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The Changing Demand for Skills in the Netherlands

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The Changing Demand for Skills in the Netherlands[1,2]

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Abstract

This study examines the wage returns and changes in the returns for workers employed in occupations that are intensive in tasks requiring non-routine analytical and non-routine interpersonal skills in the Netherlands during the period 2001-2016. We match measures of skills from the US O*NET system to the International Standard Occupation Classification (ISCO). We combine these data with information on employment and wages from administrative data from Statistics Netherlands. We document an increase in the returns to analytical skills, from 9.4 percent in 2001 to 16.0 percent in 2016. Quantile regressions show that the increase in returns from analytical skills can be observed for workers in the lower-, middle-, as well as upper-end of the wage distribution. These findings suggests that non-routine analytical skills are increasingly rewarded on the Dutch labour market. This is consistent with the idea that computer technologies are complementary to the skills required to perform non-routine tasks. With respect to interpersonal skills, we only document a small increase in the wage premium for full-time workers in the upper-end of the wage distribution, from 5.8 percent in 2001 to 7.4 percent in 2016. This finding suggests that increased organisational complexity – induced by technological advances – has put greater demands on interpersonal and managerial skills.

1. Introduction

It is widely acknowledged that skills play an important role in knowledge-based economies (Hanushek & Woessmann, 2008; Hanushek & Woessmann, 2012). However, estimates of how skills are valued in the labour market rely for a large part on schooling attainment measures of human capital (see e.g. Card, 1999; Harmon, Oosterbeek & Walker, 2003; Heckman, Lochner & Todd, 2006; Montenegro & Patrinos, 2014; Psacharopoulos & Patrinos, 2004). Although basic Mincer equation estimates consistently show that higher levels of educational attainment are associated with higher earnings (Harmon et al., 2003), earnings differentials across college majors can sometimes be larger than the college-high school earnings premium (Altonji, Blom & Meghir, 2012; Kirkebøen, Leuven & Mogstad, 2016). In some countries the wage dispersion among workers with similar levels of schooling has substantially increased in recent decades (Acemoglu & Autor, 2011; Budría & Moro-Egido, 2008; Gosling, Machin & Meghir, 2000; Ingram & Neumann, 2006). These observations point toward unobserved skill heterogeneity within education groups and illustrate that educational attainment alone is not a complete measure of skill.[4] The increased earnings inequality within education groups suggests that the type of skills that are acquired both within and outside formal education are an important determinant of graduates' labour market success (Altonji et al., 2012). Providing insight into how skills are rewarded in the labour market will help to inform those who develop educational curricula as well as those investing in their human capital about the skills that are required in employment today, and in the future.

This paper examines how different types of skills are rewarded on the Dutch labour market and how this has changed over the period 2001-2016. In particular, we investigate how the wage premium for being employed in a job that is intensive in non-routine tasks has developed over the past two decades. According to the routinization hypothesis (Autor et al., 2003), technological improvements have reduced the demand for skills required to perform routine tasks, while they have increased the demand for skills required to perform non-routine abstract tasks.[5] Skills (embodied in human labour) and technologies (embodied in capital) can be considered competing inputs for the performance of different tasks (Acemoglu & Autor, 2011). Firms decide on the optimal

4 Advocates of the sorting model argue that formal schooling does not necessarily raise skills, but acts as a signalling device for unobservable ability. According to this model, students sort into an educational level to signal their ability to potential employers and firms infer graduates' innate ability from their educational qualifications (Bedard, 2001; Spence, 1973; Thurow, 1975).

5 With "routine" we refer to tasks that are routine from a machine execution perspective. Machines and computers can substitute for human labour in tasks that can be expressed in 'rule-based' logic. In other words, tasks can be automated when they can be codified in a sequence of logical 'if-then-do' statements that instruct machines which actions need to be performed under which conditions.

allocation of skills to tasks according to the prices of different inputs and the productivity of these inputs in specific tasks. The increase in computing power in recent decades, along with the declining price of computation, has created an economic incentive for firms to substitute machines for human labour in the performance of routine tasks (Autor, Katz & Kearney, 2006; Goos & Manning, 2007; Goos, et al., 2014; Michaels et al., 2014).[6] Given that routine tasks can be expressed in well-defined procedures, they can be easily codified in computer software and are therefore more likely to be performed by machines (Autor et al., 2003).

While technologies largely substitute for human labour in the performance of routine tasks, the skills required to perform non-routine tasks are generally complemented by machines. In accordance with Acemoglu and Autor (2001), we distinguish between two types of non-routine abstract tasks: non-routine cognitive analytical tasks and non-routine cognitive interpersonal tasks. Occupations that are intensive in non-routine abstract tasks heavily depend on the analysis of information as an input (e.g. medical knowledge, legal precedents, sales data, and the statistical analysis of data). By lowering the cost of retrieving, organizing, and manipulating information, workers in abstract task-intensive occupations will spend less time on acquiring and manipulating information. Accordingly, computerization enables workers to further specialize in their area of comparative advantage, i.e. analysing and interpreting information. The routinization hypothesis therefore predicts that non-routine analytical skills are increasingly valued on the labour market. The capital-skill complementarity also predicts an increasing demand for interpersonal skills. As computer technologies have reduced the cost of communication, as well as the cost of diminishing direct control of workers by allowing for indirect computer-based monitoring, technological improvements have induced a decentralization of the workplace (Radner, 1993). In conjunction with these organisational changes, an increased demand is placed on workers who are capable of communicating effectively and who are able to manage and work in teams (Bresnahan, Brynjolfsson & Hitt, 2002; Caroli & Van Reenen, 2001).

While some recent skill measures are available for the Netherlands (e.g. Netherlands Skills Survey, NSS) and for Europe (e.g. European Skills, Competences, Qualifications and Occupations, ESCO), these are very recent and based on few respondents. In contrast to the skill measures available for the Netherlands, the US Occupational Information Network (O*NET) provides skill measures that are primarily derived from survey responses of large, representative samples of job incumbents. O*NET is the main source of occupational competency information in the United States and its measures cover among others things analytical and interpersonal skill requirements for almost 1,000 different occupations. O*NET started its data collection efforts in 2001 and is constantly being revised.

6 Nordhaus (2007) estimates that computational capabilities have improved by a factor of at least 1.7 trillion since the mid nineteenth century. Most of that price decline occurred since 1980.

In the absence of a comparable data source for the Netherlands, we match the O*NET measures for non-routine skills to the International Standard Classification of Occupations 2008 (ISCO-08) to generate occupational skill profiles for the Netherlands. These occupational skill profiles can improve our understanding of changes in the rewards for different types of skills and, thereby, of the changing patterns in the supply and demand for skills. Skill measures from O*NET are based on the job requirements approach.[7] Job skill requirements can be retrieved from job expert assessments or employee and employer surveys. In contrast to formal qualifications, the skill measures that are based on the job requirements approach have the advantage to be more strongly linked to the skills actually used in jobs (Green, 2006). Not all skills acquired through formal schooling are used on the labour market due to skill depreciation and the continuation of skill acquisition after labour market entry.

To the best of our knowledge, this is the first study to document long-run trends in the returns to analytical and interpersonal skills for the Netherlands. In contrast to most previous studies on trends in the returns to skills (e.g. Deming, 2017; Beaudry, Green & Sand, 2016; Castex & Kogan Dechter, 2014; Ingram & Neumann, 2006), we investigate whether (changes) in the returns are driven by workers in specific segments of the wage distribution by drawing on quantile regression techniques. To examine how the rewards for skills have developed over time, we link the skills data from O*NET to rich administrative data on employment and wages from Statistics Netherlands.

The remainder of this paper unfolds as follows. The next section reviews previous studies that have estimated the returns to skills required for the performance of non-routine tasks over time in a variety of countries. Section 3 describes the data and Section 4 presents the empirical model. In Section 5, the patterns in the estimates of the returns to skills are presented. Subsequently, Section 6 shows the skill premium estimates for different segments of the wage distribution. Finally, Section 7 concludes and provides a discussion of potential implications of our findings for skill policy in the Netherlands.

7 Other datasets containing skill requirements by occupations include the IAB/BIBB surveys on Qualification and Working Conditions in Germany (see e.g. Borghans, Ter Weel & Weinberg, 2008; Spitz-Oener, 2006), the British Skills Survey (see e.g. Borghans et al., 2008), the Netherlands Skills Survey (see e.g. Ter Weel & Kok, 2013), and the Dictionary of Occupational Titles in the United States (see e.g. Autor et al., 2003), the predecessor of O*NET.

2. Related literature

Return to non-routine analytical skills

Between the 1970s and the 1990s, the wage returns to cognitive skills increased substantially in the United States (Autor et al., 2003; Ingram & Neumann, 2006). Many OECD countries also experienced a rapid growth since the 1950s in the employment share of managerial, professional and technical occupations that are intensive in non-routine cognitive skills (Handel, 2012). The literature provides two explanations for the observed shift in employment towards high-skilled workers over the past decades. Advocates of the skill biased technological change (SBTC) hypothesis argue that technological change has monotonic effects throughout the skill distribution. This model predicts a uniform shift in the demand for labour away from low-skilled and towards high-skilled workers (Autor et al., 1998; Carneiro & Lee, 2009; Katz & Murphy, 1992). According to the SBTC hypothesis, high-skilled workers are more likely to use computers and to possess skills that complement computer-based technologies (Autor, Katz & Krueger, 1999). Consequently, high skilled workers experience bigger productivity gains with improvements in computer technologies.

However, the SBTC hypothesis does not provide an explanation for why the United States and European countries witnessed an employment growth in both the highest-skilled occupations (professional and managerial) as well as the low-skilled service occupations, and a decline in the middle of the wage distribution (Autor et al., 2006; Van den Berge & Ter Weel, 2015; Goos & Manning, 2007; Goos et al., 2014; Michaels et al., 2014; Smits & De Vries, 2015). According to the task-based model, tasks can be performed by a variety of inputs, and technologies will substitute for skills depending on the price and productivity of each input (Acemoglu & Autor, 2011). The price decline of computer capital, in combination with a strong increase in computing power, has resulted in an increased substitution of computer capital for human labour. As such, the task-based model provides an explanation for why occupations in the middle of the skill distribution, that are intense in routine tasks, have experienced a strong employment decline (Autor et al., 2003; Spitz-Oener, 2006). This phenomenon is also referred to as job polarization (Goos & Manning, 2007).

After two decades of growth in occupations requiring high cognitive skills, there is evidence of a declining demand for such skills in the United States after the year 2000 (Autor, 2015; Beaudry et al., 2016; Castex & Kogan Dechter, 2014; Mishel et al., 2013). One potential explanation for changes in the demand for cognitive skills is that technological advances rapidly expand the set of tasks that can be performed by computer-based technologies (Brynjolfsson & McAfee, 2014). Computer capital might increasingly substitute for labour higher up in the skill distribution, redefining what it means for work to be ‘routine’ (Autor, 2014;

Lu, 2015). While machines already substitute human labour in performing routine tasks (e.g. assembling cars, or administrating data), computer capital becomes increasingly proficient in performing a wide range of complex tasks that are typically defined as non-routine such as driving cars and diagnosing diseases (Brynjolfsson & McAfee, 2014). If computer capital is increasingly replacing labour in the upper-end of the skill distribution, one would expect to observe an increase in computer and software investments. However, corporate computer and software investments seem to have dropped since the 2000s (Autor, 2015). Beaudry et al. (2006) argue that the declining returns to cognitive skills are the result of the *dotcom* bubble bust and that progress of information technology reached maturity in the early 2000s in the United States. These findings are supported by Castex and Kogan Dechter (2014) who document that the returns to cognitive skills slightly fell in the 2000s relative to the 1980s. They argue that this decline can be associated with a slowdown in the growth rate of technology.

Whether the Netherlands also experienced a decline in the returns to non-routine analytical skills since the early 2000s is not evident. In contrast to the recent slowdown in the growth of high-skill occupations in the Unites States, the employment share of high-skill occupations expanded between 2005 and 2015 in the EU-28 (Cedefop, 2016a; Cedefop, 2016b). Moreover, Hartog and Gerritsen (2016) demonstrate that the number of computer service and information technology agencies has mushroomed after the mid-1990s in the Netherlands. This trend suggests that the application of computer-based technologies has continued to rise in the Netherlands. Therefore, one would expect to observe an increasing return to analytical skills over the past two decades in the Netherlands.

The return to non-routine interpersonal skills

In contrast to routine tasks, non-routine tasks requiring significant interpersonal interaction have still proven difficult to automate (Autor, 2015; Autor et al., 2003; Deming, 2017; Frey & Osborne, 2017). While machines are capable of reproducing some aspects of human social interaction, the real-time recognition of human emotion and the ability to respond to such inputs remains an engineering bottleneck. The task-based model predicts an improvement in the productivity and an increasing demand for labour performing tasks that are not susceptible to computerisation (Autor, 2015). Deming (2017) documents that the probability of full-time work has increased more than fourfold between 1979 and 1997 for graduates (aged 25-33) who are endowed with high interpersonal skills in the United States. During the same period, the wage returns to interpersonal skills almost doubled. Likewise, Borghans et al. (2014) document that the number of occupations requiring interpersonal skills – along with the monetary returns – rapidly grew between the late 1970s and early 1990s in Britain, Germany and the United States.

One potential explanation for the increasing reward for interpersonal skills is skill-biased organizational change (Bresnahan et al., 2002; Caroli & Van Reenen, 2001). According to the 'skill-biased organizational change' hypothesis, technological innovations have led organization to move toward more workplace decentralisation.[8] The decentralization of authority transfers the decision-making process to teams of workers, delayers managerial functions, and increases multitasking. The change in work structure places greater demands on workers who are able to work in teams, adept to communicate effectively, and who are capable of influencing and coaching colleagues and subordinates. Because skill-biased organizational change also implies an increasing demand for workers who are able to run complex organisations, one could expect an increase in the demand for managerial skills.

A number of studies have focussed on the changing returns to interpersonal and managerial skills (related to direction and control). Borghans et al. (2008) distinguish between different interpersonal styles, namely, directness and caring. While directness facilitates accurate communication, caring is required to create a cooperative environment in which tasks have to be carried out. For example, teachers and nurses have to be relatively caring, while salespeople and managers need to be more direct in their interactions with other people. Borghans et al. (2008) demonstrate that directness yields a higher wage premium than caring and that the premium to directness has increased relative to caring in Britain (data covering 1997-2001) and Germany (data covering 1979-1998). In line with these findings, Autor et al. (2003) document that the returns to interpersonal and managerial skills rose during the 1980s and the 1990s in the United States. Weinberger (2014) finds that the leadership premium, which is measured by whether graduates participated in sports or in high school leadership activities, more than doubled from 1979 to 1999. Finally, Edin et al. (2017) report that the increasing returns to interpersonal skills between 1992-2013 in Sweden was particularly pronounced at the upper-end of the wage distribution. Many of the managerial, professional and technical occupations can be found in the higher end of the wage distribution. Prior research suggests that if interpersonal skills have become more important over time in the Netherlands, that the reward for such skills will be particularly pronounced in the upper-part of the skill-distribution.

8 The introduction of information technology reduces the cost of decreasing direct control of workers as it allows for indirect, computer-based monitoring of ex post performance. This induces organisational change. Moreover, it also reduces the cost of lateral communication among line workers. Hence, information technology reduces the benefit of hierarchical decision making, thus increasing the incentives for firms to decentralize authority.

3. Data

The analyses in this paper are based on combined data from three different sources; the European Labour Force Survey (EU-LFS), O*NET, and administrative data from Statistics Netherlands. The data cover the period 2001-2016.

European Labour Force Survey

The starting point for our database is the EU-LFS for the Netherlands. The EU-LFS is a rotating random sample survey that covers the population in private households in 33 European countries, including the 28 Member States of the European Union. The aim of the EU-LFS is to provide cross-country comparable information on the labour market participation of individuals aged 15 years and above. Since 1999, the EU-LFS is designed as a quarterly rotating panel including five waves. Every month, a sample of addresses is drawn in order to construct a new first wave. By the end of each wave, respondents are approached to participate in the successive wave. The period in between each wave is approximately 3 months and the total period in which individuals participate in the EU-LFS surveys covers twelve months.[9] Between 2001 and 2016, 115,563 unique individuals participated on average in the survey each year in the Netherlands.

We use the EU-LFS to derive information on the occupation in which individuals work, namely, the International Standard Classification of Occupations (ISCO-08) code. The 4-digit ISCO-08 code is available for workers' main job (i.e. the job with the highest weekly working hours). For our analyses, we use the ISCO-08 of workers' main job in the first wave. The EU-LFS also provides information on workers' highest attained level of education.[10]

Occupational Information Network (O*NET)

The skill requirements measures for occupations are obtained from O*NET.[11] O*NET is a systematic source of information on occupational characteristics

9 In the Netherlands, the interviews in the first wave are either conducted through face-to-face interviews or through telephone interviews. Until 2010, data were exclusively collected through face-to-face interviews in the first wave. The data collection in the second through fifth wave takes place by means of telephone interviews.

10 The levels of education are measured according to the International Standard Classification of Education (ISCED): pre-primary education (ISCED level 0), primary education (ISCED level 1), lower secondary education (ISCED level 2), upper secondary education (ISCED level 3), post-secondary non-tertiary education (ISCED level 4), first stage of tertiary education (ISCED level 5), or second stage of tertiary education (ISCED level 6).

11 O*NET is the successor of the Dictionary of Occupational Titles (DOT).

produced by the United States Department of Labor. O*NET introduced its first version in 1998 and started full-scale data collection in 2001. The O*NET database is updated periodically and includes 239 items on abilities, skills, knowledge, and work activities required in an occupation. The measures are mainly derived from job incumbent questionnaires, but also from questionnaires assigned to job analysts. O*NET publishes information at the level of occupations. A description of the data collection method can be found in Appendix 1.

We closely follow Acemoglu and Autor (2011) in measuring the use of non-routine cognitive analytical skills and non-routine cognitive interpersonal skills in occupations. We measure analytical skills as the average of the following three questions: (i) "how important is analysing data or information to the performance of your current job?", (ii) "how important is thinking creatively to the performance of your current job?", and (iii) "how important is interpreting the meaning of information for others to the performance of your current job?". The average of the following questions is taken to obtain a measure of interpersonal skills: (i) "how important is establishing and maintaining interpersonal relationships to the performance of your current job?", (ii) "how important is guiding, directing, and motivating subordinates to the performance of your current job?", and (iii) "how important is coaching and developing others to the performance of your current job?". Job incumbents indicate the importance of each item on an ordinal scale from 1-5 (1 = not important, 5 = extremely important). The Cronbach's alpha scale reliability coefficients are 0.8196 for non-routine analytical skills and 0.8176 for non-routine interpersonal skills. All items are derived from the O*NET Work Activities Survey Version 21.1.

The occupational classification of O*NET (O*NET 2010-SOC) is mapped to the ISCO-08 classification. O*NET Version 21.1 provides occupational characteristics of 964 different occupations in the United States. The mapping between the O*NET 2010-SOC and the ISCO-08 classification is facilitated by a crosswalk file that maps each O*NET code to the corresponding ISCO-08 occupation.[12] In total, there are 1,110 O*NET SOC-2010 occupations and 436 ISCO-08 occupations, making the O*NET classification more detailed than the ISCO-08. The analytical and interpersonal skill variables, measured at the level of O*NET SOC occupations, are collapsed to the ISCO-08 occupations weighted by US employment in each SOC cell. The vector of the two skills, $S_j^{(x)}$, where the measure of each skill, $S^{(x)}$, for each ISCO-08 4-digit occupation j = 1, ... J is computed as:

$$S_j^{(x)} = \sum_{\substack{k=1 \\ k \in \{S_j\}}}^{K_j} O_k^{(x)} \frac{n_k}{\sum_k n_k}$$

12 The crosswalk is available on http://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/.

13 The OES employment data can be retrieved from https://www.bls.gov/oes/tables.htm.

Here, $O_k^{(x)}$ represents the measure of skill x for O*NET SOC occupation k. The number of employed individuals in occupation k is derived from the US Occupational Employment Statistics (OES)[13] and is represented by n_k, while $\Sigma_k n_k$ indicates total employment across all occupations k. The summation is over the set $k \in \{S_j\}$ of the K_j O*NET SOC occupations that are matched to ISCO-08 4-digit occupation j. The importance scores are normalized to have a mean of 0 and a standard deviation of 1 within each year.

Statistics Netherlands

Information on workers' wages is retrieved from administrative data from Statistics Netherlands.[14] For each separate job a worker holds in a specific year, we observe the gross annual wage including national insurance contributions, the number of days a worker has been employed, and the full-time equivalent for which workers are employed. To calculate the number of full-time days an individual has worked in a specific job, we multiply the number of days a worker has been employed in a specific job by the full-time equivalent. We then calculate for each worker's job the gross daily wage by dividing the gross annual wage by the number of full-time days worked.[15] In the case that workers have multiple jobs in a specific year, we calculate the average gross daily salary across those jobs. The wages are indexed to 2015 euros.[16] The data from Statistics Netherlands also include information on the firm size[17], and on worker's gender, age, and migration background.[18] Although Statistics Netherlands also offers administrative data on the highest attained level of education, the data are only available for persons who obtained their degree after 2000. For this reason, we use self-reported attained levels of education from the EU-LFS data.

To obtain the best estimates of lifetime returns to skills, the sample is restricted to prime-age workers, defined as workers aged between 35 and 54 years (Böhlmark & Lindquist, 2006; Haider & Solon, 2006). Given that workers with high lifetime earnings tend to have steep earnings trajectories, focussing on earnings observed in the early stage of workers' careers is likely to provide a biased estimate of lifetime earnings. We trim the bottom and top one percent of the wage distribution to limit the influence of wage outliers. Table 1 shows

14 Quantitative information concerning jobs is retrieved from the dataset BAANSOMMENTAB. Statistics Netherlands also provides wage data in the POLISBUS dataset. However, the data is only available for the period 2006-2017. BAANSOMMENTAB provides wage data for the period 1999-2016.

15 Although we do observe workers' yearly income tax and yearly income tax allowance, we prefer to use workers' gross wages rather than net wages. To calculate the net wages correctly, we would also needs information on expenses that are tax deductible.

16 We use the consumer price index from Statistics Netherlands.

17 Qualitative information of jobs are obtained from the dataset BAANKENMERKENBUS. This dataset provides us with an employer identification number which is matched to the dataset BETAB which provides information on the firm size. In the case that workers hold more than one job in a specific year, we use qualitative information for the job in which a person was employed for the most number of days which is based on the number of days between the start and end date of a job.

18 Demographic information is obtained from the dataset GBAPERSOONTAB.

Table 1 **Data availability**

Year	Total number of observations
2001	19,083
2002	19,934
2003	20,666
2004	23,649
2005	22,554
2006	17,983
2007	17,652
2008	18,070
2009	14,868
2010	22,178
2011	15,582
2012	11,070
2013	32,272
2014	19,716
2015	20,342
2016	18,583

the number of observations available for each year in our dataset.
Table 2 shows how skill requirements are distributed across a broader classification of occupational groups, namely, 39 sub-major groups (2-digit ISCO occupations).[19] Analytical skills are particularly important for the ISCO major group "Professionals" which include the sub-major groups "Science and Engineering Professionals", "Health Professionals", as well as "ICT Professionals".[20] According to the O*NET measures, occupations in the ISCO major group "Managers" also score relatively high on analytical skill requirements. The O*NET skill measures are consistent with the Skill Level that ISCO assigns to the majority of the occupations in these two major groups, namely, Skill Level 4 (i.e. the highest Skill Level). Within the major group "Managers", ISCO only assigns Skill Level 3 to the sub-major group "Hospitality, Retail and other Services Managers". Occupations at Skill Level 4 generally consist of tasks that require complex problem-solving skills, decision-making skills and creativity and the application of a large body of theoretical and factual knowledge in a specialized field. Occupations at Skill Level 4 typically require high levels of literacy and numeracy as well as excellent interpersonal communication skills. According to the O*NET skill measures, the major groups "Managers" and "Professionals" require extended levels

19 In total, ISCO distinguishes between 43 2-digit major groups. O*NET provides no skill measures for the three Armed Forces Occupational groups and the Subsistence Farmers, Fishers, Hunters and Gatherers occupational group.

20 ISCO distinguishes between 10 1-digit major groups, namely, managers (1), professionals (2), technicians and associate professionals (3), clerical support workers (4), services and sales workers (5), skilled agricultural, forestry and fishery workers (6), craft and related trades workers (7), plant and machine operators, and assemblers (8), elementary occupations (9), and armed forces occupations (0). ISCO distinguishes between 43 2-digit sub-major groups, 130 3-digit minor groups, and 436 4-digit unit groups.

Table 2 Descriptive statistics

Occupational group	ISCO code	Employment share in hours in 2001 (%)	Employment share in hours in 2016 (%)	Employment share 2001-2016 (%-points)	Analytical skill importance	Interpersonal skill importance	ISCO skill level	Gross daily wage
Chief Executives, Senior officials and Legislators	11	1.98	2.28	0.30	0.96	1.99	3+4	205.93
Administrative and Commercial Managers	12	1.74	2.46	0.73	1.47	1.81	3+4	200.44
Production and Specialized Services Managers	13	5.57	3.41	-2.16	1.25	1.80	3+4	180.8
Hospitality, Retail and Other Services Managers	14	1.80	1.26	-0.54	0.79	1.91	3+4	143.73
Science and Engineering Professionals	21	2.40	2.49	0.08	1.72	0.46	4	160.27
Health Professionals	22	2.62	3.07	0.45	1.42	1.29	4	152.77
Teaching Professionals	23	4.39	6.26	1.87	1.19	1.49	4	142.55
Business and Administration Professionals	24	4.58	10.53	5.95	1.58	0.96	4	168.32
Information and Communications Technology Professionals	25	0.62	3.83	3.21	1.56	0.30	4	169.03
Legal, Social and Cultural Professionals	26	3.22	3.26	0.04	1.45	0.20	4	153.51
Science and Engineering Associate Professionals	31	6.73	3.27	-3.47	0.26	0.15	3	136.25
Health Associate Professionals	32	3.15	3.30	0.15	0.61	0.70	3	108.37
Business and Administration Associate Professionals	33	8.89	9.19	0.30	0.45	-0.03	3	138.64
Legal, Social, Cultural and Related Associate Professionals	34	1.95	1.95	-0.01	-0.03	0.03	3	102.51
Information and Communications Technicians	35	0.10	0.61	0.51	0.61	-0.76	3	126.34
General and Keyboard Clerks	41	3.41	2.54	-0.87	-0.66	-1.09	2	96.58
Customer Services Clerks	42	1.00	2.16	1.16	-0.41	-0.35	2	97.97
Numerical and Material Recording Clerks	43	3.07	5.42	2.34	-0.12	-0.72	2	116.52
Other Clerical Support Workers	44	1.80	1.24	-0.57	-1.06	-1.35	2	92.03
Personal Services Workers	51	2.26	2.81	0.55	-0.96	-0.24		92.06
Sales Workers	52	5.18	5.38	0.19	-0.10	0.03		96.62
Personal Care Workers	53	1.58	3.40	1.81	-0.29	0.17		83.09
Protective Services Workers	54	1.70	1.43	-0.27	0.50	0.98		113.09
Market-oriented Skilled Agricultural Workers	61	2.23	1.11	-1.12	-0.55	0.37		88.82
Market-oriented Skilled Forestry, Fishery and Hunting workers	62	0.09	0.02	-0.06	-0.11	0.42		116.2
Metal, Machinery and Related Trades Workers	72	4.89	2.65	-2.24	-0.34	-0.60		105.20
Handicraft and Printing Workers	73	1.05	0.35	-0.69	0.10	-1.34		101.00
Electrical and Electronic Trades Workers	74	1.77	0.85	-0.92	0.19	0.16		109.75
Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	75	1.84	1.07	-0.77	-1.04	-1.39		92.41
Stationary Plant and Machine Operators	81	2.08	0.92	-1.16	-0.62	-0.75		100.70
Assemblers	82	0.52	0.28	-0.24	-0.52	-0.67		87.62
Drivers and Mobile Plant Operators	83	6.10	3.49	-2.61	-0.33	-0.64		105.27
Cleaners and Helpers	91	0.50	1.88	1.39	-1.51	-1.22		71.32
Agricultural, Forestry and Fishery Labourers	92	0.13	0.12	-0.01	-1.53	-1.17	1	76.53
Labourers in Mining, Construction, Manufacturing and Transport	93	3.19	2.33	-0.86	-1.24	-1.01	1	84.18
Food Preparation Assistants	94	0.42	0.20	-0.23	-1.54	-0.71	1	73.06
Street and Related Sales and Services Workers	95	0.01			-1.55	0.46	1	118.24
Refuse Workers and Other Elementary Workers	96	0.13	0l27	0.14	-1.42	-1.57	1	84.98

Notes: The analytical sand interpersonal skill importance measures have a mean of 0 and a standard deviation of 1. The wages are indexed to 2015 euros. The skill importance measures and gross daily wages are calculated as the average of the underlying 4-digit ISCO occupations weighted by the share of hours worked. The skill level is defined by ISCO as a function of the complexity and range of tasks to be performed in an occupational group. Occupations at Skill Level 1 generally require basic literacy and numeracy skills. Occupations at Skill Level 2 generally require relatively advanced literacy and numeracy skills and good interpersonal communication skills. Occupations at Skill Level 3 generally require a high level of literacy, numeracy and interpersonal communication skills. Occupations at Skill Level 4 generally require extended levels of literacy and numeracy, sometimes at a very high level, and excellent interpersonal communication skills.

of interpersonal skills. Similarly, ISCO indicates that occupations at Skill Level 4 require excellent interpersonal communication skills. The high level of interpersonal skills assigned to managerial occupations does not necessarily reflect that interpersonal skills are less important in, for example, low-paid service occupations. However, the nature of the interpersonal skills required in managerial functions might differ from those required in service occupations. The measure used for interpersonal skills in this study rather relate to the guidance and supervision of subordinates in the workplace.

Occupations in which non-routine analytical and interpersonal skills are evidently less important according to O*NET are occupations in the ISCO major groups “Plant and Machine Operators and Assemblers” and “Elementary Occupations”. Most occupations in the major group “Elementary Occupations” require skills at the first ISCO skill level for the duties and tasks involved in an occupation. According to ISCO, some occupations at Skill Level 1 require basic numeracy and literacy skills. “Elementary Occupations” involve the performance of simple and routine physical or manual tasks. To adequately perform the tasks in most occupations in the ISCO major group “Plant and Machine Operators and Assemblers”, skills at the second ISCO level are required. For the majority of occupations requiring ISCO Skill Level 2, workers need to have the ability read, write, and to accurately perform simple arithmetical calculations. Analytical and interpersonal skills are also less important in the ISCO major group “Skilled Agricultural, Forestry and Fishery Workers”.

From Table 2, it can also be observed that positive employment growth, expressed in hours worked, is mostly observed in occupations in which non-routine analytical skills and non-routine interpersonal skills are relatively important. For example, an occupational group that has more than doubled in terms of its employment share between 2001 and 2016 is the sub-major group “Business and Administration Professionals”. This sub-major group also requires one of the highest levels of analytical skills and a relatively high level of interpersonal skills. The employment share of the sub-major group “Stationary Plant and Machine Operators” more than halved between 2001 and 2016. This sub-major group requires relatively low levels of analytical and interpersonal skills. Finally, Table 2 also shows that occupations that are intensive in analytical and interpersonal skills are associated with a higher gross daily wage.

4. Empirical model

We estimate the wage return to non-routine analytical skills and non-routine interpersonal skills at successive points in time. We estimate wage regressions of the following kind:

$$\log(wage_{it}) = ß_0 + ß_{1t}\, Analytical_j + ß_{2t}\, Interpersonal_j + \gamma_t X_i + \varepsilon_{ij} \quad (1)$$

where $wage_i$ indexes the gross daily wage of individual *i* in year *t* and *Analytical* and *Interpersonal* denote the importance of non-routine cognitive skills and non-routine interpersonal skills, respectively, in occupation *j*. The model includes a vector of controls *X*, including gender, ethnicity, the highest attained level of education, age, age squared, and the firm size in which person *i* is employed. The standard errors are clustered at the level of the 4-digit ISCO occupation. The regressions are run separately for each year between 2001-2016. The coefficient of interest, $ß_1$ ($ß_2$) can be interpreted as the wage premium associated with analytical (interpersonal) skills used in jobs, conditional on interpersonal (analytical) skills.

The OLS estimates will not reflect the true value of $ß_1$ and $ß_2$ when (a) workers do not actually possess the skills that are required in their occupation (a situation of skill mismatch) and (b) when the acquisition of skills is endogenously determined (such that *Analytical*, *Interpersonal* and ε are not orthogonal). Because additional skills or schooling can increase productivity, over-skilled workers might incur a wage premium over their well-matched colleagues (e.g. Quintini, 2011a; Rumberger, 1987). Hence, a situation of over-skilling will lead to an upper-bound estimate of the true skill rewards (i.e. a situation in which workers' skills match the requirements of the job). In contrast, if under-skilled workers are less productive than their well-matched colleagues, a situation of under-skilling will result in a lower-bound estimate of the true value of $ß_1$ and $ß_2$ (Quintini, 2011a). Because under-skilling is a phenomenon that occurs less frequently than over-skilling in most countries (Pellizari & Fichen, 2013), including the Netherlands, we expect $ß_1$ and $ß_2$ to reflect upper-bound estimates of the true skill premiums. Nevertheless, we expect the upward bias of our estimates to be limited for two reasons. First, the incidence of over-schooling in the Netherlands has been rather low during our sample period (ILO, 2014). Second, while over-skilled workers can receive a wage premium over their well-matched colleagues, excess skills or schooling do not always translate into raised productivity and therefore will not always be rewarded with higher earnings (Gautier et al., 2002; Rumberger, 1987; Van der Velden & Bijlsma, 2018).

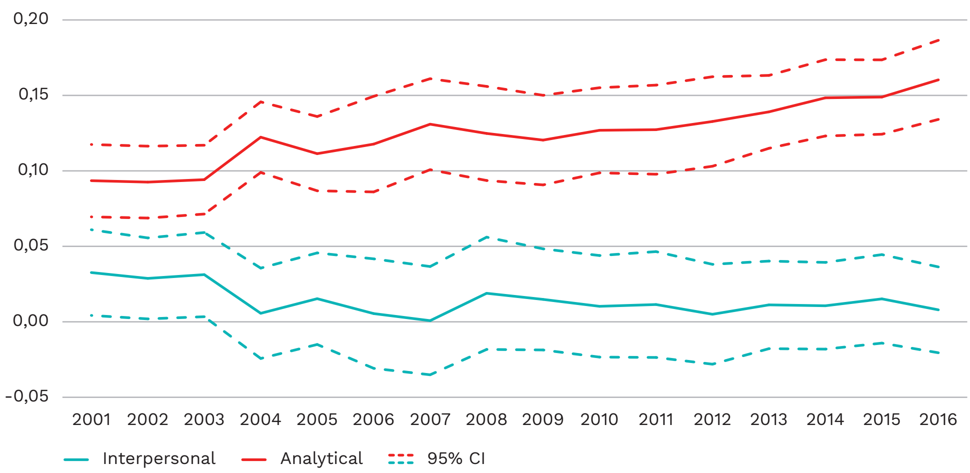
Identifying a causal relationship between a given increase in workers' skills and earnings, also requires the observed variation in skill requirements across workers' occupations to be truly exogenous. There are several potential threats to causal identification of this relationship. First, omitted variables could lead to classic omitted variable bias if they are related to skills and also directly influence earnings (e.g. family background, ability, or personality traits). For example, if family background influences skill endowment and development and if family ties also help individuals to find better jobs, the relation between skills and earnings will not merely reflect the causal effect of skills. It is important to note that the potential bias that results from omitted variables does not regard the typical 'ability bias' that is the focus of attention in the extensive literature on causal estimates of the returns to schooling. Hence, we acknowledge that the skills applied in jobs can either emerge from innate abilities, the home environment, but also from investments in schooling. The second threat to causal identification is one of reversed causality; better paying jobs might provide more opportunities for skill development through on the job training or by investments in adult education. These occupations might also have higher skill requirements. Because our data are not rich enough to identify exogenous variation in workers' skills and assignment to occupations, we rely on time series estimates of the premiums associated with different skill types. Under the assumption that the magnitude of any form of bias remains constant over time, changes that are observed in skill rewards will reflect a shift in the interaction between the demand and supply of non-routine skills.

5. The returns to analytical and interpersonal skills

The estimates of the conditional returns to analytical and interpersonal skills for the entire labour market (both public and private sector workers) are plotted separately in Figure 1.[21] Between the early 2000s and the mid 2010s, the reward for analytical skills increased from 9.4 percent in 2001 to 16.0 percent in 2016. Hence, in 2016, a person employed in a job requiring one standard deviation more analytical skills than the mean for all occupations received a gross daily wage that was 16.0 percent higher than in jobs requiring the mean. The conditional return to interpersonal skills, on the other hand, slightly decreased over the past two decades. Workers in jobs requiring a one-standard-deviation higher level of interpersonal skills, incurred a wage premium of 3.3 percent over workers in jobs requiring the mean level of interpersonal skills in the population in 2001. This premium decreased to 0.8 percent in 2016.

Given that the skill rewards in the private sector are typically driven by market forces, the skill premiums in the private sector might be a better reflection of the actual demand for skills. To test whether this is true, we restrict the sample to private sector workers. Figure 2 shows that the estimates for the private sector are very similar to the estimates obtained for the sample that includes both private sector and public sector workers. The return to analytical skills increased from 8.1 percent in 2001 to 16.4 percent in 2016 in the private sector. With respect to interpersonal skills, the conditional return to interpersonal skills declined from 4.5 percent in 2001 to 1.6 percent in 2016. Because the estimates

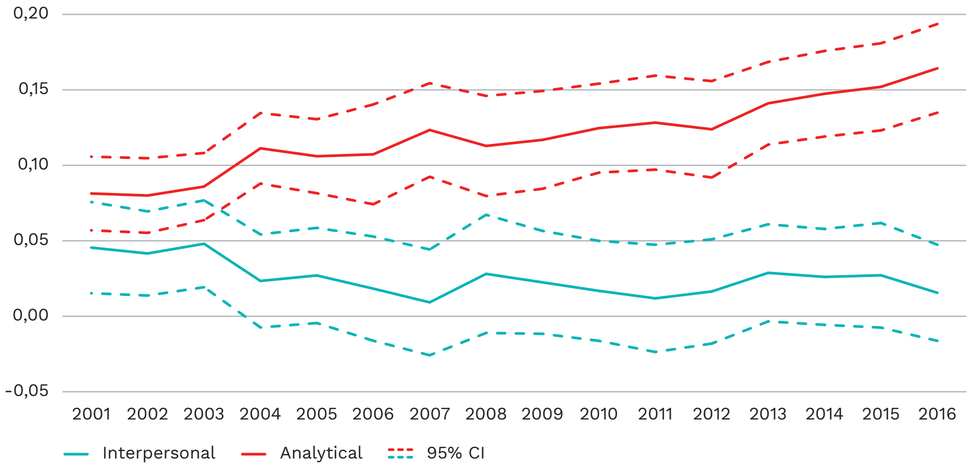
Figure 1 The returns to analytical and interpersonal skills



21 The estimates for the sample that is restricted to workers in full-time jobs are presented in Appendix 2. The results are qualitatively comparable to the sample consisting of workers in full-time as well as part-time jobs.

of the returns to both skill components are similar for the overall labour market as well as for the private sector workers only, we proceed with the sample including both the private and public sector workers in the subsequent analyses.

Figure 2 The returns to analytical and interpersonal skills – Private sector workers



6. Non-linearities in the return to skills

In this section we examine whether the trends in the return to analytical and interpersonal skills are driven by a specific segment of the wage distribution. If technology has substituted for workers in the middle of the skill distribution, as predicted by the job polarization hypothesis, greater employment growth will be observed at the lower and upper end of the skill distribution (Goos et al., 2014). However, while some of the tasks that are part of many occupations in the middle of the skill distribution are susceptible to automation, many middle skill occupations consist of a mixture of tasks requiring a different set of skills. For example, electrical and installation technicians constitute a rapidly growing category of relatively well-remunerated, middle-skill employment. While electrical and installation technicians are not required to possess a higher education degree, they are expected to master a 'middle-skill' level of analytical skills. If tasks are difficult to unbundle, machines will perform routine tasks while workers will continue to perform the set of non-routine tasks in which they hold a comparative advantage.

To analyse whether the return to skills are non-linear or not, we estimate quantile regressions corresponding to Equation (1). Figure 3 presents the quantile regressions estimates for non-routine analytical skills and Figure 4 shows the estimates for non-routine interpersonal skills. Figure 3 suggests that the return to analytical skills strongly increased in all parts of the wage distribution. In 2001, the wage premium for analytical skills was 11.4 percent in the lower end of the wage distribution (the 10th percentile and below) and 9.2 percent in the middle part of the wage distribution (at the 50th percentile). By 2016, the wage premium had grown to 15.6 percent in the lower end of the wage distribution and to 16.2 percent in the middle of the wage distribution. In the

Figure 3 The returns to analytical skills: quantile regression estimates

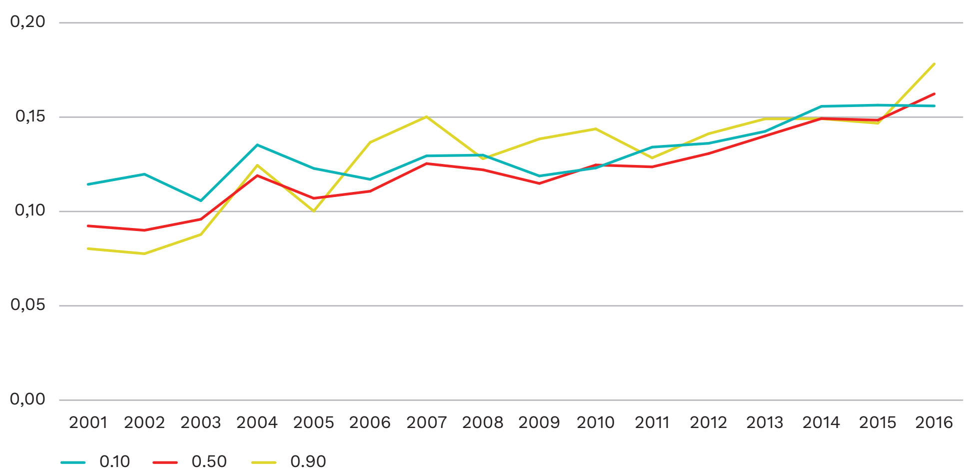
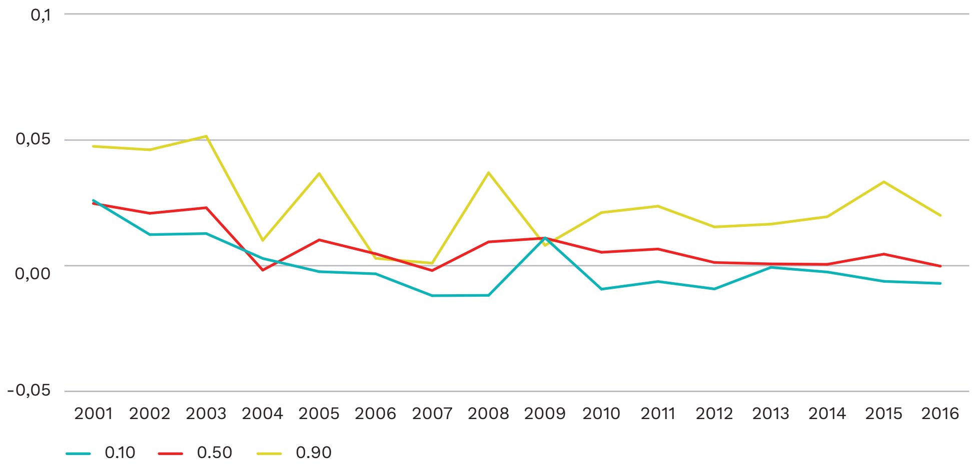


Figure 4 **The returns to interpersonal skills: quantile regression estimates**



upper-end of the wage distribution (from the 90th percentile and above), the return to analytical skills increased from 8.0 percent in 2001 to 17.8 percent in 2016.

The highest wage premium for interpersonal skills is observed in the upper-end of the wage distribution (from the 90th percentile and above). In 2001, a one standard deviation increase in interpersonal skills is associated with being employed in an occupation that offers 4.7 percent higher wages. In 2016, this premium declined to 2.0 percent for the upper-end of the wage distribution. For the lower end of the wage distribution (from the 10th percentile and below), being employed in a job that requires a one standard deviation higher level of interpersonal skills compared to the mean, is associated with a wage premium of 2.6 percent in 2001 and -0.1 percent in 2016 for the lower end of the wage distribution. In the middle part of the wage distribution, the returns to interpersonal skills decreased from 2.5 percent in 2001 to -0.01 percent in 2016.

When the sample is restricted to full-time workers, we observe a slight increase in the reward for interpersonal skills (results presented in Appendix 2). In 2001, the premium for interpersonal skills yielded 3.7 percent for the overall sample which increased to 4.0 percent in 2016. The upward trend in the returns to interpersonal skills is most pronounced for workers in the upper-end of the wage distribution where the premium for interpersonal skills rose from 5.8 percent in 2001 to 7.4 percent in 2016. In the middle part of the wage distribution, the interpersonal skills premium increased from 2.1 percent in 2001 to 2.8 in 2016. The increasing trend appears to be absent in the lower-end of the wage distribution where the return yielded 1.7 percent in 2001 and 1.8 percent in 2016.

The estimates are consistent with Deming (2017) who reports an increase in the return to interpersonal skills for full-time workers in the United States between 1980-2012. In addition, the findings are also in line with Edin et al. (2017) who document that the increasing reward for interpersonal skills in Sweden is particularly pronounced at the upper-end of the wage distribution. Deming (2017) documents that workers who possess a high level of interpersonal skills were increasingly likely to select themselves into full-time employment. Hence, our findings could reflect an increasing demand for workers in managerial jobs that are intensive in interpersonal skills and that are typically full-time positions. The constant returns to interpersonal skills for workers in the lower-end of the wage distribution is consistent with previous empirical findings indicating that high-skill occupations exhibit a greater employment increase than low-skill service jobs in the Netherlands (OECD, 2016; Terzidis, Maarseveen & Ortega-Argilés, 2017).

7. Conclusion and discussion

While skills are an increasingly important predictor of graduates' labour market success, empirical evidence on how skills are rewarded in the labour market almost exclusively rely on school attainment measures of human capital. This study investigates trends in the returns to non-routine cognitive analytical and non-routine cognitive interpersonal skills between 2001 and 2016 in the Netherlands. Given that only imperfect measures of the skills used in employment today are available for the Netherlands, we construct occupational skill profiles by matching skill measures from the US O*NET system to the occupations of Dutch workers. These data are combined with information on employment and wages from administrative data from Statistics Netherlands.

We document an increase in the premium for non-routine analytical skills. For the overall labour market, the reward for analytical skills increased from 9.4 percent in 2001 to 16.0 percent in 2016. An increase in the analytical skill premium is not only observed in the upper-end of the wage distribution (from the 90th percentile and above), but also in the middle- (50th percentile) and lower-end (the 10th percentile and below) of the distribution. Overall, our findings indicate that non-routine analytical skills are increasingly valued on the Dutch labour market. The increasing reward for analytical skills supports the idea that the demand for non-routine tasks (i.e. interpreting and analysing information) have increased as computerization has boosted the productivity of routine tasks (i.e. due to declining costs of retrieving and manipulating information). Our findings propose that workers in all segments of the wage distribution performing non-routine tasks have benefitted from the increased productivity in routine tasks. The rising premium also suggests that the demand for analytical skills has outpaced the supply of such skills over the past two decades. This makes sense given that the supply of skilled labour is rather inelastic. While the stock of workers with vocational or higher education degrees are certainly increasing in the Netherlands, it takes typically at least four years to complete a study programme in upper-secondary or tertiary education and to enter the labour market. Although certain tasks in many middle-skill jobs are susceptible to automation, the increasing return to analytical skills in the middle of the wage distribution indicates that many jobs in this segment will continue to require a changing set of skills. Hence, boosting the development of analytical skills will not only continue to be essential in higher education, but also in study programmes provided by vocational education and training.

With respect to the reward for interpersonal skills, we document a decline from 3.3 percent in 2001 to 0.8 percent in 2016 for the overall sample consisting of full-time and part-time workers. We only find a considerable increase in the reward for interpersonal skills for full-time workers higher up in the wage distribution. For workers in the upper-end of the wage distribution (from the

90th percentile and above), the interpersonal skill reward rose from 5.8 percent in 2001 to 7.4 percent in 2016. This finding is consistent with the idea that increased organisational complexity have put greater demands on interpersonal communication and managerial skills (Bresnahan et al., 2002; Caroli & Van Reenen, 2001). Therefore, the demand for workers in managerial positions might have outpaced the supply of workers possessing good interpersonal and managerial skills. This is consistent with studies reporting that managerial interpersonal skills are increasingly rewarded on the labour market (Autor et al., 2003; Borghans et al., 2007; Weinberger, 2014). Although interpersonal skills are typically also important in service jobs that can be found in lower segments in the wage distribution, the supply for interpersonal skills might have increased at a higher pace than the demand for such skills.

Finally, this study is subject to several limitations. First, O*NET assigns task measures to occupations and, thereby, ignores the heterogeneity in job tasks across individuals holding similar occupations. A number of studies highlight the relevance of within-occupation variation in tasks (Arntz, Gregory & Zierahn, 2017; Autor & Handel, 2013; Cassidy, 2017). Hence, the wage differentials across occupations and the observed changes in the skill premiums over time reported in this study should be attributed to differences in skill requirements across occupations and to developments in the occupational structure. Given that occupations alone do not fully reveal the type of tasks workers execute, future research on the returns to skills ideally relies on skill measures at the individual level of Dutch workers. Such data will also be less prone to measurement error.

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Appendix 1: Data collection O*NET

The data collection is conducted by identifying industries that comprise occupations that are targeted in a data collection cycle. A random sample of establishments within those industries are approached. Employers who agree to participate are requested to distribute the seven O*NET surveys (Abilities, Knowledge, Skills, Work Activities, Work Context, Work Style, and Education and Training) to a random group of employees who are employed in the targeted occupations. According to estimates, 70 percent of the contacted employers agree to distribute surveys among their employees, of whom 65 percent returned completed surveys (U.S. Department of Labor, 2005, p. A-13, B-28). To avoid fatigue, employees are requested to fill in a subset of the questionnaires which take about half an hour complete.

Although O*NET does not publish information on the total sample size, measures in the O*NET database are based on at least 15 respondents per occupation and often many more (U.S. Department of Labor 2005, p. B-6). An O*NET staff member estimated that approximately 125,000 questionnaires were collected from job incumbents in the most recent data collection cycle (Händel, 2016). This implies that each of the 239 measures are based on roughly 31,000 respondents, given that respondents fill in one quarter of the surveys. Hence, within each of the 809 occupations, each skill measurement is based on 39 respondents on average. The published O*NET database contains occupation mean values and the original micro-data is not publicly available.

O*NET updates skill ratings of occupations on a continuous basis in a 5-year cycle. Every year, a new O*NET edition is being released which replaces the old skill ratings for a set of occupations with new ratings.

Appendix 2: Results for workers in full-time jobs

Figure 5 The returns to analytical and interpersonal skills – Full-time worker

Figure 6 The returns to analytical and interpersonal skills: Full-time private sector workers

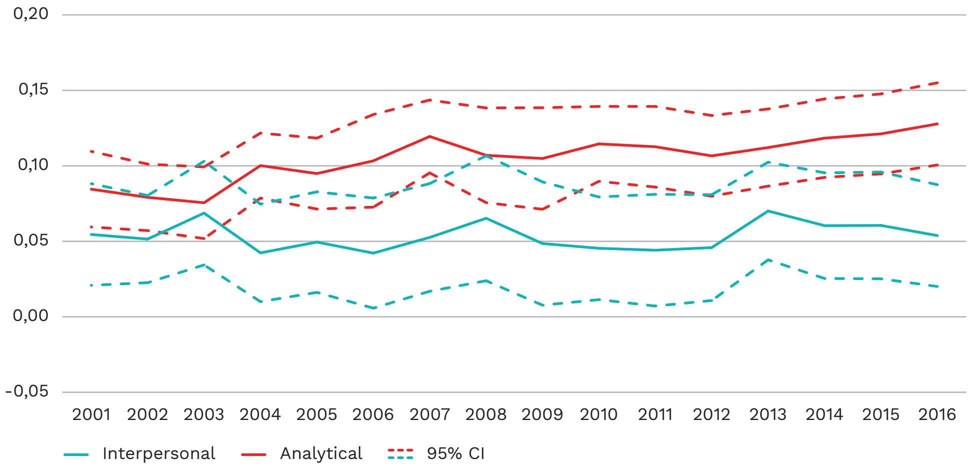

Figure 7 **The returns to analytical skills: quantile regression estimates – Full-time workers**

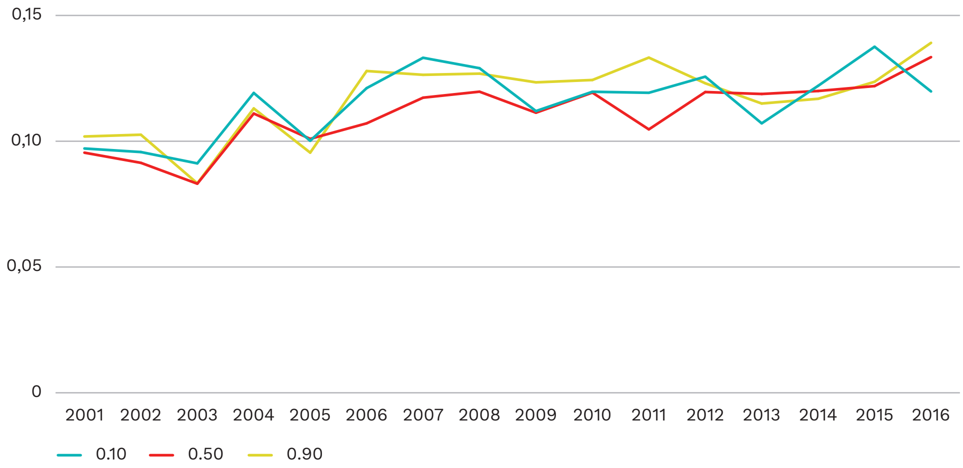

Figure 8 **The returns to interpersonal skills: quantile regression estimates – Full-time workers**