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The persistence and nature of the labor reallocation shock during the COVID-19 crisis

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Abstract — The COVID-19 crisis may have widely and permanently altered the labor market through the demand for skills. Crises tend to accelerate technological change. Previous recent crises were characterized by an acceleration of automation, which generally led to a decrease in middle-income jobs with routine skills, known as job polarization. This study finds that the COVID-19 pandemic, which is characterized by an acceleration of digitization, has led to a unique, large, and relatively persistent labor reallocation shock. Labor market dynamics in the Netherlands reveal an unprecedentedly large rise in high-income jobs and an unprecedentedly large drop in low-income jobs. These dynamics are strongly associated with a previously virtually irrelevant job characteristic in occupations, namely, the ability to work from home, and not the manual, routine, or abstract thinking skill content of jobs that had strong explanatory power in previous recent crises. This suggests an acceleration of the importance of digital skills rather than abstract thinking skills. Post-pandemic trends up to 2023Q4 indicate that there is a recovery in the types of jobs (relatively) lost but that the reallocation shock is quite persistent in the type of jobs gained. Further evidence of a persistent change in the demand for (digital) skills is found in results on job mobility. These show that the pandemic is associated with a persistent improved probability in obtaining a high-income job for persons with lower levels of education but relatively reduced chances for older persons.

Keywords — COVID-19, crisis, working from home, technological change, labor market, job mobility, digitization.

JEL — E24, E32, J24, J31, J60, O33

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1 Introduction

The COVID-19 pandemic may have been declared to be over but its likely unique impact on the labor market may persist. Crises tend to accelerate technological change by setting capital and labor free and allocating it to new purposes (Schumpeter, 1942; Hershbein and Kahn, 2018). This may lead to possible long-term mismatches on the labor market between the skills of the workforce and the skills in demand, which also imply skill-based inequalities (Jaimovich and Siu, 2020; Pizzinelli and Shibata, 2023). Previous recent crises generally accelerated automation leading to so-called job polarization with the disappearance of mostly middle-income jobs with routine skills while low-income jobs with manual skills and high-income jobs with abstract thinking skills were not strongly hit and recovered quickly (Jaimovich and Siu, 2020; Terzidis and Ortega-Argilés, 2021). Similar to previous crises there is considerable evidence on the existence of a labor reallocation shock during the COVID-19 crisis with employment-to-working population drops up to 10% in some countries followed by quick recoveries and tight labor markets (CBS, 2021b; Pizzinelli and Shibata, 2023; Drozd et al., 2024).

Despite this similarity to previous crises, there are many indications that this labor reallocation shock is of a different nature as the COVID-19 crisis was not only an economic shock but also led to limitations in human interaction. A distinct difference is that the form of accelerated technological change is more strongly characterized by digitization efforts to move activities online rather than automation (McKinsey, 2020; Barrero et al., 2021b; OECD, 2021a; Mueller-Langer and Gómez-Herrera, 2022). Concerning dynamics on the labor market, two previously unmentioned job characteristics are often mentioned instead of the manual, routine, or abstract task content associated with job polarization, namely, being designated as essential by the government and the ability to work from home. Many sources suggest that these are the most relevant job characteristics of the industries and job occupations that are growing or declining during the pandemic (Barrero et al., 2021a; OECD, 2021a; Papanikolaou and Schmidt, 2022). The relevance of these job characteristics is likely as previous work showed that working from home is more possible in high-income jobs and that many low-wage occupations are concentrated in industries that are not designated as essential with little possibility to work remotely (Barrero et al., 2020; Dingel and Neiman, 2020). This is in line with the strong decrease in low-income occupations during the pandemic, such as waiters, that are most strongly hit instead of middle-income jobs, while according to some reports high-income jobs are not affected or in some cases, like administration, even experience growth during the crisis (Cajner et al., 2020; del Rio-Chanona et al., 2020; Barrero et al., 2021a; UWV, 2021; Papanikolaou and Schmidt, 2022). Furthermore, there are suggestions that the reallocation shock may be persistent, at least in terms of the relevance of digital skills, because adopted digitized work processes and remote work practices are relatively persistent even though the relevance of essential jobs and the necessity of remote work has been reduced (McKinsey, 2020; Barrero et al., 2023; Oikonomou et al., 2023). Put together, there are many indications that a persistent labor reallocation shock may have occurred that is of a different nature as it is based on an acceleration in digitization, promotes the relevance of job characteristics related to the ability to work from home and being essential, and mostly hit low-wage jobs.

However, the exact nature and persistence of the reallocation shock at the job occupation level remains unclear. First, because the overlap in jobs between the job characteristics associated with job polarization and COVID-19 has not yet been mapped out. There is likely an overlap between abstract task content and the ability to work from home because both are concentrated in high-income jobs (Autor et al., 2003; Dingel and Neiman, 2020). Hence there are possibly rivaling explanations for labor market dynamics. Furthermore, little is known about the characteristics that are correlated with the status of essential jobs. Second, because recent labor market dynamics at the job occupation level have not been mapped out to evaluate the size and nature of the labor reallocation shock in comparison to earlier time periods. Third and most importantly, because these recent labor market dynamics have not been associated yet with these job characteristics to evaluate the changes in the relevance of different skills over time of these changes. Fourth, there have not been any recent updates on these topics to evaluate the claims on the persistence of the changes on the labor market.

This paper addresses these four points by examining labor market dynamics in the Netherlands from 2003Q1 to 2023Q4. More specifically, I link job market dynamics to five key job characteristics: manual task content, routine task content, abstract task content, the ability to work from home, and the classification of essential jobs. While the first three characteristics are established in job polarization literature, the novelty lies in the inclusion of two COVID-19 crisis-specific attributes: the feasibility of remote work, following Dingel and Neiman (2020), and a job's designation as essential by the Dutch government during lockdowns.

The results are as follows: first, I find that job characteristics are associated with different wage levels. It was already known that low-paying occupations are more often predominantly manual; middle-paying more often routine; and high-paying more often abstract. The new measure being essential is roughly equally distributed over the wage distribution of jobs with a minor concentration in middle-paying jobs. The capacity to work from home, on the other hand, is strongly concentrated among higher-income jobs, which is in line with Davis et al. (2020). There is hence a correlation between higher incomes, the ability to work from home, and abstract task content.

Second, time trends of employment per income category of occupations show that the COVID-19 crisis has led to a strikingly large and unique labor reallocation shock. First of all, the number of high-income jobs grows at an unprecedented rate during the pandemic (8.2%/year vs. a previous record of 5.7%/year in 2018-2019) while the number of low-income jobs drops at an unprecedented rate (-12.3%/year vs. a previous record of -2.4%/year in 2009-2010) but the number of middle-income jobs remains relatively stable. This is in stark contrast with the Financial crisis where I find trends that confirm the job polarization already documented by (Jaimovich and Siu, 2020; Terzidis and Ortega-Argilés, 2021). That is a strong decline in middle-income jobs and relative growth in low-income and high-income jobs. Altogether the time trends suggests that the COVID-19 crisis does not lead to job polarization as previous recent crises but rather to a growing concentration of jobs in high-income occupations.

Third, regression results on the association between job characteristics and employment levels per occupation group over time show that the nature of labor reallocation shock is also unique. I compare the explanatory power of the five job characteristics on the growth rates of Full Time-Equivalent (FTE) jobs per job category during the Financial crisis, the years leading up to the pandemic, during the pandemic, and after the last COVID-19 restriction measures have been lifted. The regression results show that during the pandemic the strongest predictor of growth is the ability to work from home. More specifically, when 100% of jobs within a job category allow for remote working instead of 0% *ceteris paribus* the increase in growth rate over two years is 18.5%pt. For example, software developers rank among the occupations with the strongest growth levels. The ability to work from home is irrelevant in predicting job growth before the COVID-19 crisis, including during the Financial crisis, for which I find labor market dynamics in line with job polarization. The ability to work from home is also unprecedentedly strong in explanatory power during the COVID-19 crisis being almost 13 times larger than any other coefficient on job characteristics in other time periods. Furthermore, routine task content is positively associated with employment growth during the COVID-19 crisis although only with a 2.8%pt. increase in growth for a standard deviation increase in this task content. This growth seems mostly concentrated in routine essential clerical jobs in production and transportation. In sharp contrast, manual task content in jobs is associated with employment loss at a rate of 4.6%pt. per standard deviation increase. These effects are largely robust to different definitions and when adding fixed effects on industries, regions, and a variety of demographic factors. This suggests that the documented changes hold across the workforce and hence also *within* sectors.[1] All together, the results suggest that digital skills related to working in online environments have become much more important on the labor market as well as to a much lesser extent routine skills, related to essential jobs.

Fourth, this unique labor reallocation shock is relatively persistent in the type of jobs gained but not persistent in the type of jobs (relatively) lost. The loss of low-income jobs has recovered somewhat in 2023Q4, although still at 92.3% of the level in 2019Q4. The growth in the high-income jobs continues up to 2023Q4 albeit at a lesser pace. In terms of job characteristics, there is below-average job growth between 2022Q1 and 2023Q4 in essential jobs and no job growth to a minor decline in jobs that allow one to work from home. This suggests that these type of jobs gained during the pandemic are relatively persistent while other types of jobs are recovering and catching up. This is in contrast with previous crises that were followed by jobless recoveries in middle-income routine jobs (Jaimovich and Siu, 2020; Terzidis and Ortega-Argilés, 2021). Additionally, I find evidence that jobs gained during the pandemic can also more often be executed by software, or AI or be off-shored. After the pandemic, those that can be performed by software see a small decrease in FTE while the other job types are persistent for the time being. All in all, the main results here indicate that the COVID-19-induced reallocation shock is rather large and persistent in the few essential jobs and many working-from-home jobs gained but not in the relative losses in the types of other jobs. The persistence in the relevance of job characteristics associated with the COVID-19 pandemic suggests that it has had a lasting impact on the labor market.

In addition to the main results, I also explore changes in job mobility and the total working population as another approach to observe changes in required skills and to evaluate the distributional consequences of the labor reallocation shock. Changes in job mobility and in the working population may signal new labor mismatches and inequalities, which may further confirm the rise in digital skills found. The results show that, unsurprisingly, the probability of obtaining a high-income job increases both during and after the pandemic. However, this increase in probability is much stronger for those who have lower levels of education while relatively weaker for those who are older. The former is likely explained by the tightness of the labor market and possibly the preference for digital skills over education levels, while the latter is likely explained by the suggested lower prevalence of up-to-date computer skills in higher age groups, which calls for human capital development policies (OECD, 2016; Bonacini et al., 2021; OECD, 2021b). The changes in the working population also suggest stronger mismatches on the national labor market as there is an unprecedented increase in in-migration in high-income jobs, which may be due to the need of attracting workers with the required digital skills insufficiently available on the labor market.

This paper is organized as follows: Section 2 discusses the related literature on the relation between crises and technological change on the labor market, and the COVID-19 literature on the existence of the labor reallocation shock, its nature in terms of the relevant job characteristics, trends of technological change and workers affected, and its persistence; Section 3 introduces the

[1] Note that it is likely that there are also changes in job content within occupations but these cannot be measured in the data used here.

microdata and methodology used; Section 4 presents the results; and Section 5 concludes.

2 Theory

2.1 Crises and technological change

Technology-based structural change tends to be accelerated by crises. Schumpeter (1942, p.82-83) already recognized that the "*process of industrial mutation that continuously revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one*" known as creative destruction is not equally distributed over time. During crises less productive firms operating under older paradigms tend to close down setting labor and capital free, which can be absorbed by more advanced more productive firms. As a result, attention should not only be paid to the extent to which a region or country can bounce back to pre-crisis growth paths but also to the extent of technological change during crises (Boschma, 2015). Technological change is often associated with skill mismatches on the labor market and may call for policy intervention in terms of (re)training parts of the (future) workforce (OECD, 2021a; Carrillo-Tudela et al., 2023).

On the labor market, the most relevant prepandemic trend of technological change since the advent of the computer in the 1970s is generally known as job polarization: the "hollowing" out of the job market with relatively stronger growth in both the low-income and high-income jobs but loss in the middle-income jobs. Computer technology is seen as a substitute for many middle-income jobs, which consist of routine repetitive tasks that can be taken over by robots or software, such as machine operators and clerks. However, it is seen as a complement to high-income jobs, which consist of abstract analytical and problem-solving tasks for which computers provide access to routine information inputs, such as engineering professionals. Computer technology neither strongly complements nor substitutes low-income jobs that consist of manual tasks requiring eye-hand-foot coordination, such as waiters. However, these jobs are in higher demand due to high-skilled workers outsourcing home production tasks (Autor et al., 2003; Goos et al., 2009; Autor and Dorn, 2013).[2][3] Various sources call for policy intervention to promote the development of analytical and interactive skills as there is a skill mismatch on the labor market leading many middle-income workers with lower education levels to experience downward job mobility (CPB, 2015; OECD, 2019).

In line with the notion of economic crises accelerating technological change, Jaimovich and Siu (2020) find that 88% of the job loss in routine middle-skilled occupations occurred during recessions since the mid-1980s. The labor reallocation shocks are strongly persistent as each crisis is followed by a so-called jobless recovery in routine occupations. This is in contrast with manual jobs or abstract jobs, which either do not decline during crises or bounce back relatively quickly to pre-crisis levels. Terzidis and Ortega-Argilés (2021) show a similar acceleration in job polarization in the Netherlands during the 2008 Financial crisis.[4]

[2]Note that before the computer revolution, production methods were actually highly dependent on routine workers as electricity-based mechanization complements the skills of this type of workers (Goldin and Katz, 1998).

[3]Additionally, in the cases when production and clerical work cannot be automated it can often still be offshored to low-wage countries (Blinder and Krueger, 2013). Although offshoring is a relevant trend on the labor market that is not strongly correlated to automation, the focus here is on the latter as the literature suggests it has the strongest impact on the heterogeneity of job growth across skill levels (Blinder and Krueger, 2013; Autor et al., 2015; Hershbein and Kahn, 2018; Autor, 2019). Nonetheless, I also estimate the impact of offshorability on job growth in Appendix A.1.7.

[4]Relatedly, Hershbein and Kahn (2018) show that skills requirements in posted vacancies persistently increase during recessions in particular concerning non-routine skills complementary to computers. This suggests that routine-biased technological change *within* occupations also accelerates during crises. However, the data used here does not allow for monitoring changes within occupations.

2.2 The COVID-19 crisis

The crisis induced by the COVID-19 pandemic resembles previous crises due to the drastic drop in demand but also starkly differs from previous crises due to the health risks and governmental policies that restricted the physical contact between humans. There is evidence of a labor reallocation shock but also that its nature and persistence are different from previous shocks. This may entail that other job characteristics than those relevant in previous recent crises matter at the occupation level to understand the labor reallocation shock.

There is ample evidence of a considerable reallocation shock. Similar to previous crises, there has been a strong economic downturn following the start of the COVID-19 pandemic. The drop in GDP during the year 2020 is even the largest ever recorded by Statistics Netherlands, which was even 0.1 percent point larger than the drop in 2009 following the Financial crisis (CBS, 2021a). There are also numerous signs of accelerated technological change during this downturn that resemble those of previous crises. Barrero et al. (2021b) show that firms in the U.S.A. that were less productive before COVID-19 also face a larger drop in sales during the pandemic. In the Netherlands, company closures were at an all-time high even though bankruptcies were at an all-time low due to more generous government support (van Dijk and Stam, 2021). Relatedly, Groenewegen et al. (2021a) show that Dutch companies that have better management practices also were more likely to receive government aid. The data used here shows that in the Netherlands, unemployment rose by $200,000$ persons by June 2020 before falling back to the pre-pandemic levels by November 2021. Like in many countries, the oversupply of workers turned into an undersupply in less than a year, resulting in a tight labor market that persists to the time of writing (Pizzinelli and Shibata, 2023). The amount of mismatch on the labor markets is also documented to have risen and fallen sharply during the pandemic at the sector level in the U.K. and U.S., which suggests considerable churn on the labor market. (Pizzinelli and Shibata, 2023; Drozd et al., 2024). Further accounts on mismatch suggest that in the U.K. many workers in declining occupations have difficulties moving to expanding occupations, although the net mobility between sectors has been documented to be higher than during the Financial crisis (Carrillo-Tudela et al., 2023). All in all, there are ample reasons that at the occupation level, a considerable amount of labor may have been reallocated to new purposes during the pandemic-induced crisis.

The nature of this labor reallocation shock may also be different compared to previous crises. This is illustrated by: the characterization of the type of innovations that accelerated during the crisis; the skill levels of jobs lost and gained; and the job characteristics that seem to matter at the occupation level, the focus of this study. Where the innovations promoting job polarization are characterized as automation, the COVID-19 crisis seems to have promoted more strongly an already ongoing trend of moving activities online. Surveyed firms indicate having accelerated the digitization of internal operations, customer interaction, product portfolio, and supply chain management by up to seven years in the first few months of the pandemic. Thereby relying more on digitally skilled workers (McKinsey, 2020). Similarly, the positive trend in the number of start-ups with no physical shops and the negative trend in those with a physical shop has accelerated during the pandemic (van Dijk and Stam, 2021; Groenewegen et al., 2021b). Relatedly, an increase in patenting of technologies that support working from home (Bloom et al., 2021); and a shift in hiring from on-site jobs to remote work (OECD, 2021a; Mueller-Langer and Gómez-Herrera, 2022). However, automation may have also received an impulse because of the record-breaking adoption of robots during the pandemic (IFR, 2022).

The nature of the skill level of jobs lost and gained in the labor reallocation shock also differs from previous crises. Job loss is mostly concentrated in low-income jobs, mostly in personal services like catering (Cajner et al., 2020; Barrero et al., 2021b; Papanikolaou and Schmidt, 2022; Carrillo-Tudela et al., 2023). While some also report job growth in certain high-income jobs, such as in administration (Carrillo-Tudela et al., 2023).

The nature of the relevant job characteristics of jobs lost and gained in the labor reallocation shock also differs compared to previous crises. Two job characteristics are often mentioned, which did not have much relevance in the literature before COVID-19: jobs designated as essential and the ability to work from home. Sectors deemed essential have employment decline rates 5 times smaller than non-essential sectors (Papanikolaou and Schmidt, 2022). While demand for essential occupations like delivery and packaging workers has increased (Barrero et al., 2021b; OECD, 2021a). Note that these accounts seem to suggest that essential jobs are concentrated in low-income jobs, this is not the case as will be shown in Section 4.1. The ability to work from home is associated with growth in the number of workers both at the sector level and the occupation level (Barrero et al., 2021b; Brinca et al., 2021; Papanikolaou and Schmidt, 2022; Oikonomou et al., 2023; Carrillo-Tudela et al., 2023). The rising prominence of these job characteristics may suggest that the labor reallocation shock is the result of an underlying shift in the required skills in the workplace. Notably, the ability to work from home is associated with specific digital skills that are also growing in relevance during the pandemic, notably interaction with colleagues, customers, and content through digital channels (McKinsey, 2020; OECD, 2021a).

Furthermore, the reallocation shock is suggested to persist after the end of the pandemic for digital skills while less is known about the role of essential jobs. This is in spite of the ending necessity of working from home. Surveyed firms indicate that the changes made during the pandemic are likely here to stay (McKinsey, 2020). Work practices also persistently changed. The rate of working from home was 7% of working days in the U.S. before the pandemic, reaching up to 60% during the early phase of the pandemic and stabilizing around 28% in 2023 Barrero et al. (2023). This signals that there may be to some extent a persistent shock in the type of skills required in the workplace.

However, the exact nature and persistence of the reallocation shock at the job occupation level remains unclear. It could be that this crisis also accelerated job polarization or has led to other types of job reallocation. A large part of this unclarity stems from the lack of understanding of the role of the new relevant job characteristics, essential jobs, and the ability to work from home, in relation to the labor reallocation shock but also in relation to the "*old*" main relevant job characteristics during job polarization, manual, routine or abstract task content. The role of essential jobs and the ability to work can have similar or dissimilar impacts on the labor market with regard to the manual, routine, or abstract task content. The association between essential jobs and the extent of the other job characteristics is currently unknown. For the ability to work from home it is known to be strongly positively correlated with income (Dingel and Neiman, 2020) Hence, it is likely positively correlated with abstract task content and negatively with manual task content (Autor et al., 2003; Dingel and Neiman, 2020). However, these aspects may be allocated differently over jobs with some having more abstract task content and others more possibilities to work from home. Routine jobs may face increased automation because robots are immune to COVID-19 but may also face increases in demand due to the reshoring of global value chains and the essential nature of keeping these value chains running (Brakman et al., 2021; OECD, 2021a; IFR, 2022).

All in all, there is sufficient to ground to focus on the relationship between the five job characteristics and labor market dynamics to understand the nature of the reallocation shock and its persistence at the job occupation level.

In addition, to further understand the nature of the labor reallocation shock, I also explored job mobility patterns of different socioeconomic groups before, during, and after the COVID-19 crisis. Changes in job mobility for specific socioeconomic groups give further indications of changes in the demands for skills. The noted increase in digitization and the ability to work from home may bring about opportunities or challenges for different socioeconomic groups. For example, lower educated and older workers are expected to face challenges due to the adoption of new digital technologies (Bonacini et al., 2021; OECD, 2021b; Oikonomou et al., 2023).

3 Data & Methodology

3.1 Data

3.1.1 Working age population data

I use the micro-data of the quarterly labor survey (*Enquête Beroepsbevolking*) by Statistics Netherlands (*Centraal Bureau voor de Statistiek (CBS)*). The survey consists of a rotating panel where every quarter a set of new respondents is contacted and questioned every quarter for a total of five times. In 2021 a total of 168,000 persons were contacted. Statistics Netherlands assigns a weight to every person based on gender, age, region, country of origin, and address type to arrive at estimates for population totals, which are also used for their own reports and datasets among others those on (regional) unemployment levels. These weights are calculated using data from the inhabitants register (*Basisregistratie Personen*), which contains personal data on all (former) registered inhabitants in the Netherlands, the unemployment register (*Ingeschrevenen UWV Werkbedrijf*), containing data on all persons registered at the national unemployment agency, and the income register (*Polisadministratie*), which consists of personal income data on persons.

Here, I use the information on the number of persons per quarter in the working age population (age: 15-75) according to job status: unemployed; not in the labor force; and one of the 436 ISCO 2008 4-digit job categories. Although note that some job categories are not or are too little present in the Netherlands to be reliably captured by the data collection of *Statistics Netherlands*. Also, agricultural workers and civil servants are also dropped, following Terzidis and Ortega-Argilés (2021), as these are less influenced by market developments. The ISCO 2008 4-digit codes are matched to variables, discussed next, characterizing the task content of these jobs in terms of the manual, routine, and abstract tasks, the capacity to work from home, and if a job is deemed essential to continue operation normally during COVID-19 lockdowns by the Dutch government. In most regressions use is made of Full Time Equivalent (FTE) jobs, which is 36 hours per week in the Netherlands, rather than the total number of jobs.

3.1.2 Job characteristics

Manual, Routine, and Abstract task content

Data on task content was kindly provided by Anna Salomons, see Goos et al. (2014). They base themselves on the work of Autor et al. (2003) who took the U.S. Dictionary of Occupational Titles (DOT) and measure manual task content based on the DOT variable measuring an occupation's demand for "eye-hand-foot coordination"; Routine task content is measured as the average of two DOT variables, "set limits, tolerances and standards" measuring an occupation's demand for routine cognitive tasks, and "finger dexterity," measuring an occupation's use of routine manual tasks, which can respectively generally be outsourced to software or robots (Webb, 2019); Abstract task content is measured as the average of the two DOT variables: "direction control and planning," measuring managerial and interactive tasks, and "GED Math,", which measure requirements in problem-solving and complex communication. The DOT values have been transformed to percentiles according to the 1960 distribution of task input by Autor et al. (2003). This data, originally available in the relatively less detailed reduced U.S. census job occupation classification, has been made available by Goos et al. (2014) at the two-digit ISCO level.

Note that, unlike previous literature, I do not use Routine Task Intensity (RTI), which is measured as the log of routine tasks minus the logs of the manual and abstract tasks, in the main analysis. Because the employment dynamics of the COVID-19 crisis are not only characterized by its effects on jobs with routine tasks but also on those with manual and abstract tasks. Therefore, it differs from the previous literature on labor market polarization where automation and hence RTI had a central role. Adding Manual Task Intensity and Abstract Task Intensity to the regression would lead to structural multicollinearity as each of these variables is constructed based on the same variables. Note that RTI is included in a sensitivity analysis in Appendix A.1.7.

Work from home
The extent to which one job is suitable for working from home is based on Dingel and Neiman (2020). They classify if jobs can be performed from home based on surveys of the U.S. Occupational Information Network (O*NET). They also show that their measure agrees to a great extent with actual rates of working from home per occupation when the COVID-19 crisis started. Note that the ability to work from home was calculated before the COVID-19 crisis. As a result, it is exogenous to endogenous effects of the COVID-19 crisis on the ability to work from home in occupations. This also suggests that the ability to work from home is underestimated in this definition given the improvements in the ability to work from home during the pandemic (Bloom et al., 2021).

With concordance tables of the U.S. Bureau of Labor Statistics (BLS) the detailed 6-digit SOC codes are matched to the 4-digit ISCO classification used here. Although working from home is a dummy variable in the data of Dingel and Neiman (2020) it becomes a share in our classification because sometimes multiple 6-digit SOC codes match a single 4-digit ISCO code.

Essential jobs
If a job is deemed essential was manually coded based on the list of essential jobs published online by the Dutch government on March 16th, 2020, the first day of the first lockdown of the COVID-19 pandemic (Rijksoverheid, 2020). When belonging to one of these job categories, parents or caretakers of children could make use of child daycare and continue their job as normally as possible. This variable is a dummy variable. Note that the unweighted correlation between the capacity to work from home and essential jobs across occupations is small and negative with -0.27.

3.2 Methodology

The goal is to understand the size, nature, and persistence of the labor reallocation shock of the COVID-19. First, I will explore the correlation between wages and each of the five job characteristics to develop an understanding of the "new" job characteristics related to the pandemic in comparison to the "old" job characteristics related to job polarization.

Second, I will present trends in unemployment, the population out of the labor force, and three occupation groups, roughly following the division lines of, respectively: low-income, middle-income, and high-income jobs. This gives an intuitive idea of the size and nature in terms of income-level-type of jobs of the labor reallocation shock during the COVID-19 crisis and how the patterns differ from the previous period and the previous Financial crisis. The differences prove to be sizeable and can, hence, be clearly distinguished in figures.

Third, the main goal is to explain the observed trends by exploring to what extent job characteristics are associated with changes in employment levels per ISCO job category over four time periods: the Financial Crisis (two year average of 2007Q2-2012Q2); pre-COVID-19 crisis (2018Q1-2019Q4), COVID-19 crisis (2020Q1-2021Q4); and post-COVID-19 crisis (2022Q1-2023Q4). The start and end of the last time period correspond, respectively, with the ending of the last COVID-19 restrictions and the most recent available data at the time of writing. The Financial crisis is included to reproduce the results on job polarization documented by among others Jaimovich and Siu (2020); Terzidis and Ortega-Argilés (2021), while including the COVID-19 related job characteristics. While the other three time periods serve the main goal of describing the relevance of the job characteristics in explaining the labor market dynamics before, during and after the COVID-19 crisis. Furthermore, this analysis and the figures in the second point also allow to address the fourth research goal of this paper: evaluating the persistence of the labor reallocation shock.

The weighted regression formula on the relation between labor market dynamics and job characteristics is presented in equation 1. ΔFTE gives the percentage change in the number of Full Time Equivalent (FTE) jobs within each two-year time period t for each occupation o.[5] MTC, RTC, and ATC stand, respectively, for Manual, Routine, and Abstract Task Content. WFH captures the ability to work from home and Ess is a dummy variable indicating if a job features on the list of essential jobs of the Dutch government. ϵ is the error term. The observations are weighted based on the number of FTE at the start of time period t. The three task content variables are standardized, while using the number of FTE as weights, to have a mean of zero and a standard deviation of one to facilitate the interpretation of the regression results.

$$\Delta FTE_{o,t} = Constant + \beta_1 MTC_o + \beta_2 RTC_o + \beta_3 ATC_o + \beta_4 WFH_o + \beta_5 Ess_o + \epsilon_{o,t}, \quad (1)$$

In the main analysis, the results of equation 1 are given by calculating the dependent variable separately for each of the time periods: the Financial Crisis; pre-COVID-19 crisis , COVID-19 crisis; and post-COVID-19 crisis. Various different specifications are explored in a number of sensitivity analyses and extensions to evaluate; different definitions of time periods; different dependent variables and independent variables of interest; the effect of different fixed effects; the role of offshoring and routine task intensity, following Blinder and Krueger (2013) and Goos et al. (2014); and the role of robots, software, and AI, following Webb (2019). See Appendix 5 for more details.

In extension, the reallocation in the labor market is explored both in terms of job mobility and changes in the total working population to observe changes in required skills and distributional consequences of the labor reallocation shock. The quarterly survey allows to follow the professional career track of persons over time and where they end up, in case of changes, before, during, and after the COVID-19 crisis, and their personal characteristics. The respective methodology is explained in more detail in Appendix A.2.

3.3 Descriptive statistics

Table 1 shows the descriptive statistics of the variables used in the main analysis. The dependent variable is the percentage change in FTE over two years. The reported values indicate that on average 6.5% growth in FTE occurs per job occupation over each time period. This variable contains strong outliers because a few occupations with few employees contain large fluctuations due to the representation issues in the sample. Although, these have little influence due to

[5] Note that variations on the dependent variable are tested in Appendix A.1.3, which lead to similar results.

Table 1 – Descriptive statistics

Statistic	Mean	St. Dev.	Min	Max
Percentual change in FTE	0.065	0.274	−0.319	0.518
Routine tasks	3.956	1.478	1.817	6.953
Abstract tasks	3.602	1.631	0.935	6.558
Manual tasks	1.334	0.637	0.221	3.174
Work from home	0.371	0.423	0	1
Essential job (dummy)	0.350	0.477	0	1
Total FTE	18,551.970	27,358.180	1.991	293,354.2

Note: the number of observations is 1,212.

the small weights these outliers have been capped by setting values below the 10^th percentile and above the 90^th percentile to the respective 10^th percentile and 90^th percentile. Note that Appendix A.1.1 shows that results are highly similar when not capping these outliers or when dropping them from the sample.

Within the occupations that have at least 30,000 employees the largest employment losses occur in the categories: waiters; motor vehicle mechanics; car/taxi drivers; and child care workers during the COVID-19 crisis and (although smaller) in welders and statistical/Financial clerks in the period before the COVID-19 crisis. The largest increases in FTE during COVID-19 are found in: specialist medical practitioners; advertising and marketing professionals; transportation clerks; production clerks; personnel and career professionals; and software developers. Before the COVID-19 crisis, these were mechanical engineers and software developers, although less strong than during the COVID-19 crisis. After the COVID-19 crisis, the fastest growing occupations are waiters, personnel and careers professionals, security guards, and again software developers although less strongly than during the COVID-19 crisis. During the Financial crisis the largest percentage of employment losses were among statistical/Financial clerks, shopkeepers, and brick layers while there were job growth among child care workers, home-based personal care workers, social work associate professionals, and management/organization analysts

The task measures give the extent to which the task content of manual, routine, and abstract tasks of a job category rank in the percentiles of the total distribution of task inputs of 1960 in the original data by Autor et al. (2003). Note that these three task content variables are standardized to have a mean of zero and a standard deviation of 1 in the regressions.

The work-from-home variable shows that on average 37.1% of jobs within each ISCO occupation category can be performed from home, following Dingel and Neiman (2020). The essential job variable shows that an (unweighted) 35% of all job categories are listed by the Dutch government as essential. Finally, total FTE is the weighing factor for job occupations. The descriptive statistics show that the largest job category, shop sales assistants, provided 293,354.2 Full-Time Equivalent jobs at the onset of the Financial crisis.

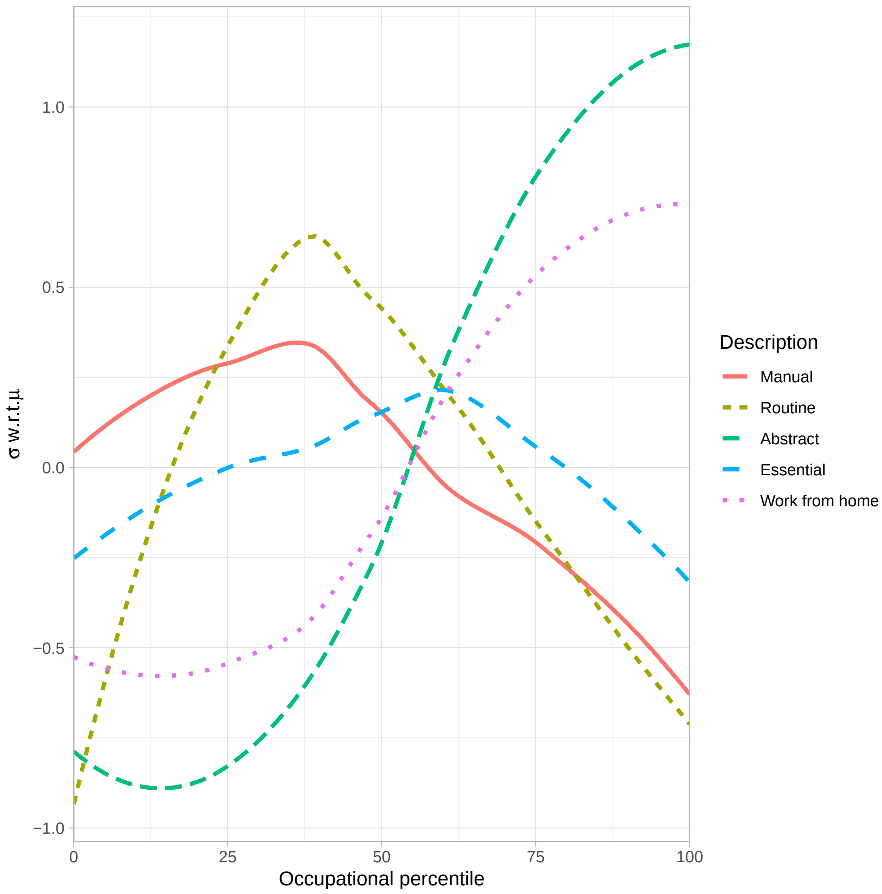
4 Results

4.1 Job characteristics per percentile

Here, I present the relation between wages and each of the job characteristics in Figure 1. It depicts the smoothed estimated LOWESS average standardized value for each job characteristic (y-axis) per percentile of the median wage within each occupation category (x-axis) in 2013, the first year in which wage data is available.

The variables on task content behave in line with the literature on labor polarization: manual

Figure 1 – Job characteristics per percentile.



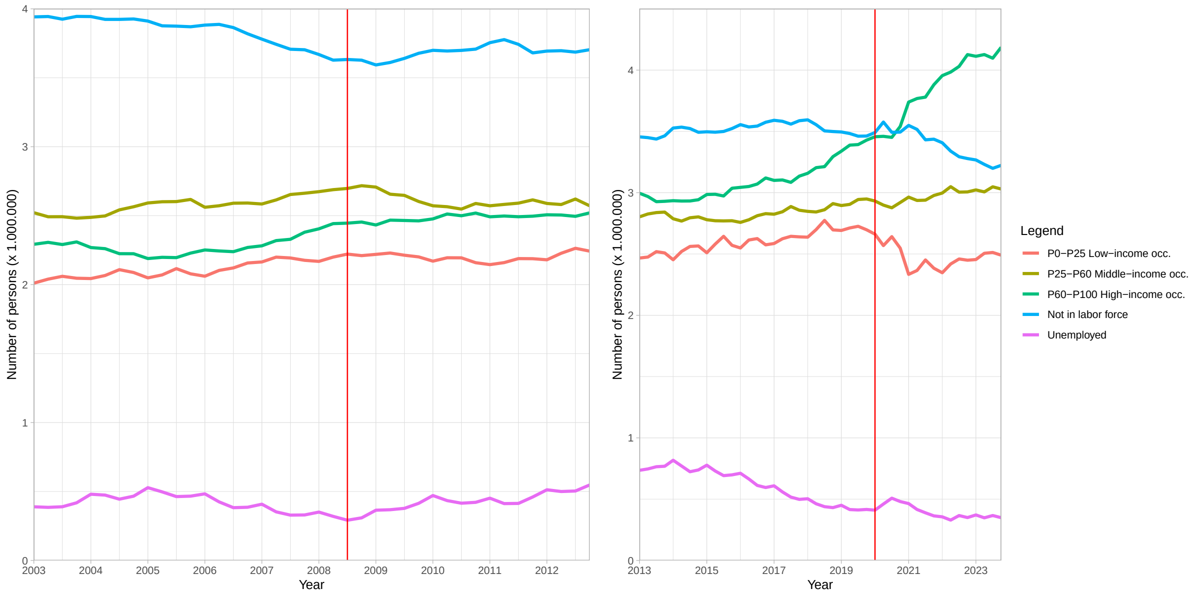
tasks are overrepresented in the lower tail of the wage distribution, while routine tasks and abstract tasks are overrepresented in, respectively, the middle and upper tail. This pattern is in line with the literature on job polarization (Autor et al., 2003; van den Berge and Weel, 2015; Terzidis and Ortega-Argilés, 2021). In this paper, I add two job characteristics that are likely relevant during the COVID-19 crisis: the capacity to work from home and being considered essential. In line with Dingel and Neiman (2020), the capacity to work from home strongly concentrates in the better-paying occupations. This is also where abstract task content concentrates, which suggests there may be rivaling explanations for explaining changes in employment levels in high-income jobs. The novel variable of essential jobs shows a more equal distribution over occupational percentiles than all other job characteristics. However, a peak is distinguishable where routine tasks and abstract tasks meet. Two large essential job categories (and largely routine) are around this peak: transportation clerks and production clerks. To my knowledge, this is the first depiction of the wage distribution of essential jobs.

4.2 Trends in the working age population

To explore trends in the working population over time, I divide the employed population into three categories based on wages, while also considering task content. Following Figure 1, I define occupations in the percentile range 0-25 as low-paying (and also generally manual); those in the percentile range 25-60 as middle-paying (and also generally routine); and those in the percentile range 60-100 as high-paying (and also generally abstract).

Figure 2 with the trends in the working age population gives a first intuitive impression of how the COVID-19 crisis differs from the previous time period and also the Financial crisis. It depicts the trends in the number of persons of all persons between 15 and 75 years in the categories: unemployed; out of the labor force; and the three job categories between 2003 and 2012 in Figure 2a and between 2013 and 2023 in Figure 2b. Note that the numbers of persons are not directly comparable across both figures due to changes in the calculation methods and survey design of Statistics Netherlands in 2012.

Figure 2 – Number of persons per category over time



(a) Between 2003Q1 and 2012Q4 (b) Between 2013Q1 and 2023Q4

Notes: The vertical red line in Figure 2a denotes the start of the Financial Crisis and the vertical red line in Figure 2b denotes the start of the COVID-19 crisis. Also, note that the number of persons per job category is not directly comparable across both figures due to changes in the calculation methods and surveys of Statistics Netherlands in 2012.

The vertical red lines in Figures 2a and 2b denote the start of, respectively, the Financial crisis and the COVID-19 crisis. The start of the Financial crisis naturally co-occurs with the trough in unemployment levels. Also, the population out of the labor force unsurprisingly increases shortly afterward. Employment in middle-paying occupations, which require more routine skills, is strongly hit while employment levels in high-paying occupations and low-paying occupations remain mostly stable. Exactly, in line with the findings of Jaimovich and Siu (2020); Terzidis and Ortega-Argilés (2021) that job polarization mostly occurs during crises.

In Figure 2b, one can see that unemployment levels peaked in 2014 and that shortly after employment in low-paying occupations and employment in high-paying occupations started to rise again. At the same time, employment in middle-paying occupations remained relatively stable. The population out of the labor force only peaked in 2018 after which middle-income employment levels also started to increase, which suggests that there was also a mostly *jobless recovery* of the economy for routine occupations, in line with the findings on the U.S. of Jaimovich and Siu (2020). At the same time, growth in high-paying jobs accelerates after 2018.

The impact of the COVID-19 crisis on employment trends is markedly different compared to the

Financial crisis. First of all, employment in high-paying occupations shows an unprecedentedly high growth rate of 8.2% in a year between 2020Q1-2021Q1 compared to previous records of 5.7% in 2018Q1-2019Q1 and 5.3% in 2007Q1-2008Q1. Furthermore, the employment loss during this crisis is not concentrated within middle-paying jobs, which have a small but positive growth rate, but in low-paying jobs, which experience an unprecedented drop of -12.3% in 2020Q1-2021Q1 compared to a previous record of -2.4% in 2009Q1-2010Q1. This loss in low-paying jobs has also been documented elsewhere, see Cajner et al. (2020); Barrero et al. (2021b); Papanikolaou and Schmidt (2022); Carrillo-Tudela et al. (2023). The similarity with previous crises lies in the increase in unemployment and out-of-the-labor force levels. However, within two years these levels peak and then fall even below the pre-crisis levels, with a decrease of about 1.5% and 11.3% of the number of persons that are, respectively, not in the labor force and unemployed in 2021Q4 compared to 2020Q1. Altogether, these dynamics suggest an unprecedentedly large labor reallocation shock during the COVID-19 crisis.

It is likely that the unique nature of the COVID-19 crisis makes that this crisis turns out differently than patterns witnessed in previous crises. The health risks and restrictions on human proximity make that jobs that are not deemed essential by the government or that allow for remote working lose up to 100% of their productivity. Low-paying jobs that are mostly lost score poorly on both of these measures, while middle-paying jobs do better in terms of being deemed essential, and high-paying jobs that are growing the strongest mostly do better in the capacity to work from home, as suggested in Figure 1. The next section tests more systematically to what extent associations between employment change and job characteristics exist.

4.3 Labor market dynamics and job characteristics

Table 2 produces the results of the weighted regression on average FTE growth per two-year period specified in equation 1 while grouping the data in four time periods: The Financial Crisis (two-year average between 2007Q2 and 2012Q2); pre-COVID-19 crisis (2018Q1-2019Q4), COVID-19 crisis (2020Q1-2021Q4); and post-COVID-19 crisis (2022Q1-2023Q4). In addition, the three task content variables are interacted with the COVID-19 relevant job characteristics: the ability to work from home and essential jobs in the even numbered columns. A first glance at the table already reveals that the COVID-19 crisis is of an uniquely different nature but the discussion will start with the results for the Financial crisis.

In column (1), the only two statistically significant coefficients are the negative one on routine tasks and the positive one on abstract tasks. These coefficients suggest that an increase of one standard deviation in the routine task content, respectively, abstract task content is associated with a decrease of 1.2%pt. and an increase of 2.8%pt. in the number of FTE within that occupation over a period of two years. This is strongly in line with the literature on job polarization, which suggests that outdated activities, namely routine tasks that can be automated, are hit the most during crises because firms operating under outdated paradigms are more likely to close down (Hershbein and Kahn, 2018; Jaimovich and Siu, 2020). At the same time, abstract tasks are in demand as these make use of automated technologies to invent and organize activities (Autor et al., 2003). Employment growth associated with manual tasks, which is necessary for job *polarization*, occurs much less than that of abstract tasks during the crisis but rather mostly after the crisis, as shown earlier by Terzidis and Ortega-Argilés (2021).

Note that in column (1) the effects of the COVID-19 crisis-related variables, the capacity to work from home and essential jobs, are close to zero and highly insignificant, which signals their irrelevance in explaining the dynamics during the Financial crisis. Note that the interpretation of these coefficients is slightly different compared to the task content variables as these are not standardized. Working from home is expressed in percentages. An increase from 0 to 100%

Table 2 – Growth of occupations in different time periods

(Dependent variable: Δ FTE per occupation (percentage))

Time period:	*Financial Crisis (2007Q2-2012Q2)**		*Before COVID-19 (2018Q1-2019Q4)*		*During COVID-19 (2020Q1-2021Q4)*		*After COVID-19 (2022Q1-2023Q4)*	
	Base	*With Interactions*	*Base*	*With Interactions*	*Base*	*With Interactions*	*Base*	*With Interactions*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Work from home	−0.012	−0.018	−0.018	−0.044	0.185***	0.195***	−0.128***	−0.146***
	(0.024)	(0.032)	(0.044)	(0.044)	(0.037)	(0.033)	(0.037)	(0.033)
Essential	−0.006	−0.011	0.032	0.011	0.045	0.029	−0.022	−0.025
	(0.012)	(0.017)	(0.022)	(0.024)	(0.029)	(0.028)	(0.029)	(0.028)
Routine tasks	−0.012*	−0.018**	−0.012	0.008	0.028*	0.016	−0.045***	−0.040
	(0.007)	(0.008)	(0.013)	(0.015)	(0.016)	(0.027)	(0.016)	(0.027)
Abstract tasks	0.028***	0.038	0.032**	0.100***	0.061***	0.062	0.022*	0.070*
	(0.010)	(0.024)	(0.015)	(0.036)	(0.013)	(0.041)	(0.013)	(0.041)
Manual tasks	0.006	0.014	0.008	0.006	−0.046***	−0.047**	0.028***	0.064***
	(0.006)	(0.015)	(0.012)	(0.017)	(0.009)	(0.020)	(0.009)	(0.020)
Work from home×		0.020		−0.025		−0.025		−0.021
Routine tasks		(0.015)		(0.028)		(0.040)		(0.040)
Work from home×		−0.0001		−0.083**		−0.031		−0.070
Abstract tasks		(0.031)		(0.041)		(0.053)		(0.053)
Work from home×		−0.021		−0.021		0.009		−0.069**
Manual tasks		(0.024)		(0.026)		(0.029)		(0.029)
Essential×		0.003		−0.030		0.075*		−0.018
Routine tasks		(0.013)		(0.028)		(0.045)		(0.045)
Essential×		−0.017		−0.070***		0.002		−0.041
Abstract tasks		(0.019)		(0.026)		(0.039)		(0.039)
Essential×		0.001		0.009		0.019		−0.027
Manual tasks		(0.013)		(0.018)		(0.020)		(0.020)
Constant	0.0004	0.006	0.046	0.072*	−0.039	−0.040	0.119***	0.131***
	(0.016)	(0.025)	(0.031)	(0.037)	(0.025)	(0.027)	(0.025)	(0.027)
Observations	303	303	303	303	303	303	303	303
R^2	0.085	0.099	0.036	0.069	0.285	0.305	0.093	0.119

Notes: *For the financial crisis the two year average change in FTE is used as the time period is longer than the other two. Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

in the share of workers that can work from home within that occupation is associated with a statistically non-significant decrease of 1.2%pt. in employment. Also, the constant in this column gives that on average for non-essential jobs with no capacity to work from home and the average of the task content characteristics (the reference category) the growth rate in FTE was 0.04%. whereas a not statistically significant decrease of 0.06%pt is predicted to occur when a job was deemed as essential by the Dutch government, *ceteris paribus*.

Column (2) shows that results are highly similar when adding interaction terms between the task measures and the COVID-19-related variables. Note that the coefficient on abstract tasks does turn statistically insignificant in column (2) but that it is not statistically significantly different from the one in column (1).

Columns (3) and (4) present the results before COVID-19. Starting with Column (3), the constant is positive, showing that on average there was a growth of 4.6% in FTE for the reference category. Although it is not statistically significant it is larger than in the previous columns, which is to be expected outside of crises. The other job characteristics, except the one on abstract tasks, do not show statistically significantly different growth patterns from the average growth rate given by the constant. The coefficient on abstract tasks shows that employment growth in jobs with a standard deviation more abstract tasks is even 3.2%pt. larger over a period of two years compared to the average growth rate. This suggests that the increasing trend in high-income jobs in the pre-COVID-19 time period noticeable in Figure 2 are likely due to jobs with abstract task content.

Column (4) shows that there is quite some variety in the dynamics of jobs with abstract task content. The coefficient on abstract task content is much larger with a growth rate of 10%pt. on top of the larger average growth rate of 7.2% given by the constant for the reference category. However, when abstract task content is present in essential jobs the interaction term show that this growth is 7%pt. lower. This makes sense as essential jobs with high abstract task content, such as medical specialists, are not as much in demand compared to high abstract content jobs that are more strongly influenced by market conditions.

Columns (5) and (6) show the results of the COVID-19 crisis. The constant shows that for the average non-essential job with no possibility to work from home the decrease in FTE was not statistically significant but large, around 3.9% according to column (5). This shows that despite generous governmental Financial aid the loss in employment was still large. At the same time, this was not the case for all jobs. The coefficient on the essential dummy, although not statistically significant, is almost the same size as the constant but positive, which suggests that an occupation that is deemed essential by the government with the average of all task content characteristics and no capacity to work from home has exactly zero percent change in employment levels. Most striking is the coefficient on the ability of working from home: -.185 according to column (5), which suggests that when 100% of the jobs instead of 0% within an occupation can be done from home the growth rate over a period of two years is 18.5%pt. higher, *ceteris paribus*. Note hereby that from 0% to 100% ability to work from home indicates an increase of about 2.3 standard deviations, the unit of measurement for the task content variables. The magnitude stands out when comparing this to the other coefficients in previous time periods. The largest coefficient in the base estimations is 0.032 on abstract task content in Column (3).[6] This suggests that the magnitude is about $0.185 * 2.3/0.032 \approx 13$ times larger than the largest coefficients before the pandemic, when ignoring the constants as these are not statistically significant. Also note the large R-squared, which is about 3-8 times larger when comparing to the R-squared values in other columns, which suggests that the selected job characteristics capture to a much larger extent the variation in the data. The explanatory power of abstract task content is about twice the size of its counterpart in the pre-COVID-19 time period, which suggests that this aspect also played a strong role. Routine task content is also statistically significantly associated with growth in jobs in this time period, which is in line with the growth of middle income jobs observed in Figure 2. Do note that results in Appendix A.1.4 suggest that the difference between the two time periods in the role of abstract and routine task content is not statistically significant. All in all, Column (5) suggests that the documented unprecedented increase in growth in high-income jobs during COVID-19 is likely largely due to the ability to work from home. This contrasts with the Financial crisis and the pre-COVID-19 period when the growth in high-income jobs was more strongly associated with abstract task content.

In column (6) the non-interacted coefficients are not statistically significantly different from those in column (5). The interaction effects do not show any statistically significant coefficients suggesting that there are no large differences when jobs combine task content characteristics and being essential or being able to work from home or not. Nonetheless, it is interesting to note that the growth in jobs with routine tasks seems concentrated in those that are deemed

[6] Note that this is likely the largest coefficient in previous time periods because it was when the largest growth in any of the working categories occurred before the COVID-19 crisis, see Section 4.2.

essential. Further evidence for the relevance of this interaction effect is found in Appendix A.1.1. A closer look on some of the fastest growing occupation groups during the pandemic, discussed in Section 3, shows that this interaction effect is likely driven to a large extent by two routine and essential occupations: transportation clerks and production clerks. This makes sense as these workers are required in organizing and supervising shipments and production management schedules in factories and laboratories, which likely needed more coordination and supervision when these had to operate with as little physical contact between humans as possible.

Columns (7) and (8) give the results for the post-COVID-19 crisis time period. Here the constant is strong and statistically significant suggesting an average growth rate of 11.9% for the reference category according to Column (7). Interestingly, the coefficient on ability to work from home is slightly (not statistically significantly) larger than the constant but with opposite sign. This suggests that the reference job occupation when 100% instead of 0% of the workers can work from home has about no growth or a slight decline. This is also the case when focusing on only 2023 the last year of post-COVID-19, see Appendix A.1.6. All together, this suggests that the working-from-home-related jobs gained during the pandemic are not or only slightly disappearing after the end of the pandemic, which suggests that the labor reallocation shock is relatively persistent in the jobs gained. On the other hand, the strong positive coefficients on manual task content and abstract task content and the constant suggest that other types of jobs that were (relatively) losing employment during the pandemic are growing strongly and hence catching up. This suggests that there is a quick recovery in these jobs post-pandemic, unlike the jobless recoveries documented for previous recent crises (Jaimovich and Siu, 2020; Terzidis and Ortega-Argilés, 2021). Jobs with routine task content are also negatively associated with job growth. An increase of a standard deviation in routine task content is associated with a decrease in average growth rate of 4.5%pt. This is in line with the little growth in middle-income jobs documented in Figure 2. The interaction effects in Column (8) mostly bring new insights on the type of jobs with manual task content that are growing strongly, namely those that do not allow to work from home or are deemed essential. This is in line with waiters being one of the fastest growing occupation groups after the COVID-19 crisis. This may suggest that the labor market dynamics discussed here are industry-specific but adding various controls on this and other aspects, as in Appendix A.1.2, show that the documented changes hold across the workforce.

All in all, the results suggest that the labor reallocation shock during COVID-19 is large, unique and relatively persistent in the type of jobs gained during the crisis.

4.4 Sensitivity analyzes & extensions

Checking thresholds and definitions

In Appendix A.1.1, I try out other definitions and thresholds to check to what extent the results are robust when using different definitions and thresholds. The results are strongly convincing of the robustness of the positive effects of the capacity to work from home during the COVID-19 crisis. The positive effects of abstract tasks and routine essential jobs and the negative effects of manual tasks found in the main results are less strong in these specifications but not statistically significantly different from the main results.

Adding various fixed effects

Another concern is that the employment dynamics are not driven by job characteristics but by developments in certain sectors, regions, or societal groups based on gender, age, or ethnicity. In particular, one can be concerned that the strong developments in certain sectors following COVID-19 restriction measures may drive the results rather than the job characteristics as Barrero et al. (2021b); Papanikolaou and Schmidt (2022) show that working-from-home-intensive *industries* are growing.

In Appendix A.1.2, I reproduce results while adding fixed effects for industrial sectors, regions, genders, age groups, and migration. Results are not statistically different from the main results. This suggests that changes are across the workforce and not specific to any of these groups. This is in line with the observation that low-wage occupations and not just low-wage industries are hit during the COVID-19 pandemic, see Carrillo-Tudela et al. (2023), or that job polarization occurs across the workforce instead of just within a few industries, see Goos et al. (2014).

Different dependent variables
In the main analysis employment growth is expressed as the percentage point growth in the number of FTE per occupation per time period. In Appendix A.1.3, I reproduce the main results with as dependent variable the change in the number of FTE; the percentage point change in the share of number of FTE as in Autor and Dorn (2013); Goos et al. (2014); Terzidis and Ortega-Argilés (2021), the absolute change in the share of number of FTE of an occupation in the total number of FTE; and the percentage change in the total number of jobs. Results are highly similar.

Comparing the time periods before, during, and after the COVID-19 crisis
In the main analysis separate regressions are run grouping data per time period. In Appendix A.1.4, I more rigorously evaluate the differences in the role of job characteristics between the time periods before, during and after the COVID-19 crisis. Here, equation 1 is run while interacting each variable with a dummy variable indicating each of these time periods. To further increase statistical efficiency the percentage change in FTE per quarter is used instead of two-year changes, which increases the number of observations.

As expected, the results show that the effect of the ability to work from home during the COVID-19 time period is statistically significantly different from the pre-COVID-19 time period with a 3.2%pt. increase in percentage growth per quarter while manual task content is statistically signifcantly negatively associated with a decrease in growth rate of 0.6%pt. On the other hand, the role of abstract task content is not statistically different from the pre-COVID-19 time period. Unless one controls for the ability to work from home when it is slightly positive with 0.8%pt. This shows that there is influence of the correlation between abstract task content and working from home but that the latter is the more relevant during the pandemic.

None of the coefficients on the job characteristics are statistically significantly different post-COVID-19 from those pre-COVID-19. This suggests that even though the coefficients on the ability to work from home are large in the main results, these are not statistically significantly different from those pre-COVID-19.

Early and late phase of the COVID-19 crisis
In the main analysis the COVID-19 crisis is defined as a single time period from 2020Q1 to 2021Q4. In Appendix A.1.5, I reproduce the main results while splitting the COVID-19 crisis into two time periods, namely, the four quarters of 2020 and the four quarters of 2021. Interestingly, the splitting of the COVID-19 crisis shows that manual task content is negatively associated with growth predominantly in 2020 while the capacity to work from home has a strong positive impact on growth both in 2020 and in 2021.

Early and late phase of the post-COVID-19 crisis
Similarly, in Appendix A.1.6, the post-COVID-19 crisis is split up into the four quarters of 2022 and the four quarters of 2023. These results show that growth rates across types of job characteristics are very similar in 2022 and in comparison to the pre-COVID-19 crisis time period. It is in 2023 that jobs disproportionally hit during the pandemic, notably those that do not allow to work from home, grow much more strongly. At the same time, average growth

rates remain high suggesting that there is only limited but not statistically significantly strong job loss in the jobs gained. This confirms the suggestion that the labor reallocation shock is relatively persistent in the jobs gained but not in the jobs lost.

Routine-biased technological change and offshoring
The literature on job polarization is mostly concerned with two specific relevant job characteristics: routine task intensity (RTI) and offshoring. To see how the effect of these two variables compare to those in this work, I replicate the main results using offshoring, following Blinder and Krueger (2013), and RTI, following Goos et al. (2014), as explanatory variables in Appendix A.1.7.

The results show that adding offshorability and RTI does not lead to statistically significantly different results of the effects of working from home and essential jobs. This confirms that RTI and offshorability are not the most relevant job characteristics to explain the job dynamics during the pandemic. It also confirms that the offshorability measure and the capacity to work from home are very distinct (Davis et al., 2020). Likely, because of the required skills and local context-specific knowledge that are required for the latter jobs.

Next to providing evidence on the robustness of the main results, the control variables added here and in the next section give more insight into the nature of the reallocation shock. Due to the drastic changes in work practices and disruption of global value chains during the pandemic some of the jobs gained may have been a temporal response but may be offshored (this section), or taken over by robots, software, or Artificial Intelligence (AI) (next section) in the near future. Also conceptually, the digitization of many work tasks during the pandemic may be a stepping stone to outsourcing these tasks to other countries, software applications, or AI.

Concerning offshoring, the results suggest a short-lived rise in offshorable jobs during the COVID-19 crisis. These are concentrated in essential jobs and in jobs that allow to work from home, which is plausibly related to the hiring of essential workers in reshored global value chains and the hiring of workers nationally that can work remotely full-time. Even though these jobs are offshorable and the pandemic has ended these jobs have not disappeared again (yet) by 2023Q4.

Artificial intelligence, robots, and software
In Appendix A.1.8, I replace the task content variables on job polarization by the extent to which tasks score in terms of similarity to those that can be executed by robots, software, and AI, as developed by Webb (2019). Where the former two relate to different aspects of automation, routine tasks in, respectively, machine operation and clerical work. The latter refers to the more recent rapid development of machine learning that can complete tasks by independently identifying patterns in data. Although, the future impact of AI remains uncertain there are many concerns about possible displacement effects on the labor market (Webb, 2019; Acemoglu et al., 2022).

First of all, the addition of these variables does not statistically significantly change the main results. Thereby confirming the robustness of the strong effect of the ability to work in the labor reallocation shock.

Furthermore, the results further also help to further understand the nature of the reallocation shock. In particular, there has been a strong relative rise during the COVID-19 crisis in the number of FTE in occupations that can to a high extent be executed by AI. There is no relative growth nor decline in these occupations, which suggests that this reallocation is rather persistent up until 2023Q4. This is in line with Acemoglu et al. (2022), who find that the impact of AI on the labor market is still rather limited. For occupations that compete with software, I find suggestions of a small rise in FTE in some occupations that are also deemed essential or allow to work from home. However, there is similarly a strong decline in all occupations with high software scores after the pandemic, which suggests that this reallocation is not that persistent. Possibly through automation by software. Robot score proves to be less relevant in explaining the labor reallocation shock. It is only associated with a minor job decline in a minor set of occupations that also allow to work from home during and before the pandemic but not after.

The old questionnaire
In Appendix A.1.9, I check that minor changes in the phrasing of questions in the questionnaire for persons that started in the survey in 2021 did not affect the results by using data only on the persons using the old questionnaire available until 2021Q2. The results are very similar to the main results.

4.5 Reallocation analysis

In Appendix A.2, I explore how job mobility opportunities for different socioeconomic groups and the working population composition have changed following the COVID-19 labor reallocation shock. The job mobility results are based on persons moving between the five different working population categories depicted in Figure 2. The results show that young highly-educated men are most likely to enter the highest income category (between the 60th and 100th percentile).[7] The probability of obtaining such a job increases both during and after the pandemic, which is to be expected given the rise in high-income jobs. However, the relative probability for those with less education increases while that for those that are older decreases.[8] For those with lower education levels this likely reflects the tightness of the labor market perhaps combined with a stronger relevance of digital skills compared to education levels, which gives rise to increased opportunities for upward job mobility. The demand for up-to-date computer skills likely also explains the decrease in upward job mobility for older workers as these skills are suggested to be less prevalent in these groups and hence call for human capital development policies (OECD, 2016; Bonacini et al., 2021; OECD, 2021b). These policies are still relevant because these changes in job mobility dynamics persist during the time period after the COVID-19 crisis, which suggests that the changes in demand for skills in the labor market are persistent. For women there is a relative increase in the probability of entering the high-income category, I find suggestive evidence that this may be due to the possibilities that working from home gives in combination with household tasks, but this change in job mobility does not persist after the end of the COVID-19 crisis.

The results on exiting the labor force or becoming unemployed show that the younger workers are also in a more vulnerable position as they are more likely to enter these two jobless categories. This is likely due to the relatively high prominence of permanent contracts and associated labor protection among older workers, as also discussed by Terzidis and Ortega-Argilés (2021). Those that have a lower level of education have a higher opportunity to become unemployed or exit the labor force, which even increases during the COVID-19 crisis but decreases post-COVID-19, likely reflecting the tightness of the labor market. For likely similar reasons, I find that during and after the COVID-19 crisis the probability of exiting the labor force decreases and find suggestive evidence that this among others is related to the postponement of retirement.

Part of the reallocation shock is not explained by job mobility within the Dutch working

[7] Note that here the focus is on entering the highest income working population category. Most jobs are held by highly educated men aged 31-55. I also find evidence that although probabilities of entry increase relatively stronger for those that are younger and have lower levels of education these workers also have stronger exit rates, which means that they hold on less long to jobs in the highest income category.

[8] Note that it is conceivable that moving to a job with a higher median wage percentile does not necessarily mean that each of these persons will earn that exact median wage.

population but by changes in this population, for example, due to migration, aging, or passing away. The total working population fluctuates rather strongly over time and places the results on job mobility into context and gives further insight into the nature of the labor reallocation shock. The total working population has been increasing between 2013 and 2019, then did not change much during COVID-19, after which it grew strongly again after the pandemic to reach 13.3 million persons by the end of 2023. In particular, in-migration in high-income jobs experience an unprecedented increase reaching 13.1% by the end of 2023. This gives context that part of the growth in the number of high-income jobs documented in Figure 2 is explained by the rise of migrants in this category and not only by job mobility within the Netherlands. The strong rise of migrant workers in high-income jobs also suggests a persistently high demand for (likely digital) skills and a mismatch on the local labor market.

5 Conclusion

There are many indications that the COVID-19 crisis has had a strong and possibly lasting effect on the labor market that differed strongly from previous recent crises. Where the latter are associated with an acceleration of automation, an increasing relevance of manual and abstract skills, and the loss of middle-income routine skilled jobs, the former is suggested to be associated with a persistent acceleration of digitization, an increasing relevance of the ability to work from home and essential jobs, and the loss of low-income jobs.

This paper has shed light on a few underdeveloped aspects of the size, nature, and persistence of the labor reallocation shock of the COVID-19 crisis, establishing that: 1) essential jobs are roughly equally distributed over job categories with a minor concentration in middle-income jobs, while the ability to work from home is strongly concentrated in the highest paying job occupations; 2) there has been an unprecedented rise in high-income jobs and an unprecedented drop in low-income jobs during the pandemic, while middle-income jobs show a minor increase; 3) the ability to work from home is unprecedentedly strongly associated with job growth during the pandemic, there is also some evidence that routine skills in essential jobs are positively associated with job growth. In earlier time periods the ability to work from home was not strongly associated with job growth but abstract task content was, which suggests that the growth in high-income jobs was due to a rise in abstract thinking skills during previous periods and due to working in online environments during the pandemic. This also suggests that relevance of digital skills has increased during the COVID-19 crisis; and 4) the labor reallocation shock is relatively persistent in the jobs gained but not in the jobs (relatively) lost. The number of high-income jobs keeps on growing while the number of low-income jobs has recovered somewhat. After the pandemic, there is below-average job growth in essential jobs and the ability to work from home is no longer associated with job growth but only limitedly to job loss, suggesting that these types of jobs gained during the pandemic are relatively here to stay. On the other hand, there is growth in all other skill types that did not grow during the pandemic, which suggests that these jobs are catching up and that these (relative) losses do not persist. Additionally, there is further confirmation of changes in the required skills underlying this labor reallocation shock from job mobility patterns and changes in the working population. The rise in high-income jobs in a tight labor market seem to bring up an increase in job mobility opportunities for those with lower education levels but a relative decrease for those who are older, who are generally more likely to have less digital skills. Relatedly, there is a strong influx of highly skilled migrants during and after the pandemic, likely due to mismatches on the local labor market.

These findings raise several questions for future research. The current labor allocation is likely not stable. The wave of digitization during COVID-19 may have paved the way for future developments, notably, automation, offshoring and AI. The extensions to the main results suggest that the types of tasks that can be automated by software, be offshored, or performed by AI has risen unprecedentedly. This may suggest that the current labor reallocation shock of human workers in the Netherlands may be altered by these forces in the years to come. This would require a further analysis of the relationship between the ability to work from home and each of these forces. Another avenue for future research is that the approach used here cannot asses changes in the task content *within* jobs, while it is likely that this has also persistently changed. An analysis of skills asked in job vacancies or surveys may help get insight on this issue, see for example OECD (2021a). Another possible extension is to further explore job mobility patterns in more detail, for example by including variables on the required skills in previous and new jobs.

For policy-makers the results raise concerns on skill mismatches that are of another nature than those in the past. Past policies concerned about automation focused on (future) workers to obtain skills that cannot be automated, such as those with abstract task content (CPB, 2015; OECD, 2019). The results here suggest that the ability to work in digital environments has become more relevant meaning a different type of skill mismatch and therefore other type of policies. The results on job mobility suggest that in particular older workers may be struggling in this aspect and that this persist after the end of the pandemic. All in all, the results of this paper suggest that the impact of the COVID-19 pandemic on the labor market is unique and relatively lasting.

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Appendix A

A.1 Sensitivity analyzes & extensions

A.1.1 Different groupings of data

Outliers and undersampled job categories may pose a risk to the estimation of specification 1. The data may be unreliable warns Statistics Netherlands for small groupings, such as may be the case here in certain ISCO 4-digit job categories with few observations. In the main analysis this risk is reduced by weighing the job categories by their respective number of FTE and by capping outliers in the dependent variable, *i.e.* the percentage change in employment per job category during time periods. In this section, I show results with other groupings and methods, which reduce the risk of data unreliability but also decrease sample size or increase variance.

The first column shows the baseline results as in column (6) of Table 2 in the main results. Column (2) reproduces these results without capping the dependent variable. In columns (3) to (6), I, respectively, drop all occupations with less than 15.000 FTE, use log employment instead of employment as weights and only occupations with more than 15.000 FTE, aggregate employment at the 3-digit level ISCO categories, and aggregate employment at the 2-digit level ISCO categories. These regressions naturally have less observations and as a result less statistical efficiency, which translates to higher standard errors.

Nonetheless, one can see that none of the coefficients are statistically significantly different from their counterparts in other regressions at the 99% confidence interval. This suggests that the results are highly robust to changes in thresholds and definitions.

One can note that working from home is the only factor that remains statistically significant across all specifications, which underlines the importance of this factor in this time period.

Furthermore, one can note that the R-squared value of column (2) with the uncapped dependent variable is smaller than that of column (1) with the base line results. This suggests that not capping the percentage growth rate indeed leads to more extreme values, likely due to sampling risks in small job categories, as also suggested by Statistics Netherlands.

A.1.2 Adding various fixed effects

Another concern with the results may be that the job characteristics of interest are correlated with other factors such as industrial sectors, gender, age, ethnicity, education or regions. In particular, the demand crashes in certain sectors may cause concern.

The loss in waiters, for example, is likely driven by the closure of restaurants in the pandemic rather than their incapacity to work from home or the fact that these jobs are manual. If certain job characteristics are closely correlated with sectors that experience booms or decline due to the pandemic than these dynamics should explain the rise associated with certain job characteristics of the main results rather than the job characteristics themselves.

Here, I aggregate employment according to the 2-digit ISCO level and another factor to control for, respectively, each of the 21 industrial sectors as defined by Statistics Netherlands; being male or female; being in the age groups 15-29, 30-49, and 50-75; being of Western descent or Non-Western descent; having a low-level, middle-level or high-level of education; and living in each of the twelve provinces. It is only possible to look at one of these factors at the time and by aggregating employment at a higher ISCO level because else sampling issues, discussed earlier in Appendix A.1.1, are likely to occur.

Table A2 shows the results. Column (1) gives the baseline results at the 2-digit ISCO level without using fixed effects. Note that this is not the same as in the main results, which are at the 4-digit ISCO level. In each of the following columns different fixed effects are used building on

Table A1 – Robustness analysis - Thresholds and definitions

(Dependent variable: ∆ FTE per occupation (percentage))

	Base line	*Not Capped*	*At least 15.000FTE*	*Log weight*	*Three digit*	*Two digit*
	(1)	(2)	(3)	(4)	(5)	(6)
Work from home	0.195***	0.200***	0.222***	0.182***	0.193***	0.249**
	(0.033)	(0.037)	(0.031)	(0.040)	(0.065)	(0.119)
Essential	0.029	0.030	0.035	0.011	0.040	0.051
	(0.028)	(0.035)	(0.034)	(0.041)	(0.036)	(0.118)
Routine tasks	0.016	0.002	0.007	−0.020	0.010	−0.041
	(0.027)	(0.028)	(0.035)	(0.037)	(0.027)	(0.029)
Abstract tasks	0.062	0.060	0.031	0.047	0.089*	0.038
	(0.041)	(0.046)	(0.046)	(0.054)	(0.051)	(0.090)
Manual tasks	−0.047**	−0.044*	−0.062**	−0.053	−0.050*	−0.004
	(0.020)	(0.025)	(0.030)	(0.033)	(0.028)	(0.030)
Work from home×	−0.025	−0.003	0.005	0.057	−0.026	0.009
Routine tasks	(0.040)	(0.043)	(0.042)	(0.039)	(0.070)	(0.078)
Work from home×	−0.031	−0.015	0.002	−0.039	−0.076	0.019
Abstract tasks	(0.053)	(0.064)	(0.054)	(0.061)	(0.074)	(0.133)
Work from home×	0.009	−0.002	0.015	0.018	0.087	0.049
Manual tasks	(0.029)	(0.034)	(0.036)	(0.036)	(0.059)	(0.096)
Essential×	0.075*	0.083	0.082	0.082	0.058	0.234*
Routine tasks	(0.045)	(0.053)	(0.058)	(0.053)	(0.049)	(0.120)
Essential×	0.002	0.027	0.020	0.030	−0.026	−0.037
Abstract tasks	(0.039)	(0.051)	(0.047)	(0.055)	(0.044)	(0.120)
Essential×	0.019	0.022	0.030	0.005	−0.030	−0.048
Manual tasks	(0.020)	(0.024)	(0.029)	(0.031)	(0.037)	(0.045)
Constant	−0.040	−0.045	−0.060**	−0.018	−0.041	−0.091
	(0.027)	(0.030)	(0.029)	(0.037)	(0.048)	(0.077)
Observations	303	303	115	115	87	36
R^2	0.305	0.236	0.361	0.288	0.464	0.629

Notes: Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

different aggregations, which leads to different numbers of observations because the employment change in each occupation group is subdivided among the levels of each of the factors.

One can notice that results are extremely robust across specifications with most coefficients having only fractions of their standard errors as difference between them. This gives ground to the claim that the job dynamics documented in this paper are due to the specific characteristics of jobs rather than the effects of the COVID-19 crisis on certain sectors, socioeconomic groups, or regions. This is similar to the observation by Goos et al. (2014) that job polarization happens across industries or the observation by Carrillo-Tudela et al. (2023) that low-wage occupations rather than low-wage industries are hit by the COVID-19 crisis.

A.1.3 Different dependent variables

The dependent variable chosen in this analysis is the percentage growth in FTE per job category between two time periods. This choice is similar to the approach of Jaimovich and Siu (2020), who are also interested in crises. In the job polarization literature the focus lays more often on the percentage point change in the share of a job category in total employment, see for example Autor and Dorn (2013); Goos et al. (2014); Terzidis and Ortega-Argilés (2021). This is due to a slightly different focus here. The percentage growth gives how much percent of jobs are lost and gained, which is a more relevant dimension during crises when one is also interested in the rise

Table A2 – Robustness analysis - Fixed effects
(Dependent variable: Δ FTE per occupation (percentage))

	Base line	*Industry F.E.*	*Gender F.E.*	*Age F.E.*	*Ethnicity F.E.*	*Education F.E.*	*Region F.E.*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Work from home	0.249**	0.255**	0.278**	0.295**	0.260**	0.285**	0.314**
	(0.119)	(0.103)	(0.115)	(0.115)	(0.114)	(0.117)	(0.129)
Essential	−0.041	−0.016	−0.036	−0.035	−0.037	−0.036	−0.035
	(0.029)	(0.027)	(0.028)	(0.029)	(0.029)	(0.027)	(0.029)
Routine tasks	0.038	0.051	0.034	0.031	0.057	0.043	0.045
	(0.090)	(0.096)	(0.085)	(0.085)	(0.085)	(0.085)	(0.090)
Abstract tasks	−0.004	0.006	−0.005	−0.0001	−0.004	−0.007	−0.003
	(0.030)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Manual tasks	0.051	−0.025	0.042	0.038	0.010	0.032	0.015
	(0.118)	(0.124)	(0.114)	(0.116)	(0.115)	(0.117)	(0.130)
Work from home×	0.009	0.002	−0.018	−0.010	−0.006	−0.004	−0.008
Routine tasks	(0.078)	(0.073)	(0.071)	(0.072)	(0.070)	(0.073)	(0.077)
Work from home×	0.019	−0.002	−0.012	−0.008	−0.032	−0.006	−0.023
Abstract tasks	(0.133)	(0.152)	(0.130)	(0.130)	(0.132)	(0.133)	(0.144)
Work from home×	0.049	0.081	0.054	0.056	0.065	0.065	0.077
Manual tasks	(0.096)	(0.090)	(0.097)	(0.098)	(0.099)	(0.098)	(0.115)
Essential×	0.234*	0.228**	0.237**	0.245**	0.256**	0.248**	0.266**
Routine tasks	(0.120)	(0.113)	(0.112)	(0.114)	(0.111)	(0.110)	(0.121)
Essential×	−0.037	−0.069	−0.019	−0.012	−0.047	−0.035	−0.035
Abstract tasks	(0.120)	(0.123)	(0.117)	(0.114)	(0.116)	(0.118)	(0.124)
Essential×	−0.048	−0.088**	−0.050	−0.050	−0.051	−0.051	−0.056
Manual tasks	(0.045)	(0.040)	(0.044)	(0.044)	(0.046)	(0.044)	(0.046)
Constant	−0.091	0.288	−0.095	−0.113	−0.088	−0.095	−0.110
	(0.077)	(0.301)	(0.070)	(0.074)	(0.070)	(0.093)	(0.105)
Industry Fixed Effects	No	Yes	No	No	No	No	No
Gender Fixed Effects	No	No	Yes	No	No	No	No
Age Fixed Effects	No	No	No	Yes	No	No	No
Ethnicity Fixed Effects	No	No	No	No	Yes	No	No
Education Fixed Effects	No	No	No	No	No	Yes	No
Region Fixed Effects	No	No	No	No	No	No	Yes
Observations	36	516	75	113	75	113	443
R^2	0.629	0.335	0.511	0.446	0.534	0.465	0.236

Notes: Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

of unemployment. The job polarization literature is more interested in changes within the work force over a longer time period and hence looks at changes in the shares of job categories.

Nonetheless, I reproduce the main results in Table A3 with as dependent variable, respectively; the percentage change in the number of FTE, *i.e.* the baseline results; the change in number of FTE; the percentage change in the share of FTE; the percentage point change in the share of number of FTE of an occupation in FTE; and the percentage change in the total number of jobs.

As a result, the coefficients have a different interpretation. The coefficients on working from home in columns 1 to 5 state that an increase from 0% to 100% in the number of jobs that can be done from home within a job category is associated with a growth of, respectively; 18.8%pt. in the number of FTE; 4,256.154 FTE; 18.5% of the share of FTE; 0.1%pt. in the share of FTE; 21.1% in the number of jobs.

In spite of the different interpretation, one can see that coefficients have similar signs and

Table A3 – Robustness analysis - Different dependent variables

Dependent variable:	Δ (%) Total FTE	Δ Total FTE	Δ (%) Share FTE	Δ Share FTE	Δ (%) jobs
	(1)	(2)	(3)	(4)	(5)
Work from home	0.195***	5,230.285***	0.193***	0.001***	0.214***
	(0.033)	(833.364)	(0.032)	(0.0001)	(0.041)
Essential	0.029	1,020.279	0.033	0.0001	0.028
	(0.028)	(724.563)	(0.028)	(0.0001)	(0.035)
Routine tasks	0.016	700.174	0.009	0.0001	0.021
	(0.027)	(623.130)	(0.026)	(0.0001)	(0.033)
Abstract tasks	0.062	1,264.523	0.061	0.0002	0.039
	(0.041)	(1,019.993)	(0.040)	(0.0001)	(0.047)
Manual tasks	−0.047**	−806.053	−0.044**	−0.0001	−0.059*
	(0.020)	(520.461)	(0.020)	(0.0001)	(0.032)
Work from home×	−0.025	−664.470	−0.016	−0.00004	−0.008
Routine tasks	(0.040)	(719.004)	(0.039)	(0.0001)	(0.042)
Work from home×	−0.031	−1,719.247*	−0.030	−0.0001	0.001
Abstract tasks	(0.053)	(1,007.442)	(0.052)	(0.0001)	(0.059)
Work from home×	0.009	−1,327.166*	0.009	−0.0002**	0.025
Manual tasks	(0.029)	(746.131)	(0.029)	(0.0001)	(0.040)
Essential×	0.075*	2,427.697**	0.070	0.0003**	0.055
Routine tasks	(0.045)	(977.278)	(0.047)	(0.0001)	(0.048)
Essential×	0.002	417.311	0.009	0.0001	0.019
Abstract tasks	(0.039)	(959.510)	(0.040)	(0.0001)	(0.045)
Essential×	0.019	642.814*	0.017	0.00004	0.021
Manual tasks	(0.020)	(381.400)	(0.020)	(0.0001)	(0.025)
Constant	−0.040	−1,826.570**	−0.084***	−0.0004***	−0.074**
	(0.027)	(862.388)	(0.027)	(0.0001)	(0.034)
Observations	303	303	303	303	303
R^2	0.305	0.459	0.293	0.441	0.313

Notes: Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

statistical significance. Suggesting that the dependent variable choice is not that relevant to explain the dynamics at hand.

A.1.4 Comparing the time periods before, during, and after the COVID-19 crisis

In this section the focus is on the statistical significance of the differences between the coefficients per time period, which cannot directly be observed in the main results. Table A4 produces the results based on the weighted regression specified in equation 1. While interacting all variables in the regression with dummy variables for each of the three time periods: pre-COVID-19 (reference category), during COVID-19, and post-COVID-19. The dependent variable is the percentage change in FTE *per quarter* instead of per two-year period to increase the number of observations and hence statistical efficiency. The focus is on the full specification in column (6). The constant gives a statistically significant average percentage change of 0.7% in FTE per job category per quarter for the reference category, *i.e.* jobs that are not classified as essential, have 0% jobs within that occupation that can be done from home and the average value for each of the three task content variables. The first five rows give the effect of each of the job characteristics before the COVID-19 pandemic. Here one can note that only the abstract task content is associated with a statistically significant larger growth rate of 0.4 percentage points for an increase of a standard deviation in this type of task content.

Of greatest interest here is the interaction with the dummy for the COVID-19 crisis time period, which shows the large and unique character of the labor reallocation shock. Unsurprisingly, the dummy for the COVID-19 crisis indicates a decrease in the growth rate of -1.9%pt. More surprising is the size and effect of the ability to work from home. When 100% of the jobs can be done from home instead of 0% the growth in FTE per quarter increases by a whopping 3.1%pt. This magnitude is unprecedented given the other coefficients and in particular when considering that a change from 0% to 100% is an increase of over two standard deviations, the unit of measurement for the task content variables. The unprecedented size confirms the finding of the main analysis in comparison to other time periods including the Financial crisis. One can also note that a standard deviation increase in manual task content is associated with a statistically significant growth rate of -0.7%pt. All other interaction variables are statistically insignificant. This includes the essential jobs, however, in the main analysis and in other sensitivity analyses, evidence is found that essential jobs with routine task content are growing, see Section 4 and Appendix A.1.1. Also note that abstract task content is positively and statistically significantly associated with job growth during the pandemic when not controlling for the capacity to work from home, see Column (2). These two job characteristics are highly correlated as shown in Figure 1.

Post-COVID-19, 2022Q1-2023Q4, none of the interaction effects are statistically significant. This suggests that the labor markets dynamics are not statistically significantly different from the pre-COVID-19 time period. When looking at the last year post-COVID19 2023Q1-2023Q4, see Appendix A.1.6, one can see some possible limited job loss in jobs with a high ability to work from home, while there is on average strong job growth and even more so in jobs with manual task content. This suggests that the labor reallocation shock documented here is relatively persistent, at least up to 2023Q4. It is persistent to the extent that the labor reallocation shock is not reversed because there is no or only limited job loss in the jobs related to the ability to work from home that grew during the COVID-19 crisis. On the other hand, it is not persistent to the extent that there is not a jobless recovery in jobs hit by the pandemic, mostly those that are manual and do not allow to work from home, and other job characteristics are more strongly associated with growth than the ability to work from home. This suggests that the labor reallocation is large and persistent for a large number of jobs but that some readjustments are taking place through the catching up of other types of jobs. In contrast, job polarization labor reallocation shocks during previous crises were more persistent as routine jobs did not recover after crises whereas abstract intensive and manual intensive jobs did see growth (Jaimovich and Siu, 2020; Terzidis and Ortega-Argilés, 2021).

A.1.5 Early and late phase of the COVID-19 crisis

In the main analysis the focus is on the entire 2020Q1-2021Q4 pandemic period and the entire 2022Q1-2023Q4 post-pandemic period. Possibly, there are differences within the pandemic period or within the post-pandemic period. To this end, the pandemic period is divided here in the year 2020 and the year 2021. While the next section splits up the data of the post-pandemic years 2022 and 2023.

The results are given Table A5. Note that coefficients indicate once again the percentage growth rate per quarter. Logically, the coefficients on the five job characteristics without interaction terms and the constant are the same as in the previous section A.1.4. The focus is on the full specification in column (6).

The early phase of the COVID-19 crisis is associated with a statistically significantly decrease of 2.8%pt. in the quarterly growth rate for the reference category, *i.e.* non-essential job with no capacity to work from home and the average of all three types of task content. The decrease is

Table A4 – The impact of the COVID-19 crisis on the growth of occupations
(Dependent variable: Δ FTE per occupation (percentage) per quarter)

	Routine tasks	*Abstract tasks*	*Manual tasks*	*Work from home*	*essential jobs*	*Full specification*
	(1)	(2)	(3)	(4)	(5)	(6)
Routine tasks	−0.001					−0.001
	(0.002)					(0.002)
Abstract tasks		0.003^{**}				0.004^{**}
		(0.002)				(0.002)
Manual tasks			0.0004			0.001
			(0.002)			(0.002)
Work from home				0.003		−0.001
				(0.004)		(0.006)
Essential job					0.002	0.003
					(0.003)	(0.003)
COVID-19 crisis	−0.004	−0.004	−0.004	-0.018^{***}	−0.001	-0.020^{***}
	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
COVID-19 crisis× Routine tasks	−0.003					0.004
	(0.004)					(0.003)
COVID-19 crisis× Abstract tasks		0.008^{**}				−0.0001
		(0.003)				(0.003)
COVID-19 crisis× Manual tasks			-0.010^{***}			-0.006^{**}
			(0.003)			(0.003)
COVID-19 crisis× Work from home				0.030^{***}		0.032^{***}
				(0.005)		(0.008)
COVID-19 crisis× Essential job					−0.009	0.004
					(0.007)	(0.006)
Post-COVID-19 crisis	0.0002	−0.0001	0.0004	0.003	0.001	0.007
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)
Post-COVID-19 crisis× Routine tasks	−0.002					−0.004
	(0.002)					(0.003)
Post-COVID-19 crisis× Abstract tasks		−0.001				0.001
		(0.002)				(0.003)
Post-COVID-19 crisis× Manual tasks			0.002			0.002
			(0.002)			(0.003)
Post-COVID-19 crisis× Work from home				−0.005		−0.012
				(0.004)		(0.007)
Post-COVID-19 crisis× Essential job					−0.003	−0.006
					(0.003)	(0.004)
Constant	0.007^{***}	0.007^{***}	0.007^{***}	0.006^{**}	0.006^{**}	0.007
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	6,969	6,969	6,969	6,969	6,969	6,969
R^2	0.001	0.004	0.003	0.006	0.001	0.009

Notes: Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

even stronger for job categories with more manual task content: an increase of one standard deviation of the manual task content is associated with a 1%pt. extra FTE loss. On the other hand, working from home is associated with a positive increase in the growth rate of 3.3%pt. when 100% of jobs can be done from home instead of 0%.

The effect of the late phase of the COVID-19 crisis is also associated with relatively large but not statistically significant decrease in the growth rate of 1.3%pt. for the reference category. Interestingly, this does not vary that much with the other job characteristics as only the

Table A5 – The impact of the COVID-19 crisis on the growth of occupations
(Dependent variable: Δ FTE per occupation (percentage))

	Routine tasks	*Abstract tasks*	*Manual tasks*	*Work from home*	*essential jobs*	*Full specification*
	(1)	(2)	(3)	(4)	(5)	(6)
Routine tasks	−0.001					−0.001
	(0.002)					(0.002)
Abstract tasks		0.003**				0.004**
		(0.002)				(0.002)
Manual tasks			0.0004			0.001
			(0.002)			(0.002)
Work from home				0.003		−0.001
				(0.004)		(0.006)
Essential job					0.002	0.003
					(0.003)	(0.003)
Early COVID-19 crisis	−0.012***	−0.012***	−0.012***	−0.022***	−0.010*	−0.028***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)
Early COVID-19 crisis× Routine tasks	−0.000					0.006*
	(0.005)					(0.003)
Early COVID-19 crisis× Abstract tasks		0.003				−0.006
		(0.004)				(0.005)
Early COVID-19 crisis× Manual tasks			−0.011***			−0.010***
			(0.004)			(0.003)
Early COVID-19 crisis× Work from home				0.023***		0.033***
				(0.008)		(0.011)
Early COVID-19 crisis× Essential job					−0.006	0.005
					(0.009)	(0.007)
Late COVID-19 crisis	0.003	0.002	0.003	−0.013***	0.007	−0.013
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)
Late COVID-19 crisis× Routine tasks	−0.006					0.002
	(0.004)					(0.003)
Late COVID-19 crisis× Abstract tasks		0.012***				0.005
		(0.004)				(0.004)
Late COVID-19 crisis× Manual tasks			−0.008**			−0.003
			(0.004)			(0.003)
Late COVID-19 crisis× Work from home				0.035***		0.031**
				(0.007)		(0.012)
Late COVID-19 crisis× Essential job					−0.011	0.003
					(0.007)	(0.007)
Constant	0.007***	0.007***	0.007***	0.006**	0.006**	0.007
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	4,545	4,545	4,545	4,545	4,545	4,545
R^2	0.003	0.008	0.005	0.010	0.003	0.013

Notes: The reference scenario is the time period before the COVID19 pandemic (2018Q1-2019Q4). Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

interaction term with working from home is statistically significantly positive at 3.1%pt. This suggests that jobs in general and jobs with manual task content in particular are most strongly hit in 2020 at the beginning of the pandemic, whereas the capacity to work from home remains a predictor of FTE growth in both years.

A.1.6 Early and late phase of the Post-COVID-19 crisis

Where the previous section split up the COVID-19 crisis in two time periods, here it is the Post-COVID-19 crisis that is split up in an early phase (2022Q1-2022Q4) and late phase (2023Q1-

Table A6 – Comparing the early phase to the late phase post-COVID19

(Dependent variable: Δ FTE per occupation (percentage))

	Routine tasks	*Abstract tasks*	*Manual tasks*	*Work from home*	*essential jobs*	*Full specification*
	(1)	(2)	(3)	(4)	(5)	(6)
Routine tasks	−0.001					−0.001
	(0.002)					(0.002)
Abstract tasks		0.003**				0.004**
		(0.002)				(0.002)
Manual tasks			0.0004			0.001
			(0.002)			(0.002)
Work from home				0.003		−0.001
				(0.004)		(0.006)
Essential job					0.002	0.003
					(0.003)	(0.003)
Early Post-COVID-19 crisis	0.003	0.003	0.003	0.004	0.004	0.007
	(0.003)	(0.003)	(0.003)	(0.005)	(0.003)	(0.007)
Early Post-COVID-19 crisis× Routine tasks	−0.001					−0.002
	(0.003)					(0.004)
Early Post-COVID-19 crisis× Abstract tasks		0.0005				0.001
		(0.003)				(0.003)
Early Post-COVID-19 crisis× Manual tasks			0.0005			0.001
			(0.003)			(0.004)
Early Post-COVID-19 crisis× Work from home				−0.001		−0.006
				(0.007)		(0.011)
Early Post-COVID-19 crisis× Essential job					−0.004	−0.006
					(0.006)	(0.007)
Late Post-COVID-19 crisis	−0.003	−0.003	−0.002	0.002	−0.002	0.007
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
Late Post-COVID-19 crisis× Routine tasks	−0.003					−0.007**
	(0.003)					(0.003)
Late Post-COVID-19 crisis× Abstract tasks		−0.002				0.001
		(0.003)				(0.004)
Late Post-COVID-19 crisis× Manual tasks			0.004***			0.004**
			(0.001)			(0.002)
Late Post-COVID-19 crisis× Work from home				−0.009**		−0.017**
				(0.005)		(0.009)
Late Post-COVID-19 crisis× Essential job					−0.001	−0.006
					(0.004)	(0.004)
Constant	0.007***	0.007***	0.007***	0.006**	0.006**	0.007
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	4,545	4,545	4,545	4,545	4,545	4,545
R^2	0.001	0.001	0.001	0.001	0.0004	0.004

Notes: The reference scenario is the time period before the COVID19 pandemic (2018Q1-2019Q4). Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

2023Q4). The results are given in Table A6. Note that coefficients indicate once again the percentage growth rate per quarter. Logically, the coefficients on the five job characteristics without interaction terms and the constant are the same as in the previous sections A.1.4 and A.1.5 as the reference category remains the pre-COVID-19 time period (2018Q1-2019Q4). The focus is on the full specification in column (6).

Interestingly, none of the interactions with the early Post-COVID-19 crisis are statistically significant. This suggests that the growth rates per quarter are not so different compared to the pre-COVID-19 time period. The average growth rate is 0.7%pt. per quarter higher, as one would expect based on the growth in 2022 given in Figure 2, but this is not statistically significant.

There are more pronounced dynamics during the late phase of the Post-COVID-19 crisis (2023Q1-2023Q4). The average growth rate is again 0.7%pt. per quarter higher but also again not statistically significant. Manual task content is statistically significantly positively associated with job growth, which suggests that this type of jobs are growing up at a faster rate and hence catching up after the larger losses during the pandemic. On the other hand, two job characteristics are statistically significantly negatively associated with job growth, namely, routine task content, and the ability to work from home. On the other hand, At first sight the dynamics are almost a mirror of the dynamics in the early COVID-19 crisis, see previous section, where the point estimates on average growth rate and manual task content where statistically significantly negative and the others positive or not statistically significant. However, note that even with 100% of the jobs being able to be done from home, *ceteris paribus* this does not statistically significantly balance the average growth rate plus the one of the late post-COVID-19 crisis, which suggests that there is likely only limited job loss in this type of jobs during this time period.[9] This further confirms that the labor reallocation shock is quite persistent in the jobs gained, as these are not statistically significantly declining, but not in the types of job lost, as these are catching up.

A.1.7 Routine-Task Intensity and Offshoring

The job polarization literature often jointly considers offshoring to technological change, by looking at the offshorability and Routine Task Intensity (RTI) of jobs. The focus on these two aspects is likely less useful to evaluate the labor reallocation shock during the pandemic. Offshoring has been found to be less important than routine-biased technological change in previous time periods in Western Europe (Goos et al., 2014). Furthermore, from a theoretical perspective it is also less likely to be relevant during the COVID-19 crisis because offshoring became less of a possibility due to the distortion of gloval value chains. Although it may have had as a result that offshored jobs are reshored (Brakman et al., 2021).

Routine-biased technological change is generally approximated by Routine-Task Intensity (RTI), which is the logarithm of routine task content minus the logarithms of abstract content and manual task content. Hence, it is different from routine task content. This measure is not used in the main analysis as other mechanisms than routine-biased technological change are at hand during the pandemic, such as the ability of working from home, essential jobs, and the difference between each of the aspects in manual, routine, and abstract tasks. Nonetheless, I replicate the main results using offshorability, following Blinder and Krueger (2013), and RTI, following Goos et al. (2014), as explanatory variables in Table A7.

In columns (1), (3) and (5) offshorability is added with the task content variables and COVID-19 job characteristics as in Table 2. In columns (2), (4) and (6) the task content variables are replaced by RTI instead of adding RTI to prevent multicollinearity.

Results do not change significantly. The effect of working from home remains strong during the COVID-19 period and not statistically significantly different from the one in the main results, see Table 2. This generally also holds for the other coefficients.

One can note that the positive coefficient on abstract tasks in column (1) translates to a negative coefficient in RTI in column (2) as RTI is the only task content dimension left and negatively correlated with abstract task content. During the COVID-19 crisis, the coefficient is about the

[9] Note that when combining high levels of routine task content ability to work from home, and or being essential one could identify a few job categories with statistically significantly negative coefficients.

Table A7 – Robustness analysis - Different independent variables - Automation & Offshoring
(Dependent variable: Δ FTE per occupation (percentage) during time period)

Time period:	*Before COVID-19 (2018Q1-2019Q4)*		*During COVID-19 (2020Q1-2021Q4)*		*After COVID-19 (2022Q1-2023Q4)*	
	Offshorability	*RTI & Offshorability*	*Offshorability*	*RTI & Offshorability*	*Offshorability*	*RTI & Offshorability*
	(1)	(2)	(3)	(4)	(5)	(6)
Work from home	-0.012	0.016	0.167^{***}	0.232^{***}	-0.116^{***}	-0.086^{**}
	(0.042)	(0.035)	(0.043)	(0.049)	(0.045)	(0.034)
Essential	0.031	0.033	0.046	0.037	-0.023	-0.019
	(0.022)	(0.023)	(0.029)	(0.043)	(0.020)	(0.021)
Routine tasks	-0.010		0.022		-0.042^{**}	
	(0.012)		(0.016)		(0.018)	
Abstract tasks	0.032^{**}		0.063^{***}		0.021	
	(0.015)		(0.014)		(0.015)	
Manual tasks	0.007		-0.041^{***}		0.024^{*}	
	(0.013)		(0.010)		(0.013)	
Routine Task Intensity		-0.023^{*}		-0.0002		-0.038^{**}
		(0.012)		(0.017)		(0.016)
Offshorability	-0.005	-0.002	0.016	0.033^{*}	-0.010	-0.014
	(0.017)	(0.017)	(0.019)	(0.019)	(0.013)	(0.013)
Constant	0.044	0.031	-0.032	-0.057^{*}	0.114^{***}	0.100^{***}
	(0.030)	(0.027)	(0.026)	(0.033)	(0.027)	(0.021)
Observations	303	303	303	303	303	303
R^2	0.037	0.026	0.289	0.202	0.095	0.080

Notes: Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

size of that on routine task content, likely because the rise of high-income jobs is captured by the working from home variable and the negative effect of manual tasks of column (3) is negatively correlated with RTI.

Offshorability does show an increased relevance during the COVID-19 crisis compared to the time periods before and after. This suggests that jobs gained during the pandemic can more often be offshored. I find that these are both concentrated in essential jobs and in jobs that allow to work from home. The former is in line with the reshoring of global value chains due to disruptions (Brakman et al., 2021). The latter suggests a rise in jobs that (in non-crisis circumstances) could be done online and be outsourced to other countries. The coefficients on offshoring in the post-COVID-19 crisis are not statistically significantly negative, which suggests that the new offshorable jobs have not been offshored yet by 2023Q4 even though the pandemic has been declared over.

A.1.8 Robots, software and AI

In this section, I use the job characteristics for task content developed by Webb (2019) on the extent to which job tasks overlap with tasks that can be performed by any of the following: robots, software, and Artificial Intelligence (AI). Robots and software consist of two different automation possibilities for routine task content, where the former is more often associated with substituting humans in repetitive machine operating tasks and the latter with substitution in repetitive clerical tasks. Artificial Intelligence features prominently in more recent concerns on substitution effects on the labor market following its rapid developments in the past decade (Webb, 2019; Acemoglu et al., 2022). Like in the previous section on offshorability, these variables do not only serve as different control variables in checking the robustness of the main results but also further help understand the type of jobs gained or last during the COVID-19 crisis.

Table A8 shows the results. A first observation is that the main results on the role of the ability to work from home do not statistically significantly change when using these control variables instead of the task content variables of the main analysis. This further confirms that the main results are highly robust to different specifications.

In addition, occupations with tasks that can be performed by software and notably AI seem to have grown during the pandemic, columns (3) and (4). For software these are mainly in the jobs that are essential and allow to work from home, where the interaction terms are larger than the uninteracted terms and strongly statistically significant. This is also stronger than before the COVID-19 crisis, columns (1) and (2), where similar dynamics can be noted but where the coefficient on the uninteracted software score dominates. After the pandemic, columns (5) and (6), the association with software is even more strongly negative, as only the strong negative coefficient on software score is statistically significant. This suggests some relative growth in some occupations that can be performed by software during the pandemic quickly followed by a decrease in FTE in these type of jobs. This suggests that these may have been automated by 2023Q4. For AI the growth is across the board of occupations that have AI-like tasks as it is the uninteracted term that is strongly positive and statistically significant during the COVID-19 crisis. Both before and after the COVID-19 the coefficients are not statistically significant. This suggests that relatively more jobs that can (partly) be performed by AI have been added during the pandemic and that this reallocation is persistent up until 2023Q4. This is in line with Acemoglu et al. (2022), who find that the displacement effects of AI on the labor market are (still) rather limited. The robot score is only statistically significantly associated with job decline when interacted with the ability to work from home in columns (2) and (4), which may suggest that some robotization of jobs is taking place before and during the pandemic in a limited number of job occupations.

A.1.9 Main results using old questionnaire

Starting in the first quarter of 2021 new participants in the quarterly labor survey were given questions with a slightly different phrasing following the harmonization of questions of statistics bureaus within the European Union. Most relevant for the purposes here is that it was more explicitly stated that temporary side jobs count as jobs. This led to more persons indicating being employed. Data from previous years was corrected on the basis of the difference in the results of the participants that started in 2021 with the new survey and those that started in 2020 and were still following the old model. To check whether these changes affected the difference in job dynamics during the pandemic found, I reproduce the main results using data only on the persons using the old questionnaire available until 2021Q2 from an earlier release of the data in Table A9.

Results are very similar to the main results. Note that the time periods are different as data from the old questionnaire is only available until 2021Q2 and not 2021Q4. As a result, the before COVID-19 period is also shortened and for the Financial crisis the average growth during a 1.5 year period instead of a 2 year period is used. Despite this different timing none of the coefficients but one are statistically significantly different from those in Table 2. The exception is the coefficient on the capacity to work from home during the COVID-19 crisis, which is statistically significantly smaller. However, this is also partly due to the shorter time period used in this context, which makes that less percentage growth in FTE occurs compared to the longer time period in the main results. All in all, the results suggest that changes in the job dynamics did not occur during the COVID-19 crisis because of the changes in the phrasing of questions.

Table A8 – Robustness analysis - Different independent variables - Webb tasks
(Dependent variable: Δ FTE per occupation (percentage) during time period)

Time period:	*Before COVID-19 (2018Q1-2019Q4)*		*During COVID-19 (2020Q1-2021Q4)*		*After COVID-19 (2022Q1-2023Q4)*	
	Base	*With Interactions*	*Base*	*With Interactions*	*Base*	*With Interactions*
	(1)	(2)	(3)	(4)	(5)	(6)
Work from home	−0.004	−0.038	0.193***	0.124***	−0.084**	−0.063
	(0.032)	(0.031)	(0.045)	(0.046)	(0.035)	(0.054)
Essential	0.045*	0.052**	0.028	0.056	−0.008	−0.010
	(0.024)	(0.023)	(0.037)	(0.037)	(0.025)	(0.021)
Software score	−0.027*	−0.128***	0.008	−0.105*	−0.037**	−0.105
	(0.016)	(0.043)	(0.023)	(0.062)	(0.016)	(0.072)
Robot score	−0.024	−0.009	−0.052	0.011	0.001	0.0003
	(0.017)	(0.021)	(0.032)	(0.049)	(0.015)	(0.034)
AI score	0.021	0.055	0.045**	0.100**	0.030*	0.069
	(0.017)	(0.041)	(0.019)	(0.040)	(0.018)	(0.044)
Work from home× Software score		0.154***		0.172**		0.039
		(0.043)		(0.072)		(0.084)
Work from home× Robot score		−0.110***		−0.249***		0.048
		(0.041)		(0.086)		(0.083)
Work from home× AI score		−0.028		−0.039		−0.026
		(0.043)		(0.045)		(0.047)
Essential× Software score		0.094**		0.120**		0.074
		(0.038)		(0.054)		(0.078)
Essential× Robot score		0.008		−0.057		0.003
		(0.023)		(0.042)		(0.044)
Essential× AI score		−0.023		−0.079		−0.050
		(0.041)		(0.051)		(0.054)
Constant	0.036	0.028	−0.037	−0.057**	0.093***	0.090***
	(0.024)	(0.023)	(0.029)	(0.029)	(0.026)	(0.027)
Observations	303	303	303	303	303	303
R^2	0.060	0.110	0.247	0.277	0.050	0.068

Notes: Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.2 Reallocation analysis

In this section, I explore the reallocation dynamics of the working age population that move into new jobs or stop working before, during and after the COVID-19 crisis. Understand how working career paths of different socioeconomic groups are affected by the pandemic and its consequences for the composition of the working population can give an insight on the change in the required skills on the labor market. The quarterly labor survey used here not only allows for the estimation of aggregate employment statistics but also allows to follow persons over time. This is an active goal of Statistics Netherlands. To this aim they have also developed a longitudinal weight to estimate the total number of persons that experience similar switches in occupations based on the sources mentioned in Section 3. This type of approach is followed here to examine working status changes according to the five working age population categories, as mentioned in Figure 2. In a first step, job mobility patterns are analyzed to identify changes in working career paths of the working population. In a second step, changes in the the working population are analyzed by identifying changes in migration patterns.

Table A9 – Robustness analysis - old questionnaire

(Dependent variable: Δ FTE per occupation (percentage))

Time period:	*Financial Crisis (2007Q2-2012Q2)**		*Before Covid-19 (2018Q1-2019Q2)*		*During Covid-19 (2020Q1-2021Q2)*	
	Base	*With Interactions*	*Base*	*With Interactions*	*Base*	*With Interactions*
	(1)	(2)	(3)	(4)	(5)	(6)
Work from home	-0.007	-0.012	0.018	0.002	0.099^{**}	0.092^{**}
	(0.016)	(0.021)	(0.034)	(0.033)	(0.042)	(0.045)
Essential (dummy)	-0.003	-0.006	0.032	-0.002	0.085^{***}	0.081^{***}
	(0.008)	(0.011)	(0.024)	(0.019)	(0.026)	(0.026)
Routine tasks	-0.008^{*}	-0.012^{**}	0.001	0.019	0.010	-0.004
	(0.004)	(0.005)	(0.011)	(0.016)	(0.014)	(0.024)
Abstract tasks	0.019^{***}	0.025	0.014	0.119^{***}	0.049^{***}	0.045
	(0.007)	(0.016)	(0.013)	(0.020)	(0.013)	(0.035)
Manual tasks	0.004	0.010	0.001	0.002	-0.046^{***}	-0.021
	(0.004)	(0.010)	(0.009)	(0.021)	(0.012)	(0.020)
Work from home×		0.014		-0.012		-0.029
Routine tasks		(0.010)		(0.032)		(0.042)
Work from home×		-0.0002		-0.127^{***}		-0.014
Abstract tasks		(0.020)		(0.030)		(0.058)
Work from home×		-0.015		0.004		-0.040
Manual tasks		(0.016)		(0.028)		(0.040)
Essential×		0.002		-0.028		0.060^{*}
Routine tasks		(0.009)		(0.023)		(0.035)
Essential×		-0.012		-0.121^{***}		0.006
Abstract tasks		(0.013)		(0.017)		(0.033)
Essential×		0.0005		-0.016		-0.007
Manual tasks		(0.009)		(0.020)		(0.025)
Constant	-0.001	0.002	0.014	0.053^{**}	-0.085^{***}	-0.091^{***}
	(0.010)	(0.016)	(0.025)	(0.022)	(0.027)	(0.028)
Observations	321	321	321	321	321	321
R^2	0.083	0.098	0.020	0.123	0.259	0.281

Notes: *For the financial crisis the 1.5 year average change in FTE is used as the time period is longer than the other two. Standard errors are clustered at the 2-digit occupation level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

A.2.1 Job mobility

Here, I analyze the changes in job mobility before, during and after the COVID-19 labor reallocation shock. To this end, I estimate equation A.1 in a logit model. The dependent variable is an entry variable with value one when person p enters one of the five working population category mentioned in Figure 2 in a certain quarter t and zero if a person does not. Hence, $WPC_{p,t} = \{P60P100_{p,t}, P25P60_{p,t}, P0P25_{p,t}, UNEMP_{p,t}, NILF_{p,t}\}$. Persons that were already in a certain working population category in the previous quarter can for obvious reasons not enter that category in a certain time period and are therefore dropped from the sample. The independent dummy variables for personal characteristics give if someone is: in the age group 30-55 years; 56-75 years; female; low level of education; and middle level of education.[10] Therefore, the reference category is 15-30 years old, male, and highly-educated. This is also the type of person that has the largest chance to enter in the highest-paying jobs, as will be shown furtheron. Statistics Netherlands assigns a weight to each person to arrive at the total

[10]According to the definitions of Statistics Netherlands a low level of education is defined as someone who has had either no education, only primary education, vmbo, mbo-1 or only the first three years of havo or vwo. Middle level of education is defined as someone who has finished havo, vwo or mbo.

Table A10 – Descriptive statistics - Reallocation analysis

Statistic	Mean	St. Dev.
Entering P60-P100 Abstract	0.010	0.099
Entering P25-P60 Routine	0.013	0.111
Entering P0-P25 Manual	0.016	0.124
Entering Unemployed	0.015	0.120
Entering Not in Labor Force	0.022	0.145
Age 30-55	0.420	0.494
Age 56-75	0.333	0.471
Female	0.502	0.500
Low level of education	0.244	0.429
Middle level of education	0.373	0.483
Weight	287.548	290.401

Note: all variables are dummy variables. The number of observations is 900163.

population and to correct for the undersampling of certain persons in the survey using the same other data sources mentioned in Section 3.

$$WPC_{p,t} = Constant + \beta_1 Age30to55_{p,t-1} + \beta_2 Age56to75_{p,t-1} + \beta_3 Fem_{p,t-1} + \beta_4 LowEduc_{p,t-1} + \beta_5 MiddleEduc_{p,t-1} + \epsilon_{p,t}, \tag{A.1}$$

I use the quarter-by-quarter longitudinal data from 2018Q1 to 2023Q4 to follow persons over each of the five time periods. The variables in equation A.1 are interacted by a dummy variable for the COVID-19 crisis (2020Q2-2021Q4) and the post-COVID-19 crisis (2022Q1-2023Q4).[11] Descriptive statistics are shown in Table A10. This means that the reference time period is the pre-COVID-19 crisis (2018Q1 to 2019Q4).

The marginal effects are shown in Table A11, whereas Table A13 shows the full results of the logit model specified in equation A.1. Marginal effects are calculated with the reference category as baseline, which means that each coefficient gives the change in probability of entering that working population category when the associated dummy variable is changed from 0 to 1, *ceteris paribus*. Note that most of the coefficients are statistically significant, likely due to the many observations and large population weights, although this does not mean that each coefficient has a strong influence on job mobility, *i.e.* is economically significant.

Before going into the results per column, one can note that generally older persons have a lower probability of entering all of the working population categories, except for exiting the labor force for persons aged 56-75 in column (5). This suggests that younger persons are more likely to change working population category. People in the age 15-30 are more likely to switch between education and different job types but also from side jobs during studies into full-time jobs in other working population categories. Also they are less likely to be protected from unemployment by permanent contracts compared to older workers (Terzidis and Ortega-Argilés, 2021). Groups that have less job mobility also have lower probabilities of entry because persons that are already in a working population category cannot enter that category. The exception in column (5) is likely due to retirement.

High-income jobs
Column (1) gives the marginal effects of each dummy variable on the probability of entering the

[11] Note that Statistics Netherlands removed data of persons in 2021 that started in 2020 because of the rephrasing of a few questions in 2021. Hence, it is no longer possible to follow job trajectories between 2020Q4 and 2021Q1.

Table A11 – Working population dynamics - Marginal effects

Dependent variable:	*P60-P100 Abstract jobs*	*P25-P60 Routine Jobs*	*P0-P25 Manual jobs*	*Unemployed*	*Not in labor force*
	(1)	(2)	(3)	(4)	(5)
Age 31-55 (dummy)	-0.059^{***}	-0.016^{***}	-0.019^{***}	-0.019^{***}	-0.020^{***}
	(0.001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Age 56-75 (dummy)	-0.087^{***}	-0.025^{***}	-0.022^{***}	-0.026^{***}	0.005^{***}
	(0.001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Woman (dummy)	-0.021^{***}	-0.001^{***}	0.008^{***}	0.001^{***}	0.003^{***}
	(0.001)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Low level of education (dummy)	-0.092^{***}	0.0002	0.100^{***}	0.021^{***}	0.034^{***}
	(0.001)	(0.0003)	(0.001)	(0.0003)	(0.0003)
Middle level of education (dummy)	-0.072^{***}	0.019^{***}	0.035^{***}	0.007^{***}	0.014^{***}
	(0.001)	(0.0003)	(0.0003)	(0.0002)	(0.0002)
COVID-19 crisis	0.006^{***}	-0.001^{***}	0.0003	0.0004	-0.001^{**}
	(0.001)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
COVID-19 crisis× Age 31-55 (dummy)	-0.013^{***}	-0.004^{***}	-0.002^{***}	-0.006^{***}	-0.004^{***}
	(0.001)	(0.0003)	(0.0002)	(0.0002)	(0.0003)
COVID-19 crisis× Age 56-75 (dummy)	-0.005^{***}	0.001	−0.0002	-0.004^{***}	-0.004^{***}
	(0.002)	(0.0005)	(0.0004)	(0.0004)	(0.0003)
COVID-19 crisis× Woman (dummy)	0.005^{***}	0.002^{***}	-0.001^{***}	0.001^{***}	-0.001^{***}
	(0.001)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
COVID-19 crisis× Low level of education (dummy)	0.022^{***}	0.004^{***}	0.0004	0.005^{***}	0.005^{***}
	(0.002)	(0.0005)	(0.0003)	(0.0004)	(0.0004)
COVID-19 crisis× Middle level of education (dummy)	0.007^{***}	-0.001^{***}	0.001^{*}	0.006^{***}	0.004^{***}
	(0.001)	(0.0003)	(0.0003)	(0.0004)	(0.0004)
Post-COVID-19 crisis	0.011^{***}	-0.005^{***}	-0.002^{***}	0.006^{***}	-0.003^{***}
	(0.001)	(0.0003)	(0.0003)	(0.0004)	(0.0003)
Post-COVID-19 crisis× Age 31-55 (dummy)	-0.010^{***}	-0.002^{***}	0.001^{**}	-0.007^{***}	-0.004^{***}
	(0.001)	(0.0003)	(0.0003)	(0.0002)	(0.0003)
Post-COVID-19 crisis× Age 56-75 (dummy)	-0.004^{**}	0.003^{***}	0.002^{***}	-0.004^{***}	-0.005^{***}
	(0.002)	(0.001)	(0.0004)	(0.0004)	(0.0003)
Post-COVID-19 crisis× Woman (dummy)	-0.005^{***}	0.001^{***}	-0.003^{***}	0.001^{***}	0.004^{***}
	(0.001)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Post-COVID-19 crisis× low level of education (dummy)	0.057^{***}	0.014^{***}	0.005^{***}	-0.005^{***}	-0.005^{***}
	(0.003)	(0.001)	(0.0004)	(0.0003)	(0.0003)
Post-COVID-19 crisis× Middle level of education (dummy)	0.030^{***}	0.007^{***}	0.003^{***}	-0.005^{***}	-0.003^{***}
	(0.001)	(0.0005)	(0.0004)	(0.0003)	(0.0003)
Observations	620,289	694,476	729,878	873,666	682,343

Notes: The reference categories for the dummy variables are: Age 15-30, Man, and high level of education. Note that the average probability of success, i.e. moving into each of the working population categories, for a person of the reference categories for all dummy categories are, respectively, 10%, 3%, 2.3%, 3.1%, and 3.4%. Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

job category in a certain quarter with the 60th to 100th percentile income, which are the jobs with the highest incomes with often abstract task content. Given that all coefficients on the uninteracted demographic variables, *i.e.* the first five variables, are negative it indicates that highly-educated men aged 15-30 years, the reference category, are the most likely to move to a job of the highest paying category from any of the other working population categories. The probability of entry for the reference category is about 10%. Note that the figures in Section A.2.3 signal that most high-income jobs are held by those that are highly-educated, men, and aged 31-55.

The coefficient on the COVID-19 crisis and on the Post-Covid-19 crisis suggest that this probability increases by, respectively, 0.6%pt. and 1.1%pt. during these time periods. This is in line with the strong rise in high-income jobs seen in Figure 2. For those with low or middle levels of education the probability actually increases even more strongly with an addition of, respectively, 2.2%pt. and 0.7%pt. during COVID-19 and even 5.7%pt. and 3%pt. after the COVID-19 shock. These latter two changes in probability are substantial. They are equal to about 50% of the difference in probability of entering between the reference category and having a low or middle level of education *ceteris paribus*, see the uninteracted coefficients. This likely reflects the increased tightness of the labor market where the reduced availability of those with higher education increases chances for those with lower levels of education to obtain the high-income occupations.[12] Possibly, some of those with lower levels of education are hired before finishing their studies due to attractive job offers because there is a decrease in the number of persons following education the last few years, see Figure A4b. Note that in spite of the increases in probability of obtaining high-income job occupations workers that are younger and have lower levels of education also have a higher probability of moving into the other working population categories, including becoming unemployed and exiting the labor force. This suggests that these workers also have less opportunity in keeping the high-income jobs. This is in line with Figures A3c and A3b, wich show that the total number of older workers and with a higher level of education with high-income jobs does increase more strongly than those that are younger or have a lower level of education. This in spite of the increase in upward job mobility for these socioeconomic groups.

However, the increase in upward mobility seems relatively confined to the reference category and those with lower education levels *ceteris paribus*. For those that are older, the general increase in probability during and after COVID-19 is counterbalanced as the coefficients on the interaction terms are similar in size but negative.[13] This may reflect the demand for up-to-date computer skills required in a digitized working environment that are suggested to be on average less prevalent among older workers (OECD, 2016; Bonacini et al., 2021; OECD, 2021b).

For women opportunities seem to have gone up relatively during COVID-19 but are relatively lower after COVID-19. A possible explanation is that women take up jobs during the pandemic as they tend to have a higher preference for flexible working hours enabled by working from home but see this possibility to work from home decrease after the pandemic (Arntz et al., 2020).[14] Do note that the combined effect Post-COVID-19 is still positive (1.1%pt.-0.5%pt.) and that the absolute growth of the number of women in high-income jobs is also relatively similar to that of men, see Figure A3a. Also note that this explanation is in line with the decrease in number of persons that self-identify as housewife during the pandemic, see Figure A4a.

Middle-income and low-income jobs

Columns (2) and (3) give the results for, respectively, the P25-P60 mostly routine middle-income jobs and the P0-P25 mostly manual low-income jobs. Entering these categories is most likely for, respectively, young men with a middle level of education, and young women with a low level of education. The probability of someone of the reference category to enter the middle-income job category, respectively, the low-income job category is 3%, and 2.3%. Note that the figures in

[12] Note that entering a job occupation with a median wage in the top 40% does not necessarily mean that the entering person receives that same wage.

[13] Note that there is an exception for those that are between 56-75 years old. They do see a small statistically significantly increase in the Post-COVID-19 phase as the increase is 1.1%pt. and the interaction term only -0.04%pt.

[14] Although, note that unlike Arntz et al. (2020) I find that women are not overrepresented in jobs that where one can work from home (correlation of -0.027). Nor for jobs that are essential (correlation of -0.005).

Section A.2.3 signal that most middle-income jobs are held by those that have a middle level of education, men, and aged 31-55 years and most low-income jobs by those that have a middle level of education, women, and aged 55-75 years.

During the COVID-19 crisis, there is on average not much change in the probability of entry for different categories with many coefficients being statistically significant but rather small. The largest coefficients are in column (2), where those between age 31-55 see a 0.4%pt. decrease in entering and those with a low level of education see a 0.4%pt. increase. The former likely reflects the stability of permanent contracts and less career hopping between working population categories in this category during the pandemic, which takes up again in the Post-COVID-19 period. The latter likely suggests that again there is some increased opportunity for upward job mobility opportunities for those with lower levels of education in obtaining middle-income jobs, which increases even more after the COVID-19 crisis.

The low levels of change in entry in low-income jobs contrast with the large drop in employees in this working population category during COVID-19. This suggests that quite some churn within this category is taking place as there are still similar rates of persons from other working population categories moving in. Similarly low levels of change in entry post-COVID-19, when employee numbers are growing again, suggests that there is less churn. Persons are moving in at similar rates but likely exiting at lower rates to be able to match with the growth in number of workers. The negative coefficients on the reference category during post-COVID-19 crisis, suggest that highly educated men 15-30 are not moving into this category as much as before the pandemic. Likely because there are more opportunities to obtain a high-income job. This also holds for column (2).

Becoming unemployed
The probability of becoming unemployed is larger for younger people and those with less education. It is a negligible amount of 0.1%pt. larger for women than for men. Note that the figures in Section A.2.3 signal that there are also negligeable differences between the number of men and women among the unemployed and post-pandemic also between education levels, whereas those below 31 years see the largest absolute increase in the number of unemployed. In terms of job mobility, the average probability for the reference category of moving into the unemployed working population category in a certain quarter is 2.1%. Column (4) shows that during the COVID-19 crisis the probability of becoming unemployed increases. During the COVID-19 crisis the probability of becoming unemployed does not change for the reference category but it actually becomes lower for those who are older and are more likely to be on more permanent contracts but increases for those with lower levels of education and only minorly for women. This slightly contrasts with the results for the U.S. of Drozd et al. (2024), who find that women with lower education are more strongly hit during the pandemic. Post-COVID-19 crisis the probability actually increases for the reference category while all other categories except women see a decrease. Note that the reference category is still has a lower probability of becoming unemployed than those with lower levels of education. This likely reflects the tightness of the labor market giving also those with lower levels of education more protection. The relative increase for the reference category is more difficult to explain, also given the decrease in unemployment levels, but might be due to temporary contracts given during the increased job mobility of the pandemic that have come to an end.

Exiting the labor force
Persons that are unemployed and not looking for a job are seen as not being in the labor force. The survey also gives insight in what the reasons are when one is not in the labor force. There are various options: education; being retired; having to take care of someone; having health

issues; not searching a job because one believes searching is futile; not searching a job but willing to work; and not searching a job for other reasons. To aid with the interpretation of the results of column (5), Table A12 shows the correlation between a dummy for each of these factors and the dummy variables of personal characteristics used in Table A13. The population trends in each of these categories can also be seen in Section A.2.3. Among those out of the labor force women, those with low levels of education, and are above 55 years old are overrepresented.

Column (5) shows that highly educated men aged 31-55 have the smallest chance of exiting the labor force in a certain quarter. For the reference category the probability of exiting the labor force is about 3.4%. For younger persons the increased probability of exiting is likely for education purposes, see Table A12, while for older persons being out of the labor force is more strongly associated with retirement. For women it is more strongly related to care-taking, likely due to parenthood. There are also increased probabilities of exiting for lower levels of education. These factors are associated with multiple reason for not being in the labor force, although education is a bit higher. This may suggest that some are exiting to finish education programs, which is plausible as there is a negative correlation between age and lower levels of education because younger persons are still finishing education programs and can have temporary side jobs.

During and after the COVID-19 crisis the likelihood to move out of the labor force decreases for most socio-economic categories. This is likely due to the tight labor market. This is even the case during the pandemic as the number of persons out of the labor force is also at a lower level at the end of the pandemic despite an increase at the beginning. This suggests that there are increased incentives for persons to remain in the other working population categories and not exit the labor force. In the case of workers aged 56-75 this suggests a postponement of retirement, which is also seen in the decline in number of retired persons furtheron. For women the probability of exiting the labor declines but is slightly higher (-0.3%pt.+0.4%pt.=0.1%pt.) after the pandemic. This may be associated with the earlier mentioned opportunities unleashed by the ability to work from home during the pandemic, which may have temporarily helped postponing quitting jobs after giving birth (Arntz et al., 2020). This effect is only temporary, this in spite of the tight labor market. Workers with lower levels of education were more likely to exit the labor force during the pandemic but see a larger increase in the probability of staying in the labor force after the pandemic. A possible explanation is the finding of that workers laid off with lower levels of education were postponing searching till the end of the pandemic and therefore exiting the labor force during the pandemic. The post-COVID-19 strong decrease in exiting the labor force rates is in line with the observation that entry rates in the working categories are higher.

A.2.2 Working population and migration

Reallocation dynamics are also affected by persons moving in and out of the working population of the Netherlands, *i.e.* those between the ages of 15 and 75 years and living in the Netherlands. Part of these dynamics are so-called natural changes due to the aging and the passing away of those living in the Netherlands. Next to that, the Dutch labor market is characterized by relatively large shares of migrant workers. In this section, I explore changes in the dynamics of the working population itself, which serves to place the previous findings in context and to further explore the changes and their persistence in the demand for skills during the labor reallocation shock of the COVID-19 crisis.

Figure A1 shows the cumulative number of workers per working population category. Here one can see that the total working population of the Netherlands has been growing from 12.46 million persons in 2013 to a peak of 12.95 million workers at the end of 2019 before plateauing

Figure A1 – Number of persons per category over time

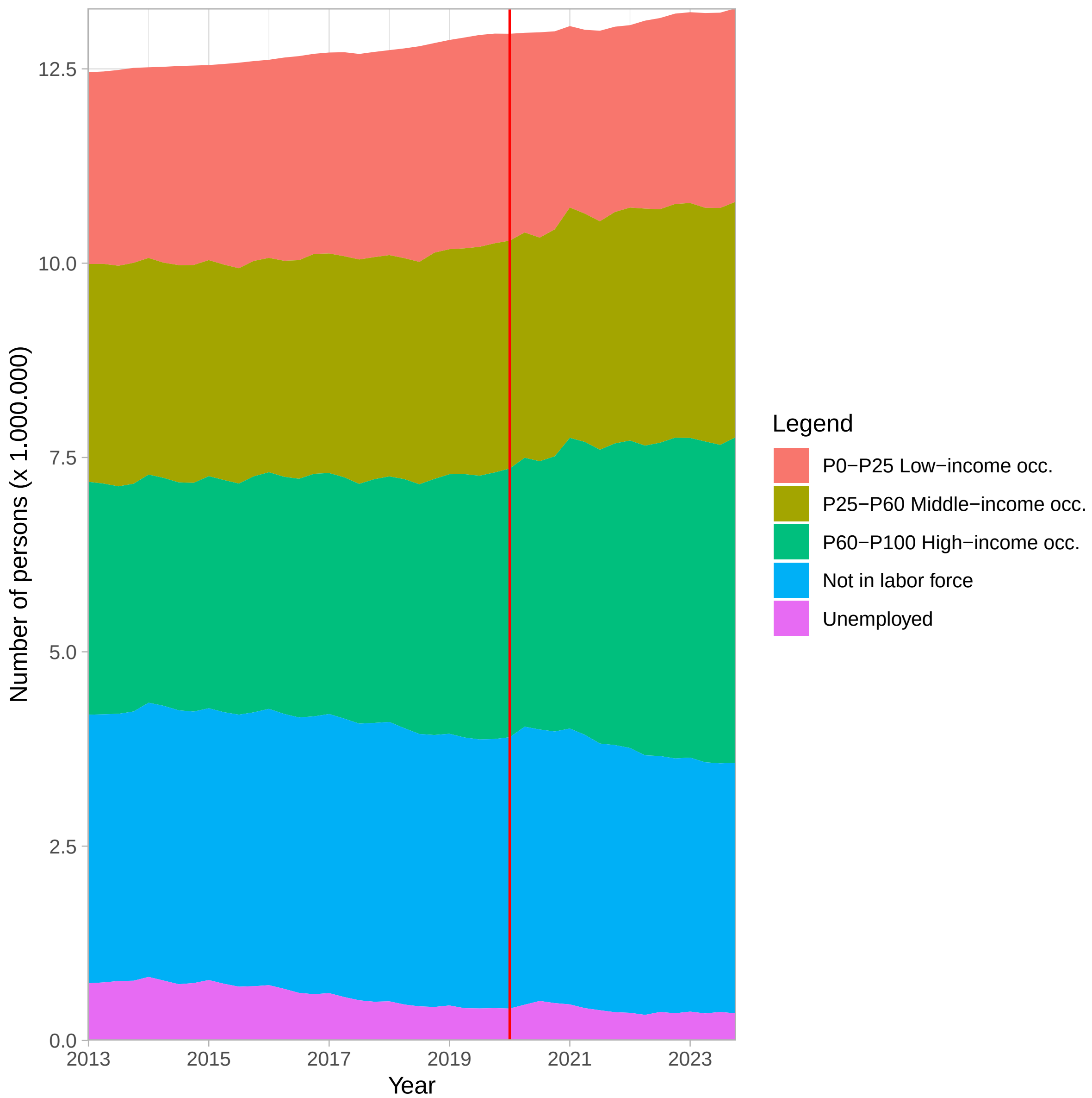


Table A12 – Correlation table - Not in the labor force

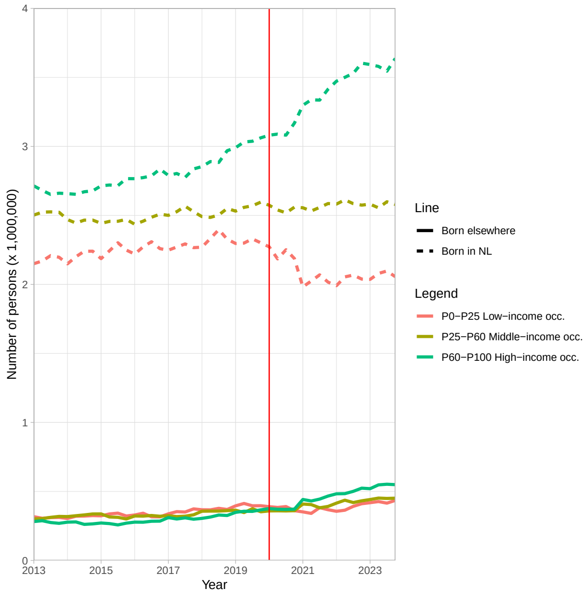
	Education	Retirement	Care-taking	Health issues	Not searching: futile	Not searching: willing	Not searching: other
Age 15-30	0.673	-0.398	-0.108	-0.194	-0.005	0.057	-0.003
Age 31-55	-0.170	-0.353	0.219	0.244	0.048	0.109	0.044
Age 56-75	-0.441	0.630	-0.085	-0.031	-0.035	-0.138	-0.034
Woman	-0.078	-0.122	0.208	0.050	-0.005	0.013	0.065
Low level of education	0.105	-0.106	0.004	0.033	-0.005	-0.005	0.015
Middle level of education	-0.010	-0.002	0.001	0.015	0.007	0.006	-0.021
High level of education	-0.102	0.145	-0.011	-0.067	-0.0001	-0.005	-0.020

during the COVID-19 crisis and then increasing to 13.3 million by the end of 2023. The graph also reflects the increasing relative size in the working population of those with high-income abstract jobs and the rise and fall during the COVID-19 crisis of those that are unemployed or out of the labor force.

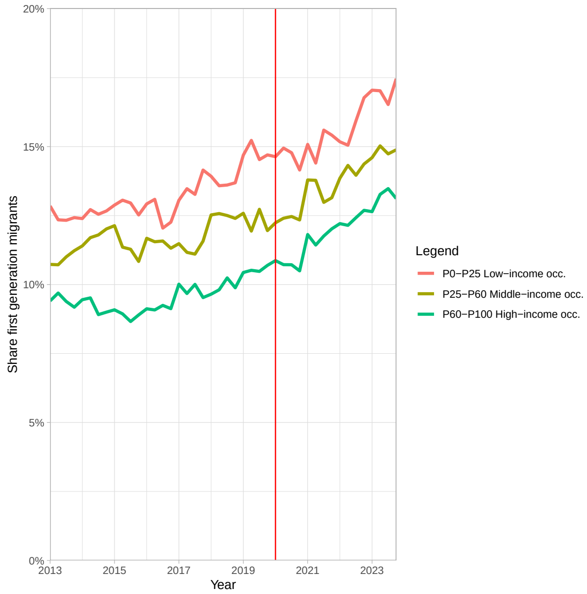
The changes in total working population over time raise questions on migration. The labor survey and weights developed by Statistics Netherlands allow to a certain extent to track migration patterns coming into to country as the country of birth is recorded and weights are developed for this purpose. This variable lumps together many motives for migration, for example, those seeking safety, family/social motives and migrant workers. Some may have plans to stay for a short while for a job or study while others may have or have obtained the Dutch citizenship and stay for a long time.[15] This makes it difficult to explain the reasons for changes in the number of migrants and total working population. Also there is no data on out migration because the data only considers the working population within the Netherlands.

Nonetheless, the migration data can give some clues on changes in the working population of the Netherlands. Figures A2a and A2b, give per job category, respectively, the number of workers that are born abroad and those born in the Netherlands, and the share of workers born abroad.

Figure A2 – Number and share of persons per working population category and if born outside the Netherlands



(a) Absolute numbers



(b) Relative shares

The figures show that at the beginning of the COVID-19 crisis the number of high-income abstract jobs remains stable both in terms of migrants and those born in the Netherlands and therefore also in the share of migrant workers in this category. Then first the number of Netherlands-born workers increases in the third quarter of 2022 and then in the last quarter also those foreign-born. This delay is likely due to uncertainty about travelling and migration due to world-wide travel restrictions in this time period. The growth rate of foreign-born is even relatively stronger, which leads to a higher share of foreign-born workers in high-income abstract

[15]Note also that not everyone born in the Netherlands obtains Dutch citizenship as this only happens when one of the parents is Dutch and applies for the nationality.

jobs. Likely, this constitutes workers commonly referred to as expats. After the end of the pandemic the rise becomes unprecedentedly stronger. Between 2016Q1 and 2019Q4 the share of foreign-born in the high-income job category went from 9.1% to 10,4% to be at 13.1% by the 2023Q4. This provides context that the rise of high-income abstract jobs witnessed in Figure 2 is not only explained by changes in job mobility of those already present within the working population but also by changes in the working population. It also suggests that demand for the skills in these types of jobs is persistently high leading to the attraction of migrant workers. The strong increase of migrant workers may also suggest a local mismatch between skills in demand and on offer.

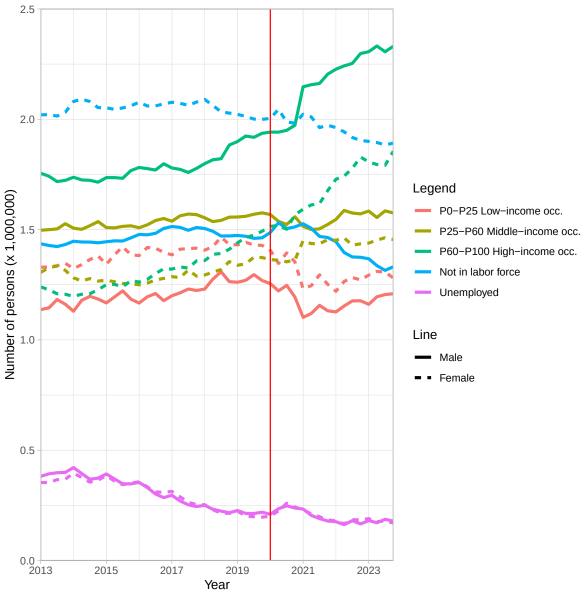
Migration in middle-income often routine jobs seems to follow a similar pattern with a slightly less strong but still unprecendented increase at the end of the pandemic. The share of foreign-born being 11.7% in 2016Q1, 12% in 2019Q4 and 14.9% in 2023Q4.

Migration in low-income often manual jobs seems to have halted during the pandemic. Interestingly, the absolute number of foreign born and Dutch born workers drop in similar proportions during COVID-19 meaning that the shares are relatively stable. Migrant workers only start to enter in this job category by the end of the pandemic this growth is not as impressively large as in previous time periods or the other working categories. This in spite of large shortages in this type of jobs. More specifically, the share of foreign-born is 12.9% in 2016Q1, 14.7% in 2019Q4 and 17.5% in 2023Q4.

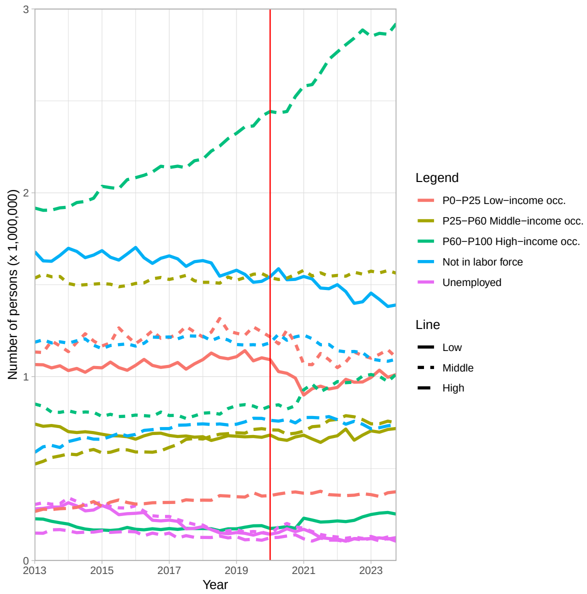
A.2.3 Trends in working population category and personal characteristics

This section shows the figures on the changes over time in the number of persons per working population category and per personal characteristics and in the different categories of persons outside the labor force, unemployed or underemployed. These are discussed in Section 4.5. The categorizations of persons outside the labor force, unemployed or underemployed are based on two different questions in the survey. Note that changes in the questions in 2021 due to harmonization of questions within the European Union have led to some changes in the number of persons per category.

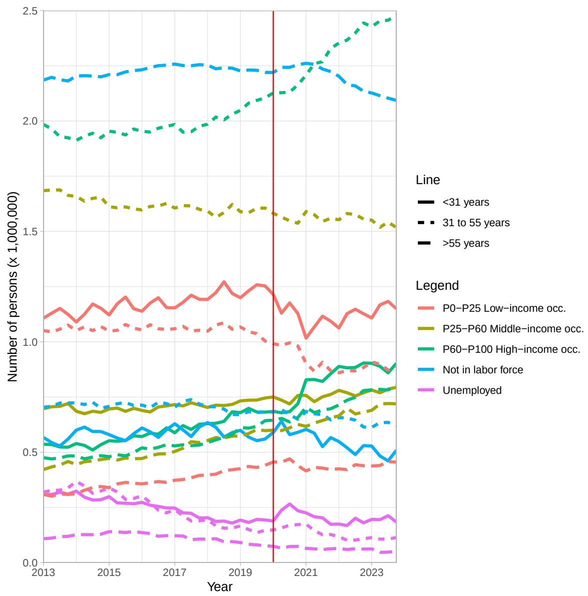
Figure A3 – Trend graphs by individual characteristics



(a) Gender

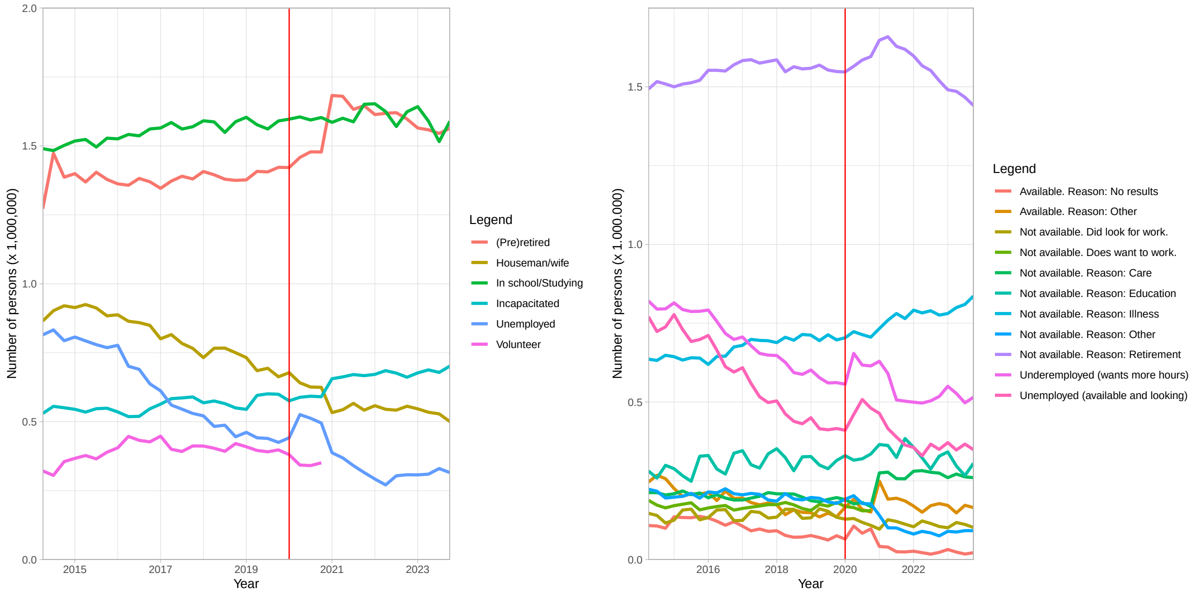


(b) Education



(c) Age

Figure A4 – Trend graphs on persons unemployed or out of the labor force



(a) Position in society

(b) Reasons

Table A13 – Working population dynamics

Dependent variable:	*P60-P100* *Abstract jobs*	*P25-P60* *Routine Jobs*	*P0-P25* *Manual jobs*	*Unemployed*	*Not in labor force*
	(1)	(2)	(3)	(4)	(5)
Age 31-55 (dummy)	-0.948^{***}	-0.762^{***}	-1.733^{***}	-0.952^{***}	-0.921^{***}
	(0.008)	(0.007)	(0.007)	(0.007)	(0.006)
Age 56-75 (dummy)	-2.101^{***}	-1.766^{***}	-2.858^{***}	-1.817^{***}	0.134^{***}
	(0.013)	(0.011)	(0.011)	(0.010)	(0.006)
Woman (dummy)	-0.252^{***}	-0.036^{***}	0.292^{***}	0.025^{***}	0.100^{***}
	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)
Low level of education (dummy)	-2.608^{***}	0.008	1.773^{***}	0.538^{***}	0.725^{***}
	(0.014)	(0.009)	(0.009)	(0.008)	(0.007)
Middle level of education (dummy)	-1.350^{***}	0.513^{***}	0.954^{***}	0.199^{***}	0.363^{***}
	(0.008)	(0.008)	(0.009)	(0.008)	(0.006)
COVID-19 crisis	0.063^{***}	-0.040^{***}	0.014	0.012	-0.022^{**}
	(0.011)	(0.012)	(0.013)	(0.011)	(0.010)
COVID-19 crisis×	-0.150^{***}	-0.133^{***}	-0.098^{***}	-0.203^{***}	-0.141^{***}
Age 31-55 (dummy)	(0.012)	(0.011)	(0.011)	(0.010)	(0.009)
COVID-19 crisis×	-0.055^{***}	0.020	-0.008	-0.151^{***}	-0.128^{***}
Age 56-75 (dummy)	(0.019)	(0.016)	(0.016)	(0.014)	(0.009)
COVID-19 crisis×	0.057^{***}	0.073^{***}	-0.055^{***}	0.033^{***}	-0.040^{***}
Woman (dummy)	(0.011)	(0.010)	(0.009)	(0.009)	(0.008)
COVID-19 crisis×	0.225^{***}	0.139^{***}	0.019	0.144^{***}	0.154^{***}
Low level of education (dummy)	(0.020)	(0.014)	(0.013)	(0.011)	(0.010)
COVID-19 crisis×	0.080^{***}	-0.038^{***}	0.025^{*}	0.179^{***}	0.110^{***}
Middle level of education (dummy)	(0.012)	(0.012)	(0.014)	(0.011)	(0.010)
Post-COVID-19 crisis	0.114^{***}	-0.203^{***}	-0.096^{***}	0.180^{***}	-0.098^{***}
	(0.011)	(0.012)	(0.013)	(0.011)	(0.010)
Post-COVID-19 crisis×	-0.120^{***}	-0.055^{***}	0.029^{***}	-0.272^{***}	-0.144^{***}
Age 31-55 (dummy)	(0.012)	(0.011)	(0.011)	(0.010)	(0.010)
Post-COVID-19 crisis×	-0.040^{**}	0.106^{***}	0.090^{***}	-0.136^{***}	-0.180^{***}
Age 56-75 (dummy)	(0.018)	(0.015)	(0.016)	(0.014)	(0.009)
Post-COVID-19 crisis×	-0.053^{***}	0.037^{***}	-0.152^{***}	0.041^{***}	0.112^{***}
Woman (dummy)	(0.011)	(0.010)	(0.009)	(0.009)	(0.008)
Post-COVID-19 crisis×	0.519^{***}	0.402^{***}	0.205^{***}	-0.178^{***}	-0.159^{***}
low level of education (dummy)	(0.019)	(0.014)	(0.014)	(0.011)	(0.010)
Post-COVID-19 crisis×	0.299^{***}	0.208^{***}	0.120^{***}	-0.187^{***}	-0.104^{***}
Middle level of education (dummy)	(0.012)	(0.012)	(0.014)	(0.011)	(0.010)
Constant	-2.195^{***}	-3.461^{***}	-3.736^{***}	-3.434^{***}	-3.346^{***}
	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)
Observations	620,289	694,476	729,878	873,666	682,343
Log Likelihood	−922,208.000	−1,189,892.000	−1,223,026.000	−1,511,644.000	−1,757,513.000
Akaike Inf. Crit.	1,844,452.000	2,379,821.000	2,446,087.000	3,023,324.000	3,515,061.000

Notes: The reference categories for the dummy variables are: Age 15-30, Man, and high level of education. Note that the average probability of success, i.e. moving into each of the working population categories, for a person of the reference categories for all dummy categories are, respectively, 10%, 3%, 2.3%, 3.1%, and 3.4%. The unit of observation is person per quarter. Each person is present in five quarters. The number of observations varies per regression as persons that are already in the working population category, the dependent variable, are removed as these cannot enter this category. Standard errors are clustered at the individual level and in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.