TECHNEQUALITY Policy Brief No 6.

Technological Progress and Changes in the Occupational Structure of the Dutch Labour Market

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TECHNEQUALITY has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement no. 822330

Key Message

The fear that technological progress will render much of human labour obsolete is not new. However, improved computing power and the decreasing cost of it, together with technological advances such as machine learning and robotics have fuelled the fear about massive job losses. On the one hand, technology does substitute for human labour, and especially those tasks that are routine and can be codified in a sequence of logical 'if-then-do' statements are at risk. On the other hand, for workers in abstract task-intensive occupations, technology is more likely to be a complement that will allow workers to be more performant. We asked experts to provide us with their judgement on which detailed tasks within occupations workers are likely to spend more or less time in the next five years, and used that data to depict the automation risk of occupations. We apply the automation risk data on time series data of employment in the Netherlands for the past 25 years. We find that employment growth in the period 1996-2020 was concentrated in occupations with low automation risk. These are occupations with a small share of automatable tasks, but a relatively large share of tasks on which workers are expected to spend more time. Hence, for those occupations, we expect that the potential loss of tasks that can be performed by machines are not compensated by an increasing demand for human labour in non-automatable tasks. But employment also grew substantially in occupations with a moderate automation risk. A potential explanation for this is that the demand for workers in non-automatable tasks has grown stronger than the substitution of workers in automatable tasks. We confirm that technological change has gone hand in hand with a relative decrease in employment shares of middling jobs. However, our automation risk indicator is highest for low-income occupations and decreases almost linearly with income ranks. One potential explanation is that our automation risk indicator only partly captures the routineness of occupations. Moreover, our automation risk indicator is future oriented, rather than past oriented.

Background

The fear that technological progress will render much of human labour obsolete is not recent (e.g., Marx, 1844; Mokyr et al., 2015; Mortimer, 1722; Ricardo, 1821). Already during the first Industrial Revolution, the adoption of power looms and mechanical knitting led to the destruction of textile machinery by the Luddite movement. More recent concerns about massive job losses have been fuelled by the improved and decreasing cost of computing power, together with technological advances in fields like machine learning and robotics (Brynjolfsson & McAfee, 2014).

Although most technologies are designed to save labour, research from our H2020 Technequality project (Hötte et al., 2021) highlights that several mechanisms can offset the initial labour saving impact of technological change. Hötte et al. (2021) point out that technology is not likely to make human capital obsolete as it has complex and differential effects on the labour market. For example, the "routine-biased technological change (RBTC)" hypothesis (Autor et al., 2003) posits that technology does not only substitute for human labour, but that it can also raise the demand for workers whose skills are complemented by it. Advancements in technology and computerisation have mainly led to the substitution of workers performing tasks that are routine and easily programmable. From a machine execution perspective, tasks can be considered routine if they can be expressed or codified in a sequence of logical 'if-then-do' statements.

Although technologies largely substitute for human labour in the performance of routine tasks, the skills required to perform non-routine tasks are generally complemented by it. For example, 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). As the costs of retrieving, organising and manipulating information has fallen dramatically (Nordhaus, 2007), workers in abstract task-intensive occupations will have to spend less time on acquiring and manipulating information. Accordingly, computerisation enables workers to further specialise in the area in which they hold a comparative advantage, namely, analysing and interpreting information. The RBTC hypothesis, therefore, predicts that the skills required to perform non-routine tasks are increasingly valued on the labour market.

In this policy report, we analyse how the occupational structure of the Dutch labour market has changed over the past two decades and how these shifts can be explained by technological change. To capture technological progress, we make use of unique automation risk data that has been collected as part of the H2020 Technequality project (Somers & Fouarge, 2019). The automation risk data are derived from expert questionnaires and have a number of advantages over existing automation risk estimates. The estimates produced by earlier studies rely on experts' assessment of the type of tasks that are (still) difficult to automate given the current state of technology (see, e.g., Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). Based on the task composition of jobs, these so-called engineering bottlenecks are used to determine the automation risk for occupations. However, the fact that certain job tasks are automatable does not automatically imply that jobs will actually be automated. As discussed in Levels et al. (2019) and Heald et al. (2019), many factors (e.g., price and access to technology, legislation, availability of training data, managerial practices and culture) can constrain the adoption and diffusion of technologies.

Data

Automation risk data

In Autumn 2019, we fielded a questionnaire among experts to gather data on country-specific automation risk assessments for occupations at the 2-digit level of the International Standard Classification of Occupations (ISCO) 2008. The target population comprised business professionals who are experts on the task content of specific occupations and include company owners, company directors and HR professionals.

The survey was disseminated by Kantar Public[1] in eight different countries, namely, Czech Republic, Germany, Great Britain, Spain, France, Norway, Estonia and the Netherlands. The countries were selected in a way that includes the largest economies. We also aimed to ensure that we include countries of different European regions (Northern-, Southern-, Western-, and Central Europe) to obtain a sample of countries that is representative for all member states of the European

[1] Kantar Public is a global research business that disseminated the survey in their NIPObase Business Panel covering business professionals who regularly participate in business-to-business research.

Union in terms of their geographical location, culture, and socio-economic and institutional structure.

The survey mainly included closed-ended questions. First, the survey participants were asked to select one or more 4-digit ISCO occupations for which they are sufficiently knowledgeable such as to provide their assessment on changes in the task importance in the next five years. In total, the ISCO classification comprises 433 occupations at the 4-digit level. We asked respondents to select occupations at the 4-digit level – which is the most detailed level of the classification – to ensure the most realistic representation of the task content of occupations. Second, for each of the selected occupations, we showed respondents the list of tasks that correspond and are unique to the selected occupation(s). For every occupation-specific task, we asked respondents to assess how the time allocation would change in light of technological change using the following question: *"Based on the most recent technological developments (e.g. in the field of robotics, computerisation, machine learning), could you indicate how much time workers will spend on the following tasks for the occupation [selected occupation] in the next five years? Please take into account factors that influence the actual adoption of technologies when providing your answer (i.e. the price of technologies; the design of the organisation, production processes and supply chains; legal constraints; and cultural expectations)."* Respondents could indicate the future importance of each task by selecting one of the following answer categories: 1) workers will not perform this task any longer, 2) workers will spend less time on this task, 3) workers will spend the same amount of time on this task, 4) workers will spend more time on this task, or 5) I don't know. See Somers and Fouarge (2019) for details on the procedure we followed.

Tasks on which workers are expected to spend less time are assumed to have a relatively high automation risk. In contrast, tasks on which workers are expected to spend more time are assumed to complement automation technologies. 868 Respondents[2] selected one or more occupations and assessed how the corresponding task content would change in light of technological change. In total, the task content of various occupations was assessed 2,328 times. As the number of assessments is insufficient to generate reliable automation risk indicators for each 4-digit occupation, we aggregate the automation risk assessments to the 2-digit level of ISCO occupations. For each 2-digit occupation (43 in total)[3], we calculate the average percentage of tasks on which workers will spend less time, more time or the same amount of time in the next five years. Each country received an equal weight when aggregating the data to the 2-digit ISCO level.

Dutch Labour Force Survey

We used data from the Dutch Labour Force Survey (LFS) for the period 1996-2020 to derive information on changes in the occupational structure of the Dutch labour market. The LFS covers approximately 50,000 Dutch households and provides information on the labour market participation of individuals aged 15 years and above (CBS, 2015). We selected employed and self-employed individuals aged 15-75 years who indicated to work at least one hour per week, and calculated the number of employed individuals per year per occupation, in order to depict employment patterns during the period 1996-2020.[4]

Statistics Netherlands

The employment data from the LFS are enriched with administrative gross wage data from Statistics Netherlands for the year 2009.[5] For each occupational group, we calculate the median gross wage by dividing the gross earnings by the number of working hours. Based on the percentile scores of the gross hourly wage, we sort all occupations into five quintiles. The first quintile represents the low-income jobs, the second until the fourth quintile represent the middle-income jobs while the fifth quintile represents the high-income jobs.

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[2] Respondents who only answered "I don't know" on the task importance questions are excluded here.

[3] The automation risk indicators are available for 40 2-digit occupations. The three armed forces occupations (01, 02 and 03) are excluded.

[4] The redesign of the LFS has caused a trend break in the total number of employed individuals by occupational group between 2012 and 2013. The size of the break was estimated for each occupational group with a time series model (Willems & Krieg, 2015). Next, the number of individuals by occupational group have been corrected for the period 1996-2012 and made comparable with the numbers from 2013 onwards.

[5] We retrieved the wage data from the dataset "Sociaal-Statistische Bestanden (SSB)".

Trends in the Dutch occupational structure

Figure 1 illustrates the development of employment compared to the base year 1996 by automation risk category. We have grouped the occupations into four categories: occupations with a high automation risk, a moderate automation risk, a low automation risk, and a very low automation risk. Occupations with a high automation risk score relatively high on the share of tasks on which workers will spend less time, and relatively low on the share of tasks on which workers will spend more time. Occupations score low (high) on the two variables when their score is below (above) the median score. Hence, for occupations with a very low automation risk, we expect that the potential loss of tasks that can be performed by machines are not compensated by an increasing demand for human labour in non-automatable tasks. Occupations with a moderate automation risk score relatively high on the share of tasks on which workers will spend less time, but also relatively high on the share of tasks on which workers will spend more time. For these occupations, we expect that a substantial share of tasks will be automated in the foreseeable future. However, there is a certain degree of uncertainty regarding whether the loss of tasks will be compensated by an increasing need for workers in the performance of non-automatable tasks. With respect to occupations with a low automation risk, we expect little change in the task content in the foreseeable future due to technological change. These occupations only contain a small share of tasks on which workers will spend less time, but also a small share of tasks on which workers will spend more time. Finally, occupations with a very low automation risk are characterized by a small share of automatable tasks, but a relatively large share of tasks on which workers are expected to spend more time.

Figure 1 illustrates that occupations with a high automation risk (dashed dark blue line) show the lowest employment growth between 1996 and 2020. Example occupations with a high automation risk include secretaries, administrative workers, and receptionists and telephone operators. These occupations are intensive in routine tasks that can be easily performed by computer technology. In contrast, occupations with a very low automation risk (the solid light blue line) demonstrate a strong employment increase over the past two decades. Occupations with a very low automation risk include hairdressers, providers of other personal services, and waiters and bar staff. Occupations with a low automation risk (solid dark blue line), such as cooks, police- and firemen, and security personnel, experienced an even stronger employment increase. The employment growth of occupations with a (very) low automation risk can most likely be explained by the fact that many of these occupations are intensive in non-automatable tasks. However, many of these occupations also include (low-income) service occupations for which the demand might have indirectly increased due to technological change. According to Manning (2004), a technology-induced demand for richer high-skilled workers can indirectly increase their consumption of goods and services provided by lower-skilled workers, thereby increasing the employment of the latter group. Finally, also occupations with a moderate automation risk (dashed light blue line) have seen an employment increase between 1996 and 2020. A potential explanation for this observed trend is that the demand for workers in non-automatable tasks has grown stronger than the substitution of workers in automatable tasks. Example occupations with a moderate automation risk include accounting personnel, transport planners and logistics staff, and assembly workers.

The RBTC hypothesis also predicts a polarisation of the employment structure. As middle-income jobs are considered to be rich in routine tasks, we would expect to observe a substantial decrease in employment for these occupations relative to low-income and high-income jobs which are thought to be relatively intensive in non-routine tasks. In Figure 2, we show the change in employment share of occupations between 1996-2020 and the change in the time spent on their task content, by their corresponding wage level in 2009.[6] Here, we measure the changing importance of tasks in occupations by subtracting the share of tasks on which workers are expected to spend less time from the share of tasks on which workers are expected to spend more time. We expect better employment perspectives for occupations that score relatively high on this indicator. As predicted by the RBTC hypothesis, the dark blue line shows that the employment share in the middle of the wage distribution has substantially decreased. In contrast, high-income jobs have experienced a considerable increase in their employment share. Low-

[6] The ranking of occupations based on their median gross hourly wage in 2009 implicitly assumes that this ranking has remained constant over the years. Fouarge et al. (2017) show that the correlation of the percentile scores over the period 1996-2015 is on average 0,98. Hence, we believe that our assumption is plausible.

income jobs also show a slight increase in their employment share over the past two decades. However, based on the RBTC hypothesis, we would expect the automation risk to be highest for occupations in the middle of the wage distribution. However, the automation risk indicator appears to be highest for low-income occupations and decreases as the income rank increases. One potential explanation is that our automation risk indicator does not actually capture the routineness of occupations. To assess this, we compared our automation risk indicator with the routine task intensity developed by Mihaylov and Tijdens (2019). Mihaylov and Tijdens (2019) manually classified all tasks of 427 4-digit ISCO occupations into routine and non-routine task categories. We ran a pairwise correlation between the share of routine tasks and the share of tasks on which workers will spend less time at the level of 2-digit ISCO occupations. The correlation yields 0.652 (p-value<0.01) and the two indicators are, therefore, moderately correlated. Hence, our automation risk indicators at least partly capture the routineness of the task content of occupations. However, it is also important to note that our survey questions are future oriented. While computer technologies have substituted workers in the performance of a wide range of routine tasks over the past decades, machines are also increasingly capable to perform tasks for which we "do not know the rules". For example, machine learning enables warehouse robots to encounter and handle unknown objects and operate in unknown environments. Hence, more recent technological advances might redefine what it means for tasks to be "routine". As a consequence, tasks that were previously defined as "non-routine" – including those of low-income jobs – might be automated in the foreseeable future. Another potential explanation for the observed "polarisation" of employment is the indirect instead of direct effect of technological change. As explained earlier, a technology-induced demand for high-skilled workers might indirectly also increase the demand for low-skilled workers through a higher demand for goods and services produced by the latter group (Manning, 2004). Hence, the observed employment increase of low-income occupations can possibly not be fully ascribed to the automatability of their task content.

Conclusion and policy recommendations

In this policy brief we used unique automation risk indicators to assess the impact of technological change on the development of the occupational structure in the Dutch labour market. We document that occupations with a high automation risk have experienced the lowest employment growth over the past two decades. In contrast, occupations with a very (low) or moderate automation risk have shown a substantial employment increase. These findings suggest that the employment perspective of occupations that are intensive in automatable tasks have significantly deteriorated. However, at the same time, technological change creates new employment opportunities in occupations that are intensive in tasks that are difficult to automate. Our research also shows that the largest employment share increase is observed for occupations at the upper-end of the wage distribution, while occupations in the middle of the wage distribution have experienced a substantial decline. These findings again confirm that occupations that are intensive in automatable tasks – i.e., those in the middle of the wage distribution typically contain a large share of routine tasks – have been negatively affected by technological change in the past two decades. In contrast, many of the high-income occupations are intensive in non-routine tasks and heavily depend on the analysis of information. The development of computer technologies has enabled workers in these occupations to spend less time on routine tasks (e.g., retrieving information) and spend more time on tasks in which they hold a comparative advantage.

Our results entail a number of policy implications. First, students' future labour market perspectives are likely to improve if their study programmes emphasize the development of skills required to perform tasks that are difficult to automate. These skills include analytical skills, but also interpersonal skills. It is also important to highlight that the development of such skills is not only important for students in higher education, but also in study programmes in vocational education and training. Although certain tasks in many middle-skill occupations are susceptible to automation, many jobs in this segment most likely will continue to require a changing set of skills. Prior research has also shown that the wage returns for analytical skills in the Netherlands has not only increased for workers in the upper-end of the wage distribution, but also for workers in the middle- and lower-end of the distribution (Somers et al., 2019). Finally, technological progress is likely to continue to affect the skills demanded on the labour market. Hence, close monitoring of changing skill requirements will help to inform those who develop educational curricula as well as those investing in their human capital.

Figure 1: The development of employment by automation risk of occupations

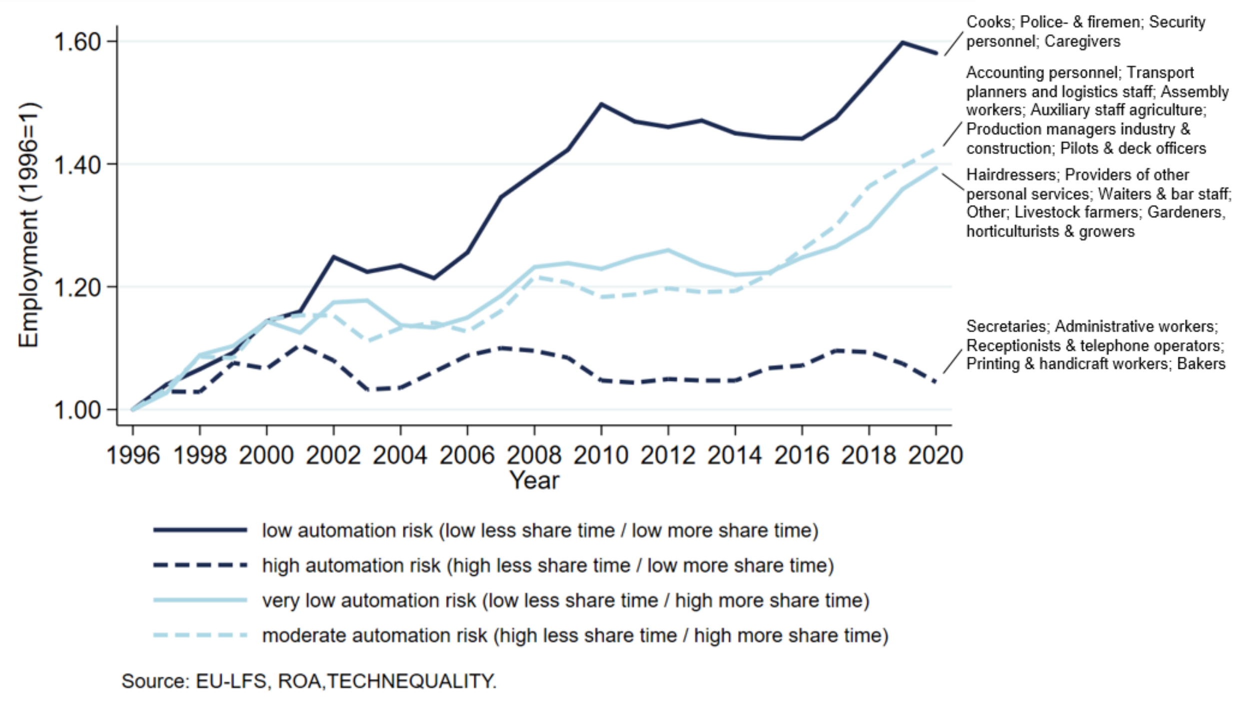

Figure 2: Change in employment shares of occupations between 1996-2020 and the changing importance of tasks in occupations, by their corresponding wage level in 2009

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