Amsterdam: Elsevier–North Holland, Volume 4b: 1043–1171.

Antonczyk, D., B. Fitzenberger and U. Leuschner (2009), Can a Task-Based Approach Explain the Recent Changes in the German Wage Structure?, IZA Discussion Paper No. 4050, Institute for the Study of Labor (IZA), Bonn, February 2009.

Arntz, M., T. Gregory and U. Zierahn (2016), The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis, OECD Social, Employment and Migration Working Papers No. 189, OECD Publishing, Paris. http://dx.doi.org/10.1787/5jlz9h56dvq7-en.

Autor, D. (2013), The "Task Approach" to Labor Markets: An Overview, NBER Working Paper No. 18711, National Bureau of Economic Research, January 2013, http://www.nber.org/papers/w18711.

Autor, D. and D. Dorn (2013), The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market, *American Economic Review*, 103(5): 1553–1597, http://dx.doi.org/10.1257/aer.103.5.1553.

Autor, D., L. Katz and M. Kearney (2008), Trends in U.S. Wage Inequality: Revising the Revisionists, *Review of Economics and Statistics*, 90(2): 300–323.

Autor, D., F. Levy and R. Murnane (2003), The Skill Content of Recent Technological Change: An Empirical Exploration, *Quarterly Journal of Economics*, 116(4): 1279-1333.

Basso, G., G. Peri and A. Rahman (2017), Computerization and Immigration: Theory and Evidence from the United States, NBER Working Paper No. 23935, National Bureau of Economic Research, October 2017, Revised October 2018, http://www.nber.org/papers/w23935.

Blinder, A. (2009), How many US jobs might be offshorable?, *World Economics*, 10(2): 41-78.

Dengler, K. and B. Matthes (2018), The impacts of digital transformation on the labour market. Substitution potentials of occupations in Germany, *Technological Forecasting and Social Change*, 137: 304-316.

Dengler, K., B. Matthes and W. Paulus (2014), Occupational Tasks in the German Labour Market. An alternative measurement on the basis of an expert database, FDZ-Methodenreport No. 12/2014 (en), Research Data Centre of the German Federal Employment Agency at the Institute for Employment Research, Nuremberg.

Dustmann, C., J. Ludsteck and U. Schonberg (2009), Revising the German Wage Structure, *Quarterly Journal of Economics* 124(2): 843-881.

European Commission (2009), Commission Recommendation of 29 October 2009 on the use of the International Standard Classification of Occupations (ISCO-08), *Official Journal of the European Union*, 292: 31-47.

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

Gathmann, C. and U. Schonberg (2010), How General Is Human Capital? A Task-Based Approach, *Journal of Labor Economics*, 28(1): 1-49.

Goos, M. and A. Manning (2007), Lousy and Lovely Jobs: The Rising Polarization of Work in Britain, *Review of Economics and Statistics*, 89(1): 118-133.

Goos, M., A. Manning and A. Salomons (2014), Explaining Job Polarization: Routine-Biased Technological Change and Offshoring, *American Economic Review*, 104(8): 2509–2526.

Goos, M., A. Manning and A. Salomons (2010), Explaining Job Polarization in Europe: The Roles of Technology, Globalization and Institutions, CEP Discussion Paper No. 1026, Centre for Economic Performance, London School of Economics and Political Science, November 2010.

ILO (2012a), International Standard Classification of Occupations 2008, Volume 1 – Structure, Group Definitions and Correspondence Tables, International Labour Office (ILO), Geneva. URL: https://www.ilo.org/public/english/bureau/stat/isco/isco08/, last accessed on April 15, 2019.

ILO (2012b), International Standard Classification of Occupations 2008, Part III - Definitions of Major Groups, Sub-Major Groups, Minor Groups and Unit Groups, International Labour Office (ILO), Geneva. URL: https://www.ilo.org/public/english/bureau/stat/isco/isco08/, last accessed on April 15, 2019.

Janser, M. (2018), The greening of jobs in Germany: First evidence from a text mining based index and employment register data, IAB Discussion Paper No. 14/2018, IAB Institute for Employment Research, ISSN 2195-2663.

Marcolin, L., S. Miroudot and M. Squicciarini (2016), The Routine Content of Occupations: New Cross-Country Measures Based On PIAAC, OECD Trade Policy Papers No. 188, OECD Publishing, Paris, http://dx.doi.org/10.1787/5jm0mq86fljg-en

Nedelkoska, L. and G. Quintini (2018), Automation, skills use and training, OECD Social, Employment and Migration Working Papers No. 202, OECD Publishing, Paris, http://dx.doi.org/10.1787/2e2f4eea-en.

OECD (2016), The Survey of Adult Skills: Reader's Companion, Second Edition, OECD Skills Studies, OECD Publishing, Paris, http://dx.doi.org/10.1787/9789264258075-en.

Peri, G. and C. Sparber (2008), Task Specialization, Immigration, and Wages, CREAM Discussion Paper No. 02/08, Centre for Research and Analysis of Migration, March 2008.

PIAAC (2010), PIAAC Background questionnaire, MS version 2.1, d.d. 15-12-2010.

Rohrbach-Schmidt, D. (2009), The BIBB/IAB- and BIBB/BAuA-Surveys of the Working Population on Qualification and Working Conditions in Germany, BIBB-FDZ Data and Methodological Report Nr. 1/2009, Version 1.1, Federal Institute for Vocational Education and Training (BIBB), Bonn.

Rohrbach-Schmidt, D. and A. Hall (2013), BIBB/BAuA Employment Survey 2012, BIBB-FDZ Data and Methodological Report Nr. 1/2013, Version 3.0, Federal Institute for Vocational Education and Training (BIBB), Bonn.

Rohrbach-Schmidt, D. and M. Tiemann (2013), Changes in workplace tasks in Germany—evaluating skill and task measures, *J Labour Market Res.* 46: 215–237, DOI 10.1007/s12651-013-0140-3.

Spitz-Oener, A. (2006), Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure, *Journal of Labor Economics*, 24(2): 235–270.

Appendix A – Employment weights

To aggregate the task indexes from four-digit to one-digit occupation level in Figure 2 and 3, and from four-digit to two-digit occupation level in Figure 4, we used employment weights. The weights are based on Dutch employment data and measure total employment per four-digit occupation in the Netherlands in 2017 (CBS, StatLine, Werkzame Beroepsbevolking, Beroep).

Statistics Netherlands provides employment data at the level of 114 four-digit occupations coded according to the BRC-2014 classification system (BRC-2014 is a Dutch coding system based on ISCO-08). To merge the employment weights with our routine indexes, we used a crosswalk between BRC-2014 and ISCO-08, provided by Statistics Netherlands. The crosswalk pairs each of the 114 BRC-2014 occupations with one or more of the ISCO-08 occupations. One limitation of the crosswalk is that it couples 1 to m occupations, which inevitably reduces the power of weighting in cases where several occupations are given the same employment weight[61]. Nevertheless, we consider the use of crude employment weights as a minor issue, because our task indexes are reported at the level of four-digit occupations in Table B1 in the Appendix, and the aggregations in Figure 2, 3 and 4 serve merely to show the global pattern of the indexes.

An alternative employment dataset

In our attempt to find more disaggregated employment data (than the 114 occupations based on BRC-2014), we contacted Prof. Wendy Smits from Statistics Netherlands and she provided us with employment statistics at the level of four-digit ISCO-08 occupations (CBS, EBB)[62]. One limitation of this dataset, however, is that it does not contain employment data for 15 of the 427 occupations in our sample. Therefore, we opted to use the aggregated employment weights (derived via a crosswalk) over the alternative of excluding 15 occupations from our analysis.

Chapter 8 is the only place in the paper where we use the employment data provided by Prof. Smits. In that chapter we estimate the number of jobs that might be at risk of automation in the Netherlands. The accent in the chapter is on the number of jobs in the Netherlands, and therefore it would not make sense to use employment data that are derived via a 1 to m crosswalk.

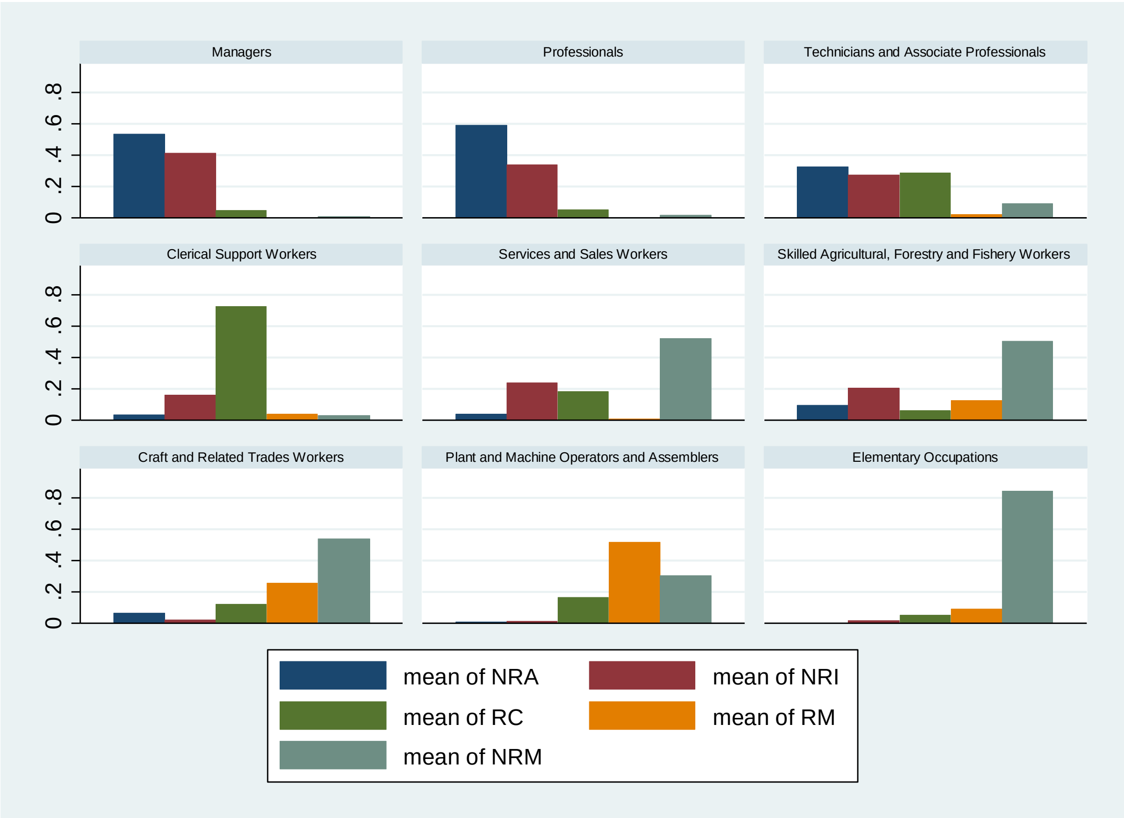
In sum, we have access to two employment data sets – one aggregated at the level of 114 four-digit BRC-2014 occupations and another one reporting employment at the level of four-

[61] For example, one BRC-2014 occupation (Business Services and Administration Managers) is linked to four ISCO-08 occupations (Finance Managers, Human Resource Managers, Policy and Planning Managers and Business Services and Administration Managers Not Elsewhere Classified).

[62] We are very grateful to Prof. Wendy Smits from Statistics Netherlands for making the employment data at four-digit ISCO-08 level available to us.

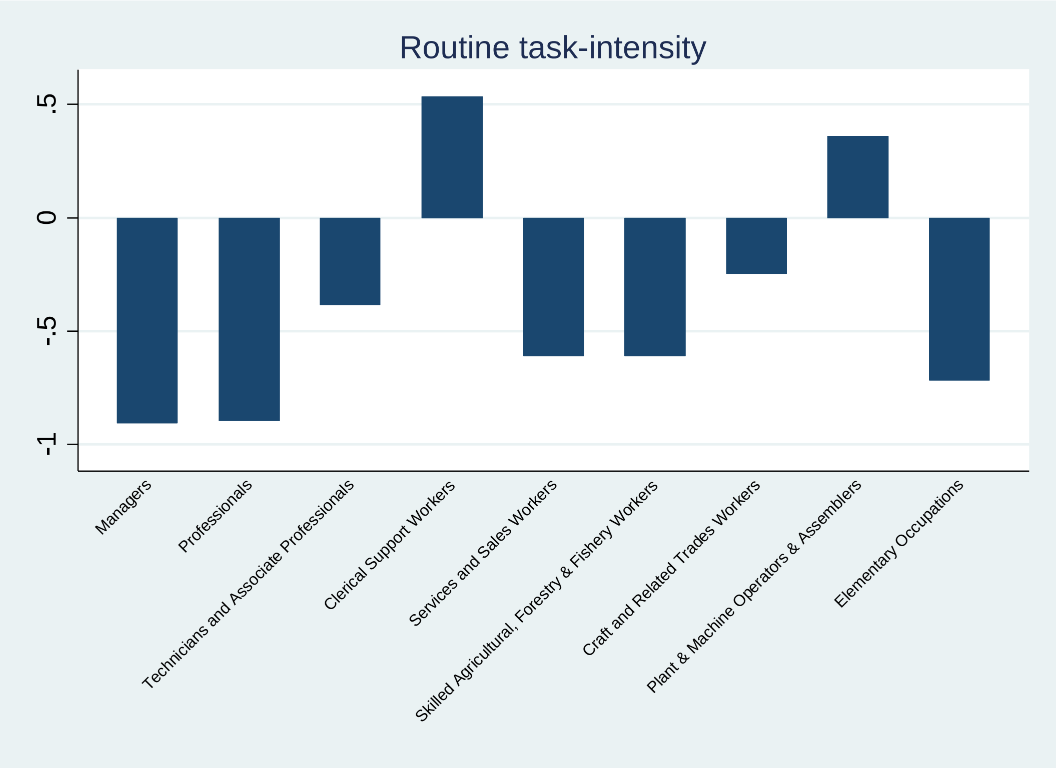
digit ISCO-08 occupations. The first dataset has no missing observations and therefore we use it throughout the paper to weight our routine indexes. The second dataset has 15 missing observations/occupations and we use it only in Chapter 8, where we estimate the number of jobs that might be at risk of automation in the Netherlands (the 15 missing occupations account for less than 5 percent of total employment in the Netherlands in 2017 and have a limited effect on our estimates for the Netherlands).

Figure A2: Task composition of nine major occupations



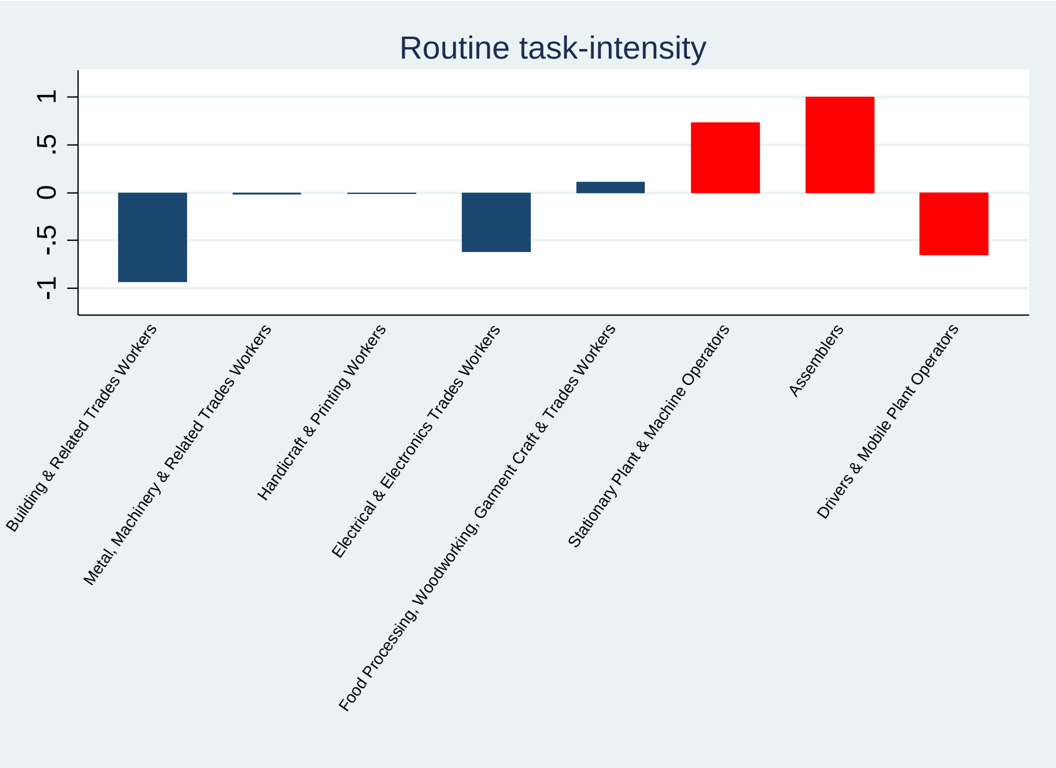
Note: NRA, NRI, RC, RM and NRM stand, respectively for non-routine analytic, non-routine interactive, routine cognitive and non-routine manual tasks. The 427 four-digit occupations are aggregated to nine major occupations without using employment weights.

Figure A3: Routine task-intensity score of nine major occupations



Note: The 427 four-digit occupations are aggregated to 9 one-digit major occupations without using employment weights.

Figure A4: Routine task-intensity score of eight sub-major occupations which form the major groups of Craft and Related Trades Workers and Plant and Machine Operators and Assemblers



Note: The four-digit occupations are aggregated to two-digit occupations without using employment weights.

Table A1: Routine task-intensity statistics, unrounded numbers

Major group	# 4-digit occupations per major group	Mean	Std. Dev.	Min	Max
Managers	30	-.9456454	.1322429	-1	-.4285715
Professionals	92	-.891105	.1956475	-1	-.2
Technicians & Associate Professionals	82	-.4363441	.5661295	-1	1
Clerical Support Workers	29	.5053743	.4289199	-.3333333	1
Services & Sales Workers	39	-.5768554	.3920597	-1	.75
Skilled Agricultural, Forestry & Fishery Workers	18	-.5885458	.1202204	-1	-.4285715
Craft & Related Trades Workers	65	-.3791395	.6627277	-1	1
Plant & Machine Operators & Assemblers	39	.3868679	.6928208	-1	1
Elementary Occupations	33	-.7969262	.3674736	-1	1

Note: The 427 four-digit occupations are aggregated to 9 one-digit major occupations using the number of employed individuals per occupation in the Netherlands in 2017 as weights (CBS, StatLine, Werkzame Beroepsbevolking).

Appendix B – Routine task content of 427 four-digit ISCO-08 occupations

Table B1 reports the six task content measures for 427 four-digit ISCO-08 occupations. NRA, NRI, RC, RM, NRM and RTI stand, respectively, for non-routine analytic, non-routine interactive, routine cognitive, routine manual and non-routine manual tasks, and RTI stands for routine task-intensity.

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
1111	Legislators	.3	.7	0	0	0	-1
1112	Senior government officials	.5	.5	0	0	0	-1
1113	Traditional chiefs and heads of villages	.1428571	.7142857	0	0	.1428571	-1
1114	Senior officials of special-interest organizations	.5	.5	0	0	0	-1
1120	Managing directors and chief executives	.625	.375	0	0	0	-1
1211	Finance managers	.5454546	.4545455	0	0	0	-1
1212	Human resource managers	.5333334	.4	.0666667	0	0	-.8666667
1213	Policy and planning managers	.5	.5	0	0	0	-1
1219	Business services and administration managers not elsewhere classified	.6153846	.3846154	0	0	0	-1
1221	Sales and marketing managers	.5833333	.4166667	0	0	0	-1
1222	Advertising and public relations managers	.5833333	.4166667	0	0	0	-1
1223	Research and development managers	.5833333	.4166667	0	0	0	-1
1311	Agricultural and forestry production managers	.5833333	.4166667	0	0	0	-1
1312	Aquaculture and fisheries production managers	.4117647	.5294118	.0588235	0	0	-.8823529
1321	Manufacturing managers	.8333333	.1666667	0	0	0	-1
1322	Mining managers	.8	.2	0	0	0	-1
1323	Construction managers	.6363636	.3636364	0	0	0	-1
1324	Supply, distribution and related managers	.6428571	.2857143	.0714286	0	0	-.8571429

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
1330	Information and communications technology services managers	.5294118	.4705882	0	0	0	-1
1341	Child care services managers	.5833333	.3333333	.0833333	0	0	-.8333333
1342	Health services managers	.5	.5	0	0	0	-1
1343	Aged care services managers	.4615385	.5384616	0	0	0	-1
1344	Social welfare managers	.5833333	.4166667	0	0	0	-1
1345	Education managers	.5454546	.4545455	0	0	0	-1
1346	Financial and insurance services branch managers	.4615385	.3846154	.1538462	0	0	-.6923077
1349	Professional services managers not elsewhere classified	.6666667	.3333333	0	0	0	-1
1411	Hotel managers	.5	.3333333	.1666667	0	0	-.6666667
1412	Restaurant managers	.25	.4166667	.25	0	.0833333	-.5
1420	Retail and wholesale trade managers	.5714286	.1428571	.2857143	0	0	-.4285715
1431	Sports, recreation and cultural centre managers	.4166667	.3333333	.25	0	0	-.5
2111	Physicists and astronomers	.8333333	.0833333	.0833333	0	0	-.8333333
2112	Meteorologists	.9	.1	0	0	0	-1
2113	Chemists	.8888889	.1111111	0	0	0	-1
2114	Geologists and geophysicists	.9166667	.0833333	0	0	0	-1
2120	Mathematicians, actuaries and statisticians	.6923077	.3076923	0	0	0	-1
2131	Biologists, botanists, zoologists and related professionals	.7777778	.1111111	.1111111	0	0	-.7777778
2132	Farming, forestry and fisheries advisers	.7692308	.2307692	0	0	0	-1
2133	Environmental protection professionals	.6	.4	0	0	0	-1
2141	Industrial and production engineers	.6363636	.3636364	0	0	0	-1
2142	Civil engineers	.6666667	.3333333	0	0	0	-1
2143	Environmental engineers	.7777778	.2222222	0	0	0	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
2144	Mechanical engineers	.5833333	.4166667	0	0	0	-1
2145	Chemical engineers	.7777778	.1111111	.1111111	0	0	-.7777778
2146	Mining engineers, metallurgists and related professionals	.6153846	.3846154	0	0	0	-1
2149	Engineering professionals not elsewhere classified	.8181818	.1818182	0	0	0	-1
2151	Electrical engineers	.5555556	.3333333	.1111111	0	0	-.7777778
2152	Electronics engineers	.6363636	.3636364	0	0	0	-1
2153	Telecommunications engineers	.6	.4	0	0	0	-1
2161	Building architects	.6	.4	0	0	0	-1
2162	Landscape architects	.6363636	.3636364	0	0	0	-1
2163	Product and garment designers	.6363636	.3636364	0	0	0	-1
2164	Town and traffic planners	.5	.5	0	0	0	-1
2165	Cartographers and surveyors	.7777778	.2222222	0	0	0	-1
2166	Graphic and multimedia designers	.6666667	.3333333	0	0	0	-1
2211	Generalist medical practitioners	.4375	.4375	.125	0	0	-.75
2212	Specialist medical practitioners	.6	.2666667	.1333333	0	0	-.7333333
2221	Nursing professionals	.5454546	.3636364	0	0	.0909091	-1
2222	Midwifery professionals	.6666667	.2222222	.1111111	0	0	-.7777778
2230	Traditional and complementary medicine professionals	.5555556	.3333333	.1111111	0	0	-.7777778
2240	Paramedical practitioners	.6363636	.2727273	.0909091	0	0	-.8181818
2250	Veterinarians	.5	.2	.1	0	.2	-.8
2261	Dentists	.7692308	.1538462	0	0	.0769231	-1
2262	Pharmacists	.2857143	.4285714	.2857143	0	0	-.4285714
2263	Environmental and occupational health and hygiene professionals	.5454546	.4545455	0	0	0	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
2264	Physiotherapists	.4444444	.4444444	.1111111	0	0	-.7777778
2265	Dieticians and nutritionists	.5555556	.4444444	0	0	0	-1
2266	Audiologists and speech therapists	.5555556	.4444444	0	0	0	-1
2267	Optometrists and ophthalmic opticians	.5555556	.3333333	.1111111	0	0	-.7777778
2269	Health professionals not elsewhere classified	.5	.4166667	0	0	.0833333	-1
2310	University and higher education teachers	.5	.5	0	0	0	-1
2320	Vocational education teachers	.3333333	.5833333	.0833333	0	0	-.8333333
2330	Secondary education teachers	.625	.375	0	0	0	-1
2341	Primary school teachers	.4545455	.5454546	0	0	0	-1
2342	Early childhood educators	.3636364	.6363636	0	0	0	-1
2351	Education methods specialists	.5	.5	0	0	0	-1
2352	Special needs teachers	.3076923	.6153846	.0769231	0	0	-.8461539
2353	Other language teachers	.7777778	.2222222	0	0	0	-1
2354	Other music teachers	.4285714	.5714286	0	0	0	-1
2355	Other arts teachers	.4615385	.5384616	0	0	0	-1
2356	Information technology trainers	.8571429	.1428571	0	0	0	-1
2359	Teaching professionals not elsewhere classified	.4285714	.5714286	0	0	0	-1
2411	Accountants	.5454546	.2727273	.1818182	0	0	-.6363636
2412	Financial and investment advisers	.3333333	.5	.1666667	0	0	-.6666667
2413	Financial analysts	.7777778	.2222222	0	0	0	-1
2421	Management and organization analysts	.6428571	.3571429	0	0	0	-1
2422	Policy administration professionals	.75	.25	0	0	0	-1
2423	Personnel and careers professionals	.5	.5	0	0	0	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
2424	Training and staff development professionals	.7	.3	0	0	0	-1
2431	Advertising and marketing professionals	.6363636	.3636364	0	0	0	-1
2432	Public relations professionals	.5	.5	0	0	0	-1
2433	Technical and medical sales professionals (excluding ICT)	.4666667	.4666667	.0666667	0	0	-.8666667
2434	Information and communications technology sales professionals	0	.75	.25	0	0	-.5
2511	Systems analysts	.75	.25	0	0	0	-1
2512	Software developers	.5555556	.4444444	0	0	0	-1
2513	Web and multimedia developers	.8	.2	0	0	0	-1
2514	Applications programmers	.8333333	.1666667	0	0	0	-1
2519	Software and applications developers and analysts not elsewhere classified	.6	0	.4	0	0	-.2
2521	Database designers and administrators	.8571429	.1428571	0	0	0	-1
2522	Systems administrators	.5	.1666667	.3333333	0	0	-.3333333
2523	Computer network professionals	.7777778	.1111111	.1111111	0	0	-.7777778
2529	Database and network professionals not elsewhere classified	.75	.25	0	0	0	-1
2611	Lawyers	.4545455	.5454546	0	0	0	-1
2612	Judges	.7142857	.2857143	0	0	0	-1
2619	Legal professionals not elsewhere classified	.5	.25	.25	0	0	-.5
2621	Archivists and curators	.6923077	.2307692	.0769231	0	0	-.8461539
2622	Librarians and related information professionals	.6363636	.1818182	.1818182	0	0	-.6363636
2631	Economists	.8571429	.1428571	0	0	0	-1
2632	Sociologists, anthropologists and related professionals	.8888889	.1111111	0	0	0	-1
2633	Philosophers, historians and political scientists	.7777778	.2222222	0	0	0	-1
2634	Psychologists	.6363636	.3636364	0	0	0	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
2635	Social work and counselling professionals	.3333333	.5833333	.0833333	0	0	-.8333333
2636	Religious professionals	.1818182	.8181818	0	0	0	-1
2641	Authors and related writers	.8571429	0	.1428571	0	0	-.7142857
2642	Journalists	.6153846	.3076923	.0769231	0	0	-.8461539
2643	Translators, interpreters and other linguists	.4285714	.2857143	.2857143	0	0	-.4285714
2651	Visual artists	.875	0	0	0	.125	-1
2652	Musicians, singers and composers	.375	.375	.25	0	0	-.5
2653	Dancers and choreographers	.1428571	.4285714	0	0	.4285714	-1
2654	Film, stage and related directors and producers	.3636364	.5454546	.0909091	0	0	-.8181819
2655	Actors	.25	.75	0	0	0	-1
2656	Announcers on radio, television and other media	.4	.6	0	0	0	-1
2659	Creative and performing artists not elsewhere classified	0	.25	0	0	.75	-1
3111	Chemical and physical science technicians	.4	0	.6	0	0	.2
3112	Civil engineering technicians	.7	.3	0	0	0	-1
3113	Electrical engineering technicians	.625	0	.25	0	.125	-.5
3114	Electronics engineering technicians	.7	0	.1	0	.2	-.8
3115	Mechanical engineering technicians	.7777778	0	0	0	.2222222	-1
3116	Chemical engineering technicians	.8	0	.2	0	0	-.6
3117	Mining and metallurgical technicians	.7777778	0	.2222222	0	0	-.5555556
3118	Draughtspersons	.5	0	.5	0	0	0
3119	Physical and engineering science technicians not elsewhere classified	1	0	0	0	0	-1
3121	Mining supervisors	.3333333	.6666667	0	0	0	-1
3122	Manufacturing supervisors	.2857143	.4285714	.2857143	0	0	-.4285714

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
3123	Construction supervisors	.3333333	.5	.1666667	0	0	-.6666667
3131	Power production plant operators	0	.25	.5	.125	.125	.25
3132	Incinerator and water treatment plant operators	.125	0	.5	.25	.125	.5
3133	Chemical processing plant controllers	.1428571	0	.4285714	.4285714	0	.7142857
3134	Petroleum and natural gas refining plant operators	.1666667	0	.5	.3333333	0	.6666667
3135	Metal production process controllers	0	.2857143	.2857143	.4285714	0	.4285714
3141	Life science technicians (excluding medical)	.5384616	0	.4615385	0	0	-.0769231
3142	Agricultural technicians	.7777778	.1111111	.1111111	0	0	-.7777778
3143	Forestry technicians	.3846154	.3846154	0	0	.2307692	-1
3151	Ships' engineers	.3333333	0	.3333333	0	.3333333	-.3333333
3152	Ships' deck officers and pilots	.2727273	.1818182	.2727273	0	.2727273	-.4545455
3153	Aircraft pilots and related associate professionals	.2857143	.1428571	.4285714	0	.1428571	-.1428572
3154	Air traffic controllers	.25	.75	0	0	0	-1
3155	Air traffic safety electronics technicians	.8888889	.1111111	0	0	0	-1
3211	Medical imaging and therapeutic equipment technicians	.1818182	.1818182	.2727273	0	.3636364	-.4545455
3212	Medical and pathology laboratory technicians	.5454546	0	.3636364	0	.0909091	-.2727273
3213	Pharmaceutical technicians and assistants	0	.2222222	.5555556	.1111111	.1111111	.3333334
3214	Medical and dental prosthetic technicians	.25	.25	0	0	.5	-1
3221	Nursing associate professionals	.25	.25	.125	0	.375	-.75
3222	Midwifery associate professionals	.75	.25	0	0	0	-1
3230	Traditional and complementary medicine associate professionals	.125	.5	0	0	.375	-1
3240	Veterinary technicians and assistants	.2	.1	.1	0	.6	-.8
3251	Dental assistants and therapists	.5555556	.1111111	0	0	.3333333	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
3252	Medical records and health information technicians	.1428571	.1428571	.7142857	0	0	.4285714
3253	Community health workers	0	.8571429	0	0	.1428571	-1
3254	Dispensing opticians	.4	.2	.4	0	0	-.2
3255	Physiotherapy technicians and assistants	.1428571	.4285714	0	0	.4285714	-1
3256	Medical assistants	.2	.2	.3	0	.3	-.4
3257	Environmental and occupational health inspectors and associates	.4545455	.5454546	0	0	0	-1
3258	Ambulance workers	.5	.3333333	.1666667	0	0	-.6666667
3259	Health associate professionals not elsewhere classified	.3333333	.4444444	.1111111	0	.1111111	-.7777778
3311	Securities and finance dealers and brokers	.2	.6	.2	0	0	-.6
3312	Credit and loans officers	.1666667	.1666667	.6666667	0	0	.3333333
3313	Accounting associate professionals	.1666667	.1666667	.6666667	0	0	.3333333
3314	Statistical, mathematical and related associate professionals	.75	.125	.125	0	0	-.75
3315	Valuers and loss assessors	.8	0	.2	0	0	-.6
3321	Insurance representatives	0	.8571429	.1428571	0	0	-.7142857
3322	Commercial sales representatives	.125	.75	.125	0	0	-.75
3323	Buyers	.4375	.5	.0625	0	0	-.875
3324	Trade brokers	.2857143	.7142857	0	0	0	-1
3331	Clearing and forwarding agents	0	0	1	0	0	1
3332	Conference and event planners	.1428571	.8571429	0	0	0	-1
3333	Employment agents and contractors	0	.7142857	.2857143	0	0	-.4285714
3334	Real estate agents and property managers	.1428571	.4285714	.4285714	0	0	-.1428571
3339	Business services agents not elsewhere classified	0	.5714286	.4285714	0	0	-.1428572
3341	Office supervisors	.4444444	.5555556	0	0	0	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
3342	Legal secretaries	0	.1428571	.8571429	0	0	.7142857
3343	Administrative and executive secretaries	0	.25	.75	0	0	.5
3344	Medical secretaries	0	.25	.75	0	0	.5
3351	Customs and border inspectors	0	.25	.375	0	.375	-.25
3352	Government tax and excise officials	.25	.25	.5	0	0	0
3353	Government social benefits officials	0	.4	.6	0	0	.2
3354	Government licensing officials	.1666667	.1666667	.6666667	0	0	.3333333
3355	Police inspectors and detectives	.2857143	.5714286	0	0	.1428571	-1
3359	Government regulatory associate professionals not elsewhere classified	.6	0	.4	0	0	-.2
3411	Legal and related associate professionals	.3	.1	.6	0	0	.2
3412	Social work associate professionals	.2	.8	0	0	0	-1
3413	Religious associate professionals	.1428571	.8571429	0	0	0	-1
3421	Athletes and sports players	.25	.125	.125	0	.5	-.75
3422	Sports coaches, instructors and officials	.5	.3571429	.1428571	0	0	-.7142857
3423	Fitness and recreation instructors and program leaders	.2222222	.4444444	.1111111	0	.2222222	-.7777778
3431	Photographers	.375	0	.625	0	0	.25
3432	Interior designers and decorators	.6153846	.3076923	0	0	.0769231	-1
3433	Gallery, museum and library technicians	.1111111	0	.4444444	0	.4444444	-.1111111
3434	Chefs	.25	.4166667	.25	0	.0833333	-.5
3511	Information and communications technology operations technicians	.1111111	.1111111	.7777778	0	0	.5555556
3512	Information and communications technology user support technicians	.4	.1	.4	0	.1	-.2
3513	Computer network and systems technicians	.1666667	.1666667	.6666667	0	0	.3333333
3514	Web technicians	.4444444	.3333333	.2222222	0	0	-.5555556

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
3521	Broadcasting and audiovisual technicians	.2857143	0	.5714286	0	.1428571	.1428571
3522	Telecommunications engineering technicians	1	0	0	0	0	-1
4110	General office clerks	0	.125	.75	.125	0	.75
4120	Secretaries (general)	0	0	1	0	0	1
4131	Typists and word processing operators	0	0	1	0	0	1
4132	Data entry clerks	0	0	1	0	0	1
4211	Bank tellers and related clerks	0	0	1	0	0	1
4212	Bookmakers, croupiers and related gaming workers	.2	.2	.4	0	.2	-.2
4213	Pawnbrokers and money-lenders	.1666667	0	.8333333	0	0	.6666666
4214	Debt collectors and related workers	0	.6	.4	0	0	-.2
4221	Travel consultants and clerks	0	.375	.625	0	0	.25
4222	Contact centre information clerks	0	.1666667	.8333333	0	0	.6666666
4223	Telephone switchboard operators	.1666667	0	.5	.3333333	0	.6666667
4224	Hotel receptionists	0	.2222222	.7777778	0	0	.5555556
4225	Inquiry clerks	0	.4	.6	0	0	.2
4226	Receptionists (general)	0	.2	.6	0	.2	.2
4227	Survey and market research interviewers	0	.4	.6	0	0	.2
4229	Client information workers not elsewhere classified	0	.6666667	.3333333	0	0	-.3333333
4311	Accounting and bookkeeping clerks	0	0	1	0	0	1
4312	Statistical, finance and insurance clerks	0	0	1	0	0	1
4313	Payroll clerks	0	0	1	0	0	1
4321	Stock clerks	0	0	.8333333	.1666667	0	1
4322	Production clerks	.2857143	.1428571	.5714286	0	0	.1428571

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
4323	Transport clerks	0	.4545455	.5454546	0	0	.0909091
4411	Library clerks	0	0	.8333333	0	.1666667	.6666666
4412	Mail carriers and sorting clerks	0	0	.3333333	.5	.1666667	.6666667
4413	Coding, proofreading and related clerks	0	0	.8	0	.2	.6
4414	Scribes and related workers	0	.6666667	.3333333	0	0	-.3333333
4415	Filing and copying clerks	0	0	1	0	0	1
4416	Personnel clerks	0	.1428571	.8571429	0	0	.7142857
4419	Clerical support workers not elsewhere classified	.25	0	.75	0	0	.5
5111	Travel attendants and travel stewards	0	.25	.25	0	.5	-.5
5112	Transport conductors	0	.1	.3	0	.6	-.4
5113	Travel guides	.1	.3	.1	0	.5	-.8
5120	Cooks	.2222222	.1111111	.2222222	.1111111	.3333333	-.3333333
5131	Waiters	0	.1428571	.1428571	0	.7142857	-.7142857
5132	Bartenders	0	.0909091	.1818182	.0909091	.6363636	-.4545454
5141	Hairdressers	0	.125	.125	0	.75	-.75
5142	Beauticians and related workers	0	.125	.125	0	.75	-.75
5151	Cleaning and housekeeping supervisors in offices, hotels and other establishments	0	.3333333	.2222222	0	.4444444	-.5555556
5152	Domestic housekeepers	0	.1818182	.2727273	0	.5454546	-.4545455
5153	Building caretakers	0	.25	.125	.125	.5	-.5
5161	Astrologers, fortune-tellers and related workers	.5	.5	0	0	0	-1
5162	Companions and valets	0	.6666667	0	0	.3333333	-1
5163	Undertakers and embalmers	0	.3333333	.1666667	0	.5	-.6666667
5164	Pet groomers and animal care workers	0	.1111111	.1111111	0	.7777778	-.7777778

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
5165	Driving instructors	0	1	0	0	0	-1
5169	Personal services workers not elsewhere classified	0	.3333333	0	0	.6666667	-1
5211	Stall and market salespersons	.1428571	.2857143	.2857143	0	.2857143	-.4285715
5212	Street food salespersons	0	.1666667	.1666667	0	.6666667	-.6666667
5221	Shopkeepers	.2222222	.2222222	.4444444	0	.1111111	-.1111111
5222	Shop supervisors	.2222222	.2222222	.5555556	0	0	.1111111
5223	Shop sales assistants	0	.5	.3333333	0	.1666667	-.3333333
5230	Cashiers and ticket clerks	0	0	.875	0	.125	.75
5241	Fashion and other models	0	0	0	0	1	-1
5242	Sales demonstrators	0	.5	.1666667	0	.3333333	-.6666667
5243	Door-to-door salespersons	0	.375	.375	0	.25	-.25
5244	Contact centre salespersons	0	.375	.625	0	0	.25
5245	Service station attendants	0	0	.25	.125	.625	-.25
5246	Food service counter attendants	0	.1	.2	0	.7	-.6
5311	Child care workers	0	.375	.25	0	.375	-.5
5312	Teachers' aides	0	.4285714	.1428571	0	.4285714	-.7142857
5321	Health care assistants	.1428571	.1428571	0	0	.7142857	-1
5322	Home-based personal care workers	.0909091	.2727273	.0909091	0	.5454546	-.8181819
5329	Personal care workers in health services not elsewhere classified	0	0	0	0	1	-1
5411	Firefighters	0	.1666667	0	0	.8333333	-1
5412	Police officers	0	0	0	0	1	-1
5413	Prison guards	0	.2857143	0	0	.7142857	-1
5414	Security guards	0	0	0	0	1	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
5419	Protective services workers not elsewhere classified	0	0	0	0	1	-1
6111	Field crop and vegetable growers	.0714286	.2142857	.0714286	.1428571	.5	-.5714285
6112	Tree and shrub crop growers	.0714286	.2142857	.0714286	.1428571	.5	-.5714285
6113	Gardeners, horticultural and nursery growers	.0666667	.2	.0666667	.1333333	.5333334	-.6
6114	Mixed crop growers	.0714286	.2142857	.0714286	.1428571	.5	-.5714285
6121	Livestock and dairy producers	.1333333	.2	.0666667	.1333333	.4666667	-.6
6122	Poultry producers	.1875	.1875	.0625	.1875	.375	-.5
6123	Apiarists and sericulturists	.1818182	.3636364	.0909091	.0909091	.2727273	-.6363636
6129	Animal producers not elsewhere classified	.25	.25	.0833333	.0833333	.3333333	-.6666667
6130	Mixed crop and animal producers	.1428571	.3571429	.0714286	.0714286	.3571429	-.7142857
6210	Forestry and related workers	.0769231	.0769231	.1538462	0	.6923077	-.6923077
6221	Aquaculture workers	.2142857	.3571429	.1428571	.0714286	.2142857	-.5714286
6222	Inland and coastal waters fishery workers	.1	.1	.1	.1	.6	-.6
6223	Deep-sea fishery workers	.1	.3	.1	.1	.4	-.6
6224	Hunters and trappers	0	.1666667	0	0	.8333333	-1
6310	Subsistence crop farmers	0	.1428571	0	.2857143	.5714286	-.4285715
6320	Subsistence livestock farmers	.0833333	.0833333	0	.1666667	.6666667	-.6666667
6330	Subsistence mixed crop and livestock farmers	0	.1111111	0	.2222222	.6666667	-.5555556
6340	Subsistence fishers, hunters, trappers and gatherers	0	.125	0	.25	.625	-.5
7111	House builders	0	.2857143	0	0	.7142857	-1
7112	Bricklayers and related workers	0	0	0	0	1	-1
7113	Stonemasons, stone cutters, splitters and carvers	0	0	.1428571	0	.8571429	-.7142857
7114	Concrete placers, concrete finishers and related workers	0	0	0	0	1	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
7115	Carpenters and joiners	0	0	0	0	1	-1
7119	Building frame and related trades workers not elsewhere classified	0	0	0	0	1	-1
7121	Roofers	.1666667	0	0	0	.8333333	-1
7122	Floor layers and tile setters	0	0	0	0	1	-1
7123	Plasterers	0	0	0	0	1	-1
7124	Insulation workers	.1666667	0	0	.1666667	.6666667	-.6666667
7125	Glaziers	.25	0	0	0	.75	-1
7126	Plumbers and pipe fitters	.2	0	0	0	.8	-1
7127	Air conditioning and refrigeration mechanics	.2	0	.2	0	.6	-.6
7131	Painters and related workers	0	0	0	0	1	-1
7132	Spray painters and varnishers	0	0	0	0	1	-1
7133	Building structure cleaners	0	0	0	0	1	-1
7211	Metal moulders and coremakers	0	0	0	.8571429	.1428571	.7142857
7212	Welders and flame cutters	0	0	.125	.75	.125	.75
7213	Sheet metal workers	0	0	.3333333	.3333333	.3333333	.3333333
7214	Structural metal preparers and erectors	0	0	0	.5	.5	0
7215	Riggers and cable splicers	.1666667	0	0	0	.8333333	-1
7221	Blacksmiths, hammersmiths and forging press workers	0	0	.25	.625	.125	.75
7222	Toolmakers and related workers	.1538462	0	.1538462	.3846154	.3076923	.0769231
7223	Metal working machine tool setters and operators	0	0	.1666667	.6666667	.1666667	.6666667
7224	Metal polishers, wheel grinders and tool sharpeners	0	0	.1428571	.4285714	.4285714	.1428571
7231	Motor vehicle mechanics and repairers	.125	0	0	0	.875	-1
7232	Aircraft engine mechanics and repairers	.1	0	.2	0	.7	-.6

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
7233	Agricultural and industrial machinery mechanics and repairers	0	0	.2857143	0	.7142857	-.4285714
7234	Bicycle and related repairers	0	0	0	.1666667	.8333333	-.6666666
7311	Precision-instrument makers and repairers	0	0	.3333333	.0833333	.5833333	-.1666666
7312	Musical instrument makers and tuners	.0909091	0	0	0	.9090909	-1
7313	Jewellery and precious metal workers	.1818182	0	.0909091	0	.7272727	-.8181819
7314	Potters and related workers	.1666667	.0833333	.0833333	.3333333	.3333333	-.1666667
7315	Glass makers, cutters, grinders and finishers	0	0	.2307692	.6923077	.0769231	.8461539
7316	Signwriters, decorative painters, engravers and etchers	.4	0	.0666667	0	.5333334	-.8666667
7317	Handicraft workers in wood, basketry and related materials	0	0	0	0	1	-1
7318	Handicraft workers in textile, leather and related materials	0	0	.0666667	.8666667	.0666667	.8666667
7321	Pre-press technicians	.1428571	0	.5714286	.1428571	.1428571	.4285715
7322	Printers	0	0	.1111111	.7777778	.1111111	.7777778
7323	Print finishing and binding workers	0	0	0	1	0	1
7411	Building and related electricians	.25	0	.125	0	.625	-.75
7412	Electrical mechanics and fitters	.1111111	0	.2222222	0	.6666667	-.5555556
7413	Electrical line installers and repairers	0	0	.1666667	0	.8333333	-.6666666
7421	Electronics mechanics and servicers	.1111111	.1111111	.1111111	0	.6666667	-.7777778
7422	Information and communications technology installers and servicers	0	.1111111	.3333333	0	.5555556	-.3333333
7511	Butchers, fishmongers and related food preparers	0	.1111111	.1111111	.5555556	.2222222	.3333334
7512	Bakers, pastry-cooks and confectionery makers	0	0	.25	.375	.375	.25
7513	Dairy products makers	0	0	.25	.75	0	1
7514	Fruit, vegetable and related preservers	0	0	0	.8	.2	.6
7515	Food and beverage tasters and graders	.2	0	.8	0	0	.6

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
7516	Tobacco preparers and tobacco products makers	0	0	.2	.8	0	1
7521	Wood treaters	0	0	.125	.5	.375	.25
7522	Cabinet-makers and related workers	.125	0	.125	.375	.375	0
7523	Woodworking machine tool setters and operators	.1428571	0	.1428571	.4285714	.2857143	.1428571
7531	Tailors, dressmakers, furriers and hatters	0	0	0	.0833333	.9166667	-.8333334
7532	Garment and related patternmakers and cutters	.2307692	0	.1538462	.4615385	.1538462	.2307692
7533	Sewing, embroidery and related workers	0	0	0	.0833333	.9166667	-.8333334
7534	Upholsterers and related workers	0	.1666667	0	.25	.5833333	-.5
7535	Pelt dressers, tanners and fellmongers	0	0	0	1	0	1
7536	Shoemakers and related workers	.1428571	0	.0714286	.1428571	.6428571	-.5714285
7541	Underwater divers	0	.25	.0833333	0	.6666667	-.8333334
7542	Shotfirers and blasters	.1428571	.1428571	.4285714	0	.2857143	-.1428572
7543	Product graders and testers (excluding foods and beverages)	.3	.1	.6	0	0	.2
7544	Fumigators and other pest and weed controllers	0	0	0	.1428571	.8571429	-.7142857
7549	Craft and related workers not elsewhere classified	0	0	0	1	0	1
8111	Miners and quarriers	0	0	.2222222	.5555556	.2222222	.5555556
8112	Mineral and stone processing plant operators	0	0	.1818182	.7272727	.0909091	.8181819
8113	Well drillers and borers and related workers	0	.1	.1	.3	.5	-.2
8114	Cement, stone and other mineral products machine operators	0	0	.3333333	.5833333	.0833333	.8333333
8121	Metal processing plant operators	.1111111	0	.2222222	.6666667	0	.7777778
8122	Metal finishing, plating and coating machine operators	0	0	.125	.875	0	1
8131	Chemical products plant and machine operators	0	0	.1666667	.6666667	.1666667	.6666667
8132	Photographic products machine operators	0	0	.1111111	.7777778	.1111111	.7777778

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
8141	Rubber products machine operators	0	0	.1666667	.6666667	.1666667	.6666667
8142	Plastic products machine operators	0	0	.125	.75	.125	.75
8143	Paper products machine operators	0	0	0	1	0	1
8151	Fibre preparing, spinning and winding machine operators	0	0	0	1	0	1
8152	Weaving and knitting machine operators	0	0	0	.8461539	.1538462	.6923077
8153	Sewing machine operators	0	0	0	.875	.125	.75
8154	Bleaching, dyeing and fabric cleaning machine operators	0	0	0	.9230769	.0769231	.8461539
8155	Fur and leather preparing machine operators	0	0	0	.9090909	.0909091	.8181819
8156	Shoemaking and related machine operators	0	0	0	1	0	1
8157	Laundry machine operators	0	0	0	.5555556	.4444444	.1111111
8159	Textile, fur and leather products machine operators not elsewhere classified	0	0	0	1	0	1
8160	Food and related products machine operators	0	0	0	1	0	1
8171	Pulp and papermaking plant operators	.1	.1	.2	.5	.1	.4
8172	Wood processing plant operators	0	0	0	.8	.2	.6
8181	Glass and ceramics plant operators	0	0	.0769231	.9230769	0	1
8182	Steam engine and boiler operators	.1	0	.3	.4	.2	.4
8183	Packing, bottling and labelling machine operators	0	0	0	1	0	1
8211	Mechanical machinery assemblers	0	0	.8	.2	0	1
8212	Electrical and electronic equipment assemblers	0	0	.6	.4	0	1
8219	Assemblers not elsewhere classified	0	0	.8	.2	0	1
8311	Locomotive engine drivers	0	.2	0	0	.8	-1
8312	Railway brake, signal and switch operators	0	0	.4	0	.6	-.2
8321	Motorcycle drivers	0	0	.2	0	.8	-.6

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
8322	Car, taxi and van drivers	0	0	.375	0	.625	-.25
8331	Bus and tram drivers	0	0	.1428571	0	.8571429	-.7142857
8332	Heavy truck and lorry drivers	0	0	.5714286	0	.4285714	.1428572
8341	Mobile farm and forestry plant operators	0	0	0	0	1	-1
8342	Earthmoving and related plant operators	0	0	0	0	1	-1
8343	Crane, hoist and related plant operators	0	0	0	0	1	-1
8344	Lifting truck operators	0	0	.2	0	.8	-.6
8350	Ships' deck crews and related workers	0	0	0	0	1	-1
9111	Domestic cleaners and helpers	0	.1428571	0	0	.8571429	-1
9112	Cleaners and helpers in offices, hotels and other establishments	0	0	0	0	1	-1
9121	Hand launderers and pressers	0	0	0	0	1	-1
9122	Vehicle cleaners	0	0	0	0	1	-1
9123	Window cleaners	0	0	0	0	1	-1
9129	Other cleaning workers	0	0	0	0	1	-1
9211	Crop farm labourers	0	0	0	.125	.875	-.75
9212	Livestock farm labourers	0	0	.0909091	.1818182	.7272727	-.4545455
9213	Mixed crop and livestock farm labourers	0	0	.0769231	.1538462	.7692308	-.5384616
9214	Garden and horticultural labourers	0	0	0	.1	.9	-.8
9215	Forestry labourers	0	0	0	0	1	-1
9216	Fishery and aquaculture labourers	0	0	0	.1428571	.8571429	-.7142857
9311	Mining and quarrying labourers	0	0	0	0	1	-1
9312	Civil engineering labourers	0	0	0	0	1	-1
9313	Building construction labourers	0	0	0	0	1	-1

Code	ISCO-08 Title	NRA	NRI	RC	RM	NRM	RTI
9321	Hand packers	0	0	0	1	0	1
9329	Manufacturing labourers not elsewhere classified	0	0	0	.6	.4	.2
9331	Hand and pedal vehicle drivers	0	0	.2	0	.8	-.6
9332	Drivers of animal-drawn vehicles and machinery	0	0	.1111111	0	.8888889	-.7777778
9333	Freight handlers	0	0	0	.3333333	.6666667	-.3333333
9334	Shelf fillers	0	0	0	0	1	-1
9411	Fast food preparers	0	0	.2222222	0	.7777778	-.5555556
9412	Kitchen helpers	0	0	0	0	1	-1
9510	Street and related services workers	0	0	.125	0	.875	-.75
9520	Street vendors (excluding food)	0	.1666667	.1666667	0	.6666667	-.6666667
9611	Garbage and recycling collectors	0	0	0	0	1	-1
9612	Refuse sorters	0	.1666667	0	.1666667	.6666667	-.6666667
9613	Sweepers and related labourers	0	0	0	0	1	-1
9621	Messengers, package deliverers and luggage porters	0	0	.1666667	.1666667	.6666667	-.3333333
9622	Odd-job persons	0	0	0	0	1	-1
9623	Meter readers and vending-machine collectors	0	0	.4285714	0	.5714286	-.1428572
9624	Water and firewood collectors	0	0	0	0	1	-1
9629	Elementary workers not elsewhere classified	0	.1111111	.1111111	0	.7777778	-.7777778

AIAS-HSI Working Paper Series

The AIAS-HSI working paper series consists of several publications of AIAS-HSI staff and AIAS-HSI guests on a wide variety of subjects in the fields of labour economics, sociology of work, labour law, and health and safety.

Information on AIAS-HSI

AIAS-HSI is a merger of two research institutes: The Amsterdam Institute for Advanced Labour Studies (AIAS) and the Hugo Sinzheimer Institute (HSI).

AIAS-HSI is an institute for multidisciplinary research and teaching at the University of Amsterdam (UvA), the largest university in the Netherlands. AIAS-HSI has as its objective the coordination, implementation and stimulation of interdisciplinary research into the practice of labour law and social security law. Therefore it combines insights from the social sciences, legal dogmas and legal theories in its research. To put the multidisciplinary objectives of the institute into practice, AIAS-HSI initiates and conducts research, gives advice and organises meetings, conferences, courses, etc.

See for more information our website www.aias-hsi.uva.nl

Postal address
PO Box 15966
1001 NL Amsterdam
The Netherlands

Visiting address
Nieuwe Achtergracht 166
1018 WV Amsterdam
The Netherlands

AIAS HSI

+31 20 525 3400
aias-hsi@uva.nl
aias-hsi.uva.nl