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Did Covid-19 strengthen the relationship between human capital and income? Evidence from administrative data

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Abstract
This study investigates the role of accumulated human capital in how people adapt to shocks and how this is reflected in income dynamics. The analysis is based on detailed monthly administrative data from Estonia between 2016 and 2020, containing more than 800 thousand observations. The results show that people with higher human capital experience less income fluctuation and their potential for income losses is lower. The role of human capital becomes even more significant during a crisis. An important effect of subsidies was also evident during the crisis, when the risk of losing incomes for people with less accumulated human capital would have been even higher if there had been no additional state support in the form of subsidies and benefits. In light of the Covid-19 crisis and its specifics, it is crucial to continuously improve digital skills through education to cope with socio-economic development in the future.

Keywords: income, human capital, shocks, Covid-19, Estonia

Introduction

The relationship between human capital and income has been extensively studied, pointing to strong relationships between human capital, incomes, employment prospects, poverty, and income inequality (Attanasio et al., 2022; Bénabou, 1994; Chiu, 1998; Lee & Lee, 2018). According to human capital theory, human capital can be considered an investment that, on the one hand, increases employment and productivity, but on the other, it also increases wages (Becker, 1962; 1993). In the literature, the main indicators related to human capital are education and training, including both more general training, and specific training in the workplace (Becker, 1993). The OECD (2000) defines human capital as “Knowledge, skills, competencies and other attributes embodied in individuals that are relevant to personal, social and economic well-being”. In addition, a person’s productivity and income are influenced by their previous work experience and according to recent

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studies, this can describe slightly less than half of the individual's lifetime wealth (Madgavkar et al., 2022). Still, not only does higher educational levels, the quality of the education, and lifelong learning contribute to a person's personal income, but these also contribute to the added value that is created for the employer and society in general (Goczek et al., 2021; Sulaiman et al., 2015).

However, the significance of accumulated human capital in income dynamics and adapting to shocks has not received so much attention. The Covid-19 crisis that shocked the world in 2020 clearly demonstrated how a crisis can have a negative effect on various areas and socio-demographic groups, but this effect can be highly asymmetrical at the same time (Adams-Prassl et al., 2020; Cantó et al., 2022). The movement restrictions, which led to the closure of shops, restaurants, cafes, and sports centres or their restricted use, had a devastating effect on tourism, the functioning of schools, and so on. (Nicola et al., 2020). This all resulted in the necessity for rapid digital development (expanding e-shops, e-learning in general education schools, as well as online training videos, online meetings and conferences etc.), new requirements for employee skills, and the introduction of new forms of work (mainly remote work).

The aim of this study is to investigate the role of accumulated human capital in people adjusting to shocks and its effect on income dynamics in Estonia. Estonia is a particularly interesting case study because of its technological prerequisites and people's previous preferences that might have enabled it to cope better with a crisis such as Covid-19. The development of technology and digitalisation have led to the need to acquire new, higher-level skills to be competitive in the labour market (OECD, 2016). However, the successful use of a good digital system also requires higher human capital to better adapt and use the possibilities offered by the digital system. Previous studies suggest that people with a higher level of education and socioeconomic background have better digital skills, i.e. they use different devices, more advanced skills (inc. coding, creating a website, manage privacy settings, etc.) (Zhang & Livingstone, 2019). In addition, individuals with higher human capital are more capable of learning new skills and adjusting to new work conditions during crisis situations (Fasih et al., 2020).

The research questions for this study are as follows. First, how did the Covid-19 crisis affect the income dynamics of people with different human capital during the first year of the crisis? Second, did the relationship between human capital and income strengthen during the Covid-19 crisis compared to previous years? The dataset used in the study consists of monthly data from 2016 to 2020 (sample size 806,454) and includes various national registers (employment register, population register, etc.). Therefore, the monthly dynamics of employment income can be analysed by considering the seasonality of incomes and the spread of the Covid-19. The human capital indicators analysed in this study are the level of education and occupational position (manager, professional, etc.).

The motivation to conduct the analysis on the case of Estonia is as follows. First, Estonia is known as a digital country with a well-developed digital infrastructure (InterNations, 2019). In the context of the Covid-19 crisis, which led to significant movement restrictions, the need arose for digital e-learning systems and experiences, as well as all kinds of digital benefit applications (unemployment and healthcare). Digital literacy, access to the internet and a safe internet space are also crucial for continuing the functioning of society in general, as well as ensuring the potential to work remotely. In Estonia, sectors with lower wages, where remote work is more challenging (e.g., hotels, restaurants and accommodation) were the hardest hit by the Covid-19 crisis (Laurimäe et al., 2022). At the same time, for instance, employment increased in the information and communication sector, which requires higher knowledge and offers higher wages. In addition, the proportion of people working remotely increased during the pandemic, particularly among high-level professionals and in urban areas, where it was already higher before the crisis and where there were more highly educated people (Statistikaamet, 2020).

This study finds that people with higher human capital tend to adapt better to changes, and the likelihood of losing or decreasing their income is lower. Furthermore, people with higher human capital were also affected by the crisis but income decreases were less severe, and their recovery was slightly faster. People with higher human capital have more stable jobs and income during the non-crisis period, and they do not experience as many income fluctuations or seasonal effects as those with lower levels of education and lower paid occupations. However, during the crisis, the role of human capital increases even more. In addition, unemployment benefits have a significant impact and the relative risk of losing partially or entirely the income is even higher for those with lower human capital, when benefits are not considered. Considering the specifics of the Covid-19 crisis and previous studies, it can be assumed that people with higher human capital adapt better to the use of new digital opportunities, and based on this, their flexibility in adapting to new ways of working, including remote work, is greater. Therefore, their losses in income were also somewhat less severe.

The structure of this paper is as follows. An overview of the related literature is provided in the following section. Section 2 introduces the methodology and data used in the empirical analysis. Section 3 provides the findings of the empirical analysis, and the final section summarises the paper.

1. Related literature

Previous empirical analyses have found so far that the heads of the households at the top of the income distribution could be described with the following characteristics: male, white, married (Raffalovich et al., 2009). Those at the very top have a college education or higher education (Raffalovich et al., 2009; Yavorsky et al., 2019), are middle aged and employed in higher positions, such as in professional services or as managers (Raffalovich et al., 2009).

Socio-economic groups have experienced different effects from shocks in the past, indicating that people who are less educated, young, and single tend to be at greater risk (Bell & Blanchflower, 2011; Engemann & Wall, 2009). A higher educational level has been found to be crucial in coping with crisis that have implications for income and employment opportunities (Cutler et al., 2015; Engemann & Wall, 2009; Genda et al., 2010). Similar results have been found in the case of Estonia; this is, individuals with higher education were able to cope better during the financial crisis, they were less affected by the crisis' negative impact on wages, working hours, and unemployment (Espenberg, 2013). The impact of education levels on those who graduated during the crisis and returned to the labour market is still visible many years after the graduation, where it is more difficult to leave a low-paid job that was accepted during the crisis (Cutler et al., 2015; Genda et al., 2010).

The results are quite the opposite when looking at people with very high incomes. Furthermore, it has been found that people with higher incomes benefit more during economic growth (Roine et al., 2009; Rubin & Segal, 2015), but are also hit harder by recessions (Roine et al., 2009). It is likely that this disparity stems from the income type earned, as well as the existence of assets and investments. The cushioning measures offered by the government also often target more vulnerable groups and maximum rates or income tests applied on benefits can limit support for people with very high incomes.

The literature suggests that there is a bi-directional link between the effects of the Covid-19 crisis and human capital. First, people's income and employment prospects have been affected by their accumulated human capital; that is people in lower positions with lower levels of education and salaries were more affected during the crisis (Adams-Prassl et al., 2020; Qian & Fan, 2020). Second, the Covid-19 crisis has had an impact on the accumulation of human capital; that is e-learning, workload reduction and digitalisation have influenced the acquisition of new skills and knowledge, or high school completion (Ahn et al., 2020; Dvořák et al., 2020). This study focuses only on accumulated human capital and its effect on incomes during the crisis.

Previous research has found that during the Covid-19 crisis, people with lower education and/or low-skilled workers had higher risk of reduced incomes or losing their jobs during the crisis (Adams-Prassl et al., 2020; Casarico & Lattanzio, 2022; Farré et al., 2022). Therefore, the Covid-19 crisis affected low-paid jobs due to restrictions in certain fields. However, people in the highest decile also lost slightly more income compared to those in the 8th or 9th deciles when considering the impact of wage compensation measures (Almeida et al., 2021).

This study contributes to the growing literature on the effects of Covid-19 (Adams-Prassl et al., 2020; Cantó et al., 2022; Parker et al., 2020; Qian & Fan, 2020). The study makes a broader contribution to the literature that analyses the impact of human capital on income for people from different socio-demographic groups and its importance and increasing role during shocks.

2. Data and methodology

The study examines the role of human capital in helping people adapt to shocks, while also looking at their income dynamics using detailed monthly administrative data from 2016 to 2020. The selected dataset provides insights into the short-term impact of the crisis and the detailed monthly dynamics of employment income (incl. unemployment benefits) at the individual level. Individual income, income dynamics, and the relationship between human capital and income during the crisis in 2020 are compared with the pre-crisis period (2016-2019).

The data from following registers are used:

- Estonian Population Register: gender, time of birth, educational attainment;
- Estonian Education Information System: educational attainment;
- Employment Register and Register of taxable persons: main activity of the employer, start and end of employment contract, positions (specialist, etc), total monthly amount of personal (gross) employment income;
- Unemployment insurance database and the state register of job-seekers and of employment services: total monthly amount of unemployment benefits (gross).

The whole available dataset contains 1.483 million persons over the whole period - all people at least 15 years of age in January 2016 and up to 75 years of age in November 2020. Based on the research objective, we reduced the number of observations in accordance with the following principles:

- those who never earned income from work in the period 2016-2021 were excluded from the data (e.g., students; people with no work ability, pensioners, but also long-term unemployed, etc.).
- only the working-age population; that is those between 16 and 65, remained in the sample.

According to these principles, the number of unique individuals for the whole period is 806,454. The primary focus of this study is on employment income, but unemployment benefits (unemployment allowance and unemployment insurance benefit) are also considered as subsidies that replace income from work. In addition, employment income includes wage compensation together with salary directly paid to the employee during the emergency. Due to data limitations, sickness benefits are not included.

Distribution of the sample according to socio-demographic characteristics for 2016 to 2020 are presented in Table 1.

Table 1. Distribution of the sample according to socio-demographic characteristics during the period 2016 - 2020 (at the end of the year)

Variable	2016	2017	2018	2019	2020
Gender					
…Female	48.6%	48.5%	48.4%	48.2%	48.1%
…Male	51.4%	51.5%	51.6%	51.8%	51.9%
Age					
…Age 16-29	27.8%	25.4%	23.0%	20.5%	18.2%
…Age 30-49	45.2%	46.5%	47.7%	48.9%	49.9%
…Age 50-65	27.0%	28.1%	29.4%	30.6%	31.9%
Educational attainment					
...Primary or lower secondary education	14.4%	13.4%	12.3%	11.2%	10.9%
...Secondary education	23.8%	23.8%	23.9%	24.0%	23.5%
…Vocational education	27.4%	27.8%	28.3%	28.7%	28.9%
...Higher education	27.1%	27.8%	28.4%	29.0%	29.6%
…No information	7.3%	7.2%	7.1%	7.1%	7.1%
Employment status					
…Employed (received employment income)	66.9%	68.6%	71.0%	72.1%	70.5%
…Receiving unemployment benefits (unemployment allowance, unemployment insurance benefit)	1.8%	1.7%	1.7%	2.1%	3.4%
…Other (inc. missing)	31.3%	29.7%	27.3%	25.8%	26.1%
Main activity of the employer (coded into 3 groups)					
...Primary sector (% of those employed)	2.0%	2.0%	2.0%	2.0%	2.0%
...Secondary sector (% of those employed)	27.5%	27.9%	27.9%	27.4%	26.9%
...Tertiary sector (% of those employed)	69.1%	68.7%	68.6%	69.1%	69.6%
…No information (% of those employed)	1.4%	1.4%	1.4%	1.5%	1.5%
Position					
…Managers (% of those employed)	6.8%	7.5%	8.5%	8.9%	9.0%
…Professionals (% of those employed)	13.9%	15.5%	17.7%	19.1%	20.0%
…Technicians and associate professionals (% of those employed)	7.6%	8.6%	10.1%	11.1%	11.4%
…Clerical support workers (% of those employed)	4.7%	5.5%	6.8%	7.6%	7.6%
…Service and sales workers (% of those employed)	8.0%	9.5%	12.2%	13.9%	13.3%
…Skilled agricultural, forestry and fishery workers (% of those employed)	0.6%	0.7%	0.9%	1.0%	1.0%
…Craft and related trades workers (% of those employed)	7.9%	9.4%	12.0%	13.6%	13.2%
…Plant and machine operators, and assemblers (% of those employed)	6.4%	7.5%	9.0%	9.8%	9.8%
…Elementary occupations (% of those employed)	4.7%	5.6%	7.5%	8.9%	8.8%
…No information (% of those employed)	39.3%	30.2%	15.4%	6.2%	6.0%
N	806,431	798,628	789,941	780,152	769,140

Source: compiled by the authors based on detailed administrative data

It seems that the sample has remained relatively stable over the period in question and there were no significant changes between 2016 and 2020. Compared to previous years, employment has increased (66.9% in 2016 vs. 70.5% in 2020), although it decreased in 2020 due to the Covid-19 crisis. In addition, there has been a slight increase in unemployment benefit recipients. The proportion of individuals with higher education and vocational education has risen during the period to 58.5% in 2020, while the proportion of individuals with primary or lower secondary education has decreased to 11%.

The lack of information across job positions has resulted from the structural change in the Employment Register and Register of taxable persons. However, the absence of the data is not systematic and allows for the assessment of changes by position. If we exclude the missing values, in general, the share of those related to service activities increased, while the share of managers and professionals decreased somewhat between 2016 and 2019. However, in 2020, the share of those related to service activities dropped, and the share of people in higher positions increased again compared to 2019.

Most previous Covid-related thematic studies that rely on monthly data use survey data (see for example Clark et al., 2021; Qian & Fan, 2020), which might be less accurate than registry data. Moreover, the use of months is sometimes limited or there is no comparison to previous years (Zimpelmann et al., 2021). In addition, the EUROMOD microsimulation model and annual administrative or survey data have frequently been used in the past to analyse the effects of Covid-19 and implemented wage compensation measures (Christl et al., 2024; Laurimäe et al., 2022). However, since the spread of the Covid-19 crisis was not uniform across months and there is also seasonality in incomes, especially among educational levels, the use of monthly data provides an opportunity to view changes in more detail, and to assess possible volatility, seasonality, and time lags.

The first empirical section (3.1) is an analysis of panel data for 2016 to 2020, which allows us to look at the monthly income dynamics of people with different levels of accumulated human capital. This section mainly presents descriptive statistics and timelines. Analysing the timeline allows us to see the differences in the trend and compare these changes between population groups.

In section 3.2, we use a multinomial regression model. This model is used if the dependent variable of the model is a categorical variable, and it has more than two unordered choices (Wooldridge, 2002). In this study we assess the relationship between changes in incomes and accumulated human capital in May 2020 compared to January 2020. The reason for this selection is that in May 2020, the effect of Covid-19 was the highest and changes in income were the largest (based on section 3.1). A similar approach has been used in the past by Qian and Fan (2020); they used survey data and multinomial logistic regression to analyse the income changes (partial income loss, total income loss, no income loss) during the Covid-19 outbreak. However, in their study, they did not focus on human capital factors, but analysed more broadly socio-demographic characteristics. In our paper, the effects of the 2020 model are then compared with those of the 2019 model (Table 2). The dependent variable in the multinomial models is change in income during the Covid-19 crisis, which is coded as follows: 0 - income increased or remained the same (reference); 1 - partial loss of income; 2 - complete loss of income. The independent focus variables are the human capital indicators: educational attainment and occupational position. The independent background variables are socio-demographic characteristics such as gender, region, age, and the main activity of the employer.

The analysis is conducted in two ways due to the significant effect of unemployment benefits and wage compensation on income maintenance, i.e., subsidies (automatic stabilisers) are offered to those whose income is falling. This makes it possible to analyse the changes in employment income, but partially consider the contribution of the state and assess the actual disposable income. Thus, first, allowances are included in the model and considered as income and then allowances are excluded from the data. The analysis will be conducted using STATA software (STATA 16).

Table 2. The variables of the regression model

	MODEL - cross-sectional multinomial regression
Dependent variable	Change in income during the COVID crisis 0 - income increased or remained the same in May 2020 compared to January 2020 (reference) 1 - partial loss of income 2 - complete loss of income
Educational attainment	0 - higher education (reference) 1 - primary or lower secondary education 2 - secondary education 3 - vocational
Main activity of the employer	0-10 activities (reference: accommodation and restaurants sector)
Occupational position	0 - managers, professionals, specialists (reference) 1 - clerical support workers 2 - service and sales workers 3 - craft and related trade workers, elementary occupations
Gender	0 - female (reference) 1 - male
Age groups	0 - <=29 years (reference) 1 - >=30 & <=49 years 2 - >= 50 years
Region	0 - urban area, i.e., Tallinn, Tartu, Pärnu, Viljandi (reference) 1 - rural area

Source: authors' calculations

Relative risk ratios (RRR) and marginal effects (ME) are calculated to interpret the results of the regression model. RRR show how the risk of the outcome relative to the base category changes if an explanatory variable changes by one unit.

The exponentiated value of a beta coefficient shows the RRR. ME show effect on the probability for each outcome if an explanatory variable changes.

3. Empirical analysis

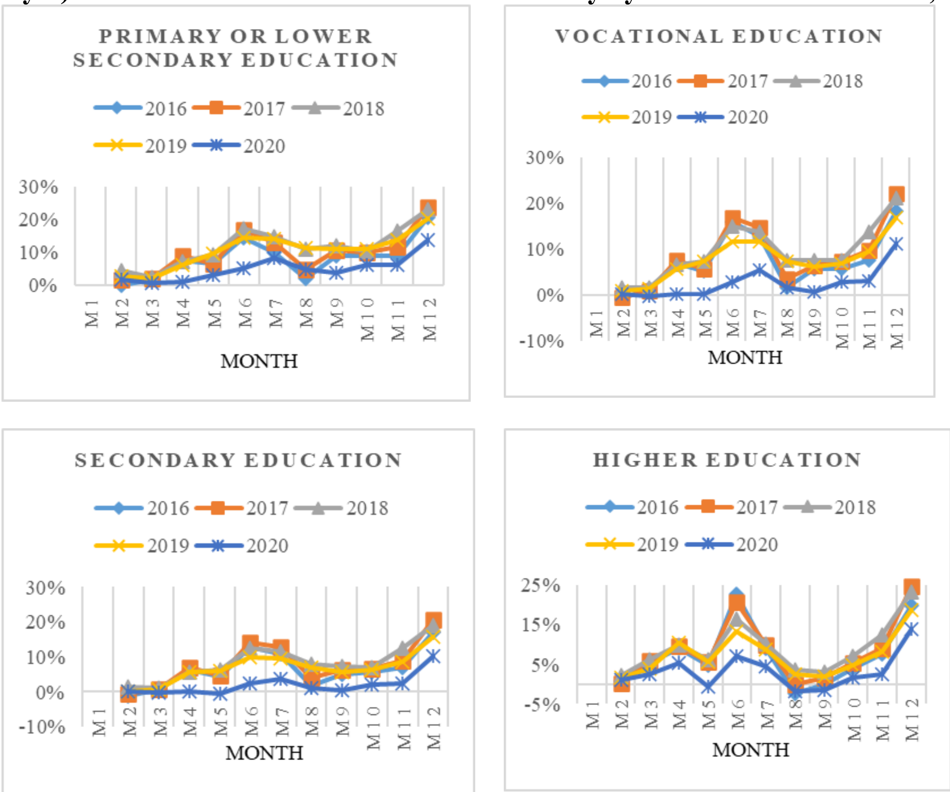
3.1. An overview of income changes in Estonia during the Covid-19 crisis

There is a strong seasonality in incomes over the period (see Figure 1). First, the increase in wages during the summer months is a result of the payment of holiday pay and seasonal work. For example, for people with higher education, the average income is higher in June, but lower in August as people receive their holiday payments in advance (taking vacations in July and August). For those with lower educational levels, the changes are also related to the seasonal work. Second, the increase in income at the end of the year is likely due to year-end bonuses. In general, average employment income together with unemployment benefits increased in almost all months in 2020 compared to January of the same year, except for September 2020. Despite this, income growth was significantly lower than in previous years (3% in 2020 compared to 7.3% in 2019). April, May, and June were the months most affected by the crisis. The difference in wage growth between 2019 and 2020 narrowed during the summer months when the pandemic showed some signs of abating and seasonal work started, but then widened again in November.

However, some differences emerged between educational levels. Average annual income growth dropped among all groups, but the decrease was greater among those with basic education (10.6% in 2019 vs. 5.0% in 2020) and with vocational education (7.8% vs 2.6%), and the lowest among people with higher education (7.3% vs. 3.2%, see Figure 1). The decline in wage growth among people with higher education already slowed in June, but it was still quite high among those with lower education. The slowing of wage growth started earlier among people with secondary education or lower, probably also due to the end of seasonal work in the summer months.

Previous studies that investigated income changes in other countries have been broader and have not paid so much attention to the significance of human capital. Nonetheless, the results vary from country to country. In the UK, it was found that the average income (employment and self-employment) decreased significantly (10-15%) in the first months of the crisis, while the median change was -6% in May, but the 25th percentile was -41% (Crossley et al., 2021).

Figure 1. The relative change in the average income of the entire workforce (15 - 64 yrs) between each calendar month and January by educational attainment, %

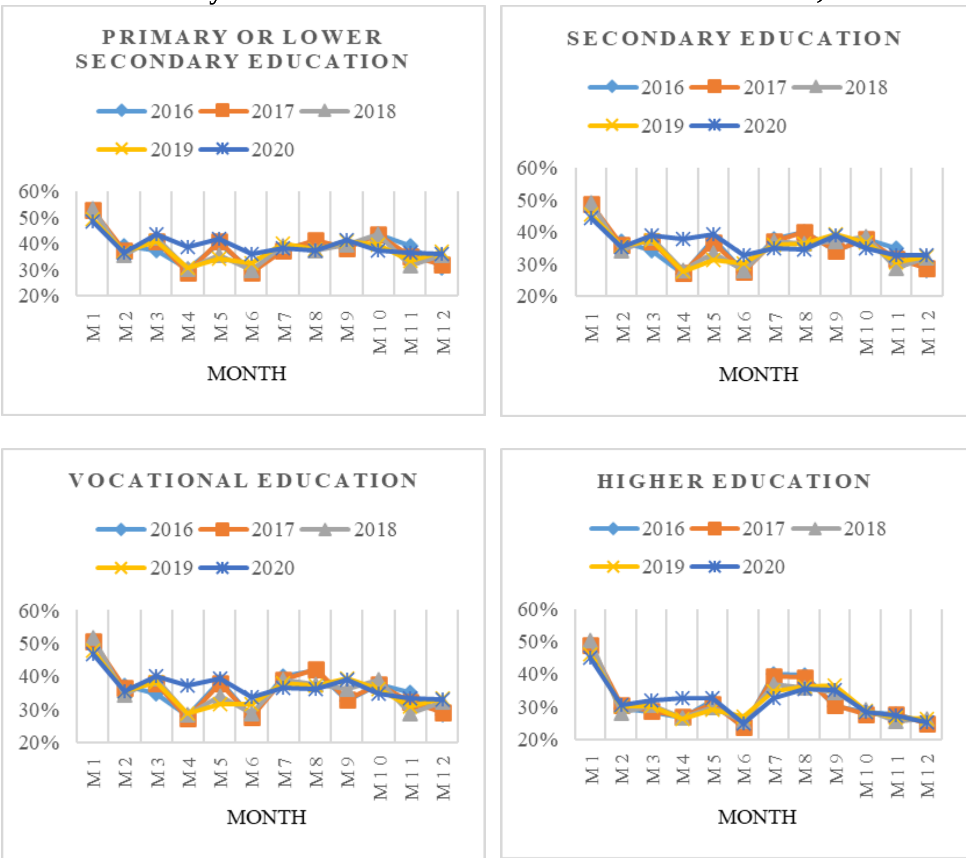


Notes: Average gross income (for those who had it) and then the change compared to the same figure in January.
Source: authors' calculations based on detailed administrative data

In the Netherlands, such significant changes in equivalent household income were not observed, and the median change was rather close to zero. The number of hours worked, and the use of remote work opportunities differed between educational levels, but there was no significant change in income (Zimpelmann et al., 2021). However, such a difference across studies results from, what has been considered as income (e.g., household income, employment income, self-employment income) and, also from the country's specifics and the crisis and labour market measures.

At the start of the Covid-19 crisis, there was a significant increase in the proportion of individuals experiencing income reduction compared to previous years (e.g., 36% vs. 28% in March 2020 and 2019). Still, there has been no noticeable change in the second half of the year. Individuals with higher education experienced a less severe impact from the Covid-19 crisis on income decreases than those with lower education levels (Figure 2).

Figure 2. The share of people whose income decreased compared to the previous calendar month by educational attainment between 2016 and 2020, %



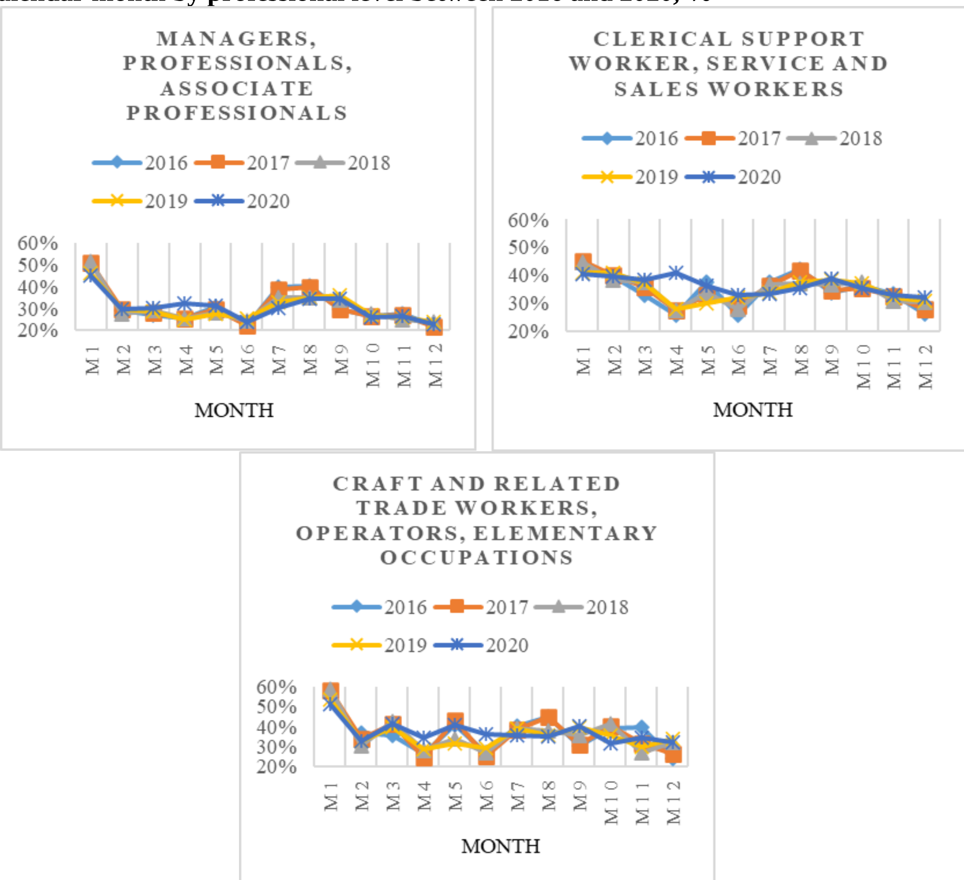
Source: authors' calculations based on detailed administrative data

In April 2020, among the highly educated, the share of those whose income decreased was 33% compared to the previous month (an increase of less than 7 p.p. compared to the same time in the previous year), but among people with a lower level of education, it was 37 - 38% (an increase of 8 - 10 p.p.). In addition, looking at the average for the year, the highly educated have almost no change compared to the previous year, but among the other education levels, the average annual change is 1.5% points.

Service personnel were the ones who were most affected by the loss of income at the onset of the crisis, as expected (Figure 3). In April 2020, the income of 41% of employees who are either clerical support workers or service and sales workers dropped compared to the previous month. Managers, professionals, and associate professionals were those who were least affected. While in June 2020, the situation among managers and service workers was at the same level as it was in the previous year, the decline continued among unskilled workers (craft and related trade workers, operators, and elementary occupations).

The earnings of workers who are more educated and in higher positions are generally less affected by seasonality. Bonuses and summer vacations cause higher fluctuations at the end of the year and mid-summer. Individuals who have a lower level of education and work in elementary occupations are more likely to experience income fluctuations throughout the year (the share of people whose income dropped ranges from 59% to 24%).

Figure 3. The share of people whose income decreased compared to the previous calendar month by professional level between 2016 and 2020, %



Source: authors' calculations based on detailed administrative data

Although the average income among the total population increased, the number of income recipients slightly decreased in 2020. The annual average shows that the change is not significant compared to previous years, and the impact occurred primarily in the first months of the crisis. Compared to the previous month, the share of those who totally lost their income (inc. unemployment benefits) was the highest in May 2020 (4.1% among employed population). There are not very large differences by level of education, but there are still somewhat more people with a total loss of income among those with a lower level of education. The trend remains the same when viewed without taking unemployment benefits into account. The reason for this is likely since many individuals did not lose their income completely, but rather received wage compensation, leading to a decrease in their income. Previous studies also point to the significant cushioning effect of wage compensation measures that had been implemented (Almeida et al., 2021; Cantó et al., 2022; Christl et al., 2024; Laurimäe et al., 2022).

However, in a broader sense, many different factors such as the level of education, low-paid work, economic sector and remote work possibilities are interconnected, which influence the greater vulnerability of certain groups to the effects of the Covid-19 crisis on their employment and income. Estonian administrative data indicates that those with a lower level of education tend to work in lower positions. Therefore, the impact on incomes and employment may be multidirectional because Covid-19 also affected specific sectors and occupations more. In addition, previous research suggests that individuals with higher education are more likely to benefit from remote work opportunities (Zimpelmann et al., 2021), depending on the role and content of their job.

To conclude, individuals who have a higher level of education or higher occupational position cope better in the context of change. Their work is more stable, and they do not experience as many income fluctuations or seasonal effects as those with lower levels of education and occupations. Considering the specifics of the Covid-19 crisis, it can be assumed that they will adapt better to the use of new digital opportunities and, based on this, their flexibility to work remotely will be greater. This, in turn, has an impact on the maintenance of income.

3.2. The role of human capital on income changes in the conditions of the Covid-19 crisis

The focus of this subsection is on the role of human capital in explaining changes in income in the context of the Covid-19 crisis. Multinomial regression analysis has been used for this. The relative risk ratios (RRR) of the multinomial model can be found in Table 3, and marginal effects in Table 4. RRR together with the confidence intervals and standard errors for the focus variables can be found in the Appendix 1. Additional empirical materials are available upon request.

The results of the multinomial logistic regression analysis show that there is a significant positive relationship between accumulated human capital and income. People with lower educational attainment compared to those with higher educational levels are more likely to experience a partial (status = 1) or total loss of income (status = 2) compared to a higher or unchanged income (reference). Compared to those with higher education, the relative risk ratio is the highest for employees with primary and lower secondary education (1.4 times), followed by employees with secondary education (1.3 times) and vocational education (1.1 times). Therefore, people with primary or lower secondary education have 1.4 times higher relative risk than people with higher education to have total loss of income compared to have unchanged or increased income. It also appears that those with a secondary education or lower have a higher relative risk of losing their entire income compared to losing it only partially. These results are in accordance with previous studies, pointing to the importance of education in maintaining income during a crisis. Qian and Fan (2020) find that the predicted probability of losing all income was approximately twice as high for individuals with the lowest level of education as for those with a university education.

Furthermore, those working in a lower position compared to managers and professionals seem to have a higher probability of losing their income entirely or partially compared to retaining the same income or experiencing income growth.

Table 3. Relationship between income changes, human capital indicators, and background characteristics in 2020 and 2019 - multinomial logistic regression analysis, RRR

	Model with benefits in 2020		Model without benefits in 2020		Model with benefits in 2019	
Reference - Income remained the same or increased in May compared to January (status=0)	Partial loss of income (status=1)	Total loss of income (status=2)	Partial loss of income (status=1)	Total loss of income (status=2)	Partial loss of income (status=1)	Total loss of income (status=2)
Gender (Reference - female)						
Male	1.019***	0.902***	0.946***	0.823***	0.933***	0.779***
Age groups (reference <=29)						
>=30 & <=49 years	0.939***	0.603***	0.939***	0.589***	0.904***	0.541***
>= 50 years	0.902***	0.573***	0.893***	0.534***	0.881***	0.436***
Educational attainment (Reference - higher education)						
Primary or lower secondary education	1.129***	1.444***	1.150***	1.533***	1.110***	1.370***
Secondary education	1.124***	1.298***	1.203***	1.365***	1.064***	1.123***
Vocational education	1.135***	1.115***	1.192***	1.207***	1.073***	1.008
Region (reference - rural area)						
Urban area	1.105***	1.149***	1.151***	1.185	1.071***	1.021
Occupational position (Reference - managers, specialists)						
Clerical support workers	1.095***	1.252***	1.139***	1.382***	1.113***	1.209***
Service and sales workers	1.359***	1.976***	1.486***	2.213***	1.490***	1.798***

Craft and related trade workers, elementary occupations	1.043***	1.876***	1.146***	1.958***	1.147***	1.867***
Main activity (reference - Hotels and restaurants)						
Agriculture	0.339***	0.328***	0.094***	0.094***	0.867***	0.831***
Mining, manufacturing, and utilities	0.466***	0.278***	0.191***	0.112***	1.007	0.538***
Construction	0.468***	0.614***	0.161***	0.203***	0.814***	1.204***
Wholesale and retail trade	0.605***	0.440***	0.233***	0.172***	1.014	0.702***
Transport and communication	0.512***	0.357***	0.161***	0.119***	1.023	0.712***
Financial intermediation	0.246***	0.205***	0.062***	0.064***	0.718***	0.567***
Real estate and business activities	0.325***	0.355***	0.103***	0.112***	0.613***	0.681***
Education	0.409***	0.233***	0.108***	0.064***	0.882***	0.461***
Health and social work	0.548***	0.391***	0.161***	0.107***	1.126***	0.712***
Arts and other creative activities	0.580***	0.610***	0.300***	0.265***	0.935**	0.910
Other activities	0.477***	0.500***	0.153***	0.164***	0.927***	0.863***
Constant	1.173***	0.241***	4.561***	1.082**	0.391***	0.078***
Number of observations	490,590		485,547		472,142	
Log-likelihood value	-414194.8		-427,082.71		-335247.04	
Pseudo R-squared	0.0204		0.0416		0.0117	

Note: *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$
Source: authors' calculations based on detailed administrative data

The significance of subsidies for individuals with a lower level of education and professional position is revealed by comparing the model that considers unemployment benefits and wage compensation and those that do not. The relative risk of losing income partially or totally for people with lower accumulated human capital is even greater when subsidies are not available.

The results show that during the Covid-19 crisis (2020) the role of accumulated human capital was slightly higher than in 2019. Therefore, the relative risk of both a partial or complete loss of income was slightly higher in 2020 than in 2019 for the less educated compared to the highly educated. However, the results regarding positions are not so clear. It seems that people employed in the lower position have higher relative risk than people in higher positions of a total loss of income compared to retaining the same or increased income during the crisis. In 2020, the risk is slightly higher than it was in 2019.

The risk estimates for partial income loss are more significant in 2019 than they were in 2020 for the model with subsidies. The relative risk ratios in the model with subsidies are at the same level or only slightly higher. Therefore, during the pre-crisis period, subsidies did not seem to have a very significant impact on the relationship between accumulated human capital and income dynamics.

In terms of background characteristics, the relative risk of losing income entirely compared to maintaining their income is higher for women, young people aged below 30, people living in the cities and people employed in accommodation and food services activities. These are all in accordance with the expectations and previous studies, because the COVID-19 crisis had a greater impact on the hotels and accommodation sector, where workplaces are located in the city and where mainly women and young people are employed.

Marginal effects (Table 4) confirm what was previously stated, but somewhat simplify the interpretation and presentation of unitary changes. The results demonstrate the importance of human capital in income dynamics, particularly during the crisis. We found that the importance of education almost doubled during the crisis in 2020. In 2019, people with secondary education compared to those with higher education have a 1.1 percentage point (p.p.) higher probability of a partial loss of income (status 1) and a 0.3 p.p. higher probability of a total loss of income (status 2). In 2020, these values increased to 2.1 p.p. and 1.2 p.p. respectively. The importance of education also increased among other educational levels, especially when it comes to the probability of a total loss of income.

The probability of partial or total income loss in occupational positions also slightly changed when we compare 2019 and 2020. In 2019, service and sales workers compared to managers and professionals have a 1.3 p.p. higher probability of a total loss of income, but this rose to 2.9 p.p. in 2020 (1.4 p.p. vs 4.1 p.p. without benefits).

Table 4. Relationship between income changes (with benefits), human capital indicators, and background characteristics in 2019 and 2020 - multinomial logistic regression analysis, ME/probabilities

	2019			2020		
	Income remained the same or increased	Partial loss of income	Total loss of income	Income remained the same or increased	Partial loss of income	Total loss of income
Gender (Reference - female)						
Male	1.8***	-1.2***	-0.7***	0.0	0.7***	-0.6***
Age groups (reference <=29)						
>=30 & <=49 years	3.5***	-1.3***	-2.2***	3.2***	-0.1	-3.1***
>= 50 years	4.4***	-1.7***	-2.7***	4.2***	-0.9***	-3.3***
Educational attainment (Reference - higher education)						
Primary or lower secondary education	-2.7***	1.8***	0.9***	-3.8***	1.9***	1.9***
Secondary education	-1.4***	1.1***	0.3***	-3.3***	2.1***	1.2***
Vocational education	-1.4***	1.4***	0.0	-3.0***	2.7***	0.3***
Region (reference - rural area)						
Urban area	-1.4***	1.4***	0.0	-2.5***	2.0***	0.5***
Occupational position						

	2019			2020		
(Reference - managers, specialists)						
Clerical support workers	-2.3***	2.0***	0.4***	-2.5***	1.7***	0.9***
Service and sales workers	-9.0***	7.8***	1.3***	-8.6***	5.7***	2.9***
Craft and related trade workers, elementary occupations	-3.9***	2.2***	1.7***	-2.9***	-0.4**	3.4***
Main activity (reference - Hotels and restaurants)						
Agriculture	3.1***	-2.6***	-0.5***	26.3***	-21.9***	-4.4***
Mining, manufacturing, and utilities	1.1***	0.7**	-1.9***	20.3***	-14.6***	-5.7***
Construction	3.1***	-4.2***	1.1***	17.4***	-16.4***	-1.0***
Wholesale and retail trade	0.5	0.7*	-1.2***	13.4***	-9.3***	-4.0***
Transport and communication	0.3	0.8**	-1.2***	17.6***	-12.9***	-4.8***
Financial intermediation	7.3***	-5.7***	-1.5***	33.7***	-27.6***	-6.1***
Real estate and business activities	9.4***	-8.5***	-0.9***	26.8***	-22.9***	-3.9***
Education	3.9***	-1.8***	-2.1***	23.6***	-17.3***	-6.2***
Health and social work	-1.6***	2.8***	-1.2***	15.9***	-11.4***	-4.4***
Arts and other creative activities	1.5***	-1.2**	-0.3	13.1***	-11.3***	-1.8***
Other activities	1.8***	-1.3***	-0.5***	17.9***	-15.3***	-2.6***

Note: average marginal effects. *** $p < 0.01$. ** $p < 0.05$. * $p < 0.1$
Source: authors' calculations

The results also show a significant change across fields of activity. The accommodation and restaurant sector suffered more due to the Covid-19 crisis and its movement restrictions. Therefore, the results indicate that all other sectors compared to hotels and restaurants are less likely to experience a partial or complete loss of income.

We also find that higher income decile groups have a higher percentage of individuals with a higher level of education (e.g., 68.5% in X decile in 2020), than those with a lower level of education (29.7%). If we compare the year before the crisis and the year of the crisis, it also seems that the share of highly educated people in higher income decile groups (V-X deciles) has increased (41.7% on average in 2019; 44.6% in 2020) and the share of people with lower education levels has decreased. In addition, education had a significant impact on the income decile group change in May 2020 compared to May 2019. Those who were highly educated had a greater likelihood of moving to a higher income decile group (45%) compared to other education levels (40% on average) and fewer people moved to the lower one.

These results show again that during the crisis, those who are more educated and in a higher position generally cope better in terms of income and employment, and this inequality can increase even more. In addition, there was a significant effect of subsidies, where without subsidies the impact of the crisis on income loss would have been even higher for people with lower accumulated human capital.

Conclusions

This study contributes to the literature by assessing the role of accumulated human capital in adjusting to shocks and how that is reflected in individual monthly income dynamics during the Covid-19 crisis. Since the Covid-19 crisis led to the spread of remote work and introduced the wider need for digital skills, Estonia is a particularly interesting case study due to its technological prerequisites and well-developed digital infrastructure.

Detailed monthly administrative data from 2016 to 2020 are used for the analysis. This facilitates working with a large dataset containing more than 800 thousand observations to analyse the detailed monthly dynamics of income during the pre-crisis and Covid-19 periods. A multinomial panel data regression analysis has been conducted to assess the impact of various human capital indicators on the income changes during the crisis.

The results of the study show that individuals who have a higher level of education or higher occupational position coped better during the Covid-19 crisis. People with higher accumulate human capital have a more stable work and they do not experience as many income fluctuations or seasonal effects as those with lower levels of education and occupations during the non-crisis period. During the Covid-19 crisis, the role of accumulated human capital became even more important. The probability of a partial or complete loss of income increased even more for the less educated and those working in a lower occupational position compared to the highly educated or managers and professionals.

In addition, the importance of subsidies became evident especially for people with lower human capital. When both unemployment benefits and wage compensation paid during the Covid-19 crisis were excluded from the analysis, the role of human capital on income changes increased even more.

It can be concluded that accumulated human capital is crucial in adapting to crises, but also recovering from them. Similar results have been found in previous studies in the context of other major crises. Considering the specifics of the Covid-19 crisis and previous studies, it can be assumed that people with higher human capital will adapt better to the use of new digital opportunities and based on this, their flexibility to adjust to the new ways of working (including remote work) will be greater. Therefore, it is important to determine which skills are required in the labour market and to invest and develop these skills through education, lifelong learning, and labour market services (e.g. career counselling, trainings, retraining). We think that these findings can be applied to other countries as well, because they have also seen an increase in the need for digital skills and remote work due to the Covid-19 crisis. However, the extent to which human capital affects income can differ depending on the level of state support.

The Covid-19 crisis is a valuable example for learning how to develop human capital to better support adapting to shocks. First, the increase in remote work refers to the need to continuously develop digital skills. During the crisis, there was a noticeable increase in remote work, and even after the Covid-19 crisis and restrictions had been lifted, this option is still available for many and will be part of future work. Second, implementing retraining is important, especially in the context of the Covid-19 crisis when specific sectors were affected more than others. The Eurofound report states that the majority of employees in the EU felt that their work environment does not provide a supportive environment for the development of their skills, and half do not have the opportunity to apply their skills and knowledge at work (Eurofound et al., 2022). Therefore, one of the positive consequences of the Covid-19 crisis was that of pushing people into the rapid development of their skills, and the acquisition of new knowledge and lessons was inevitable. These new challenges will have a significant impact on improving the qualifications of workers, allowing them to be more flexible in labour markets and to adapt to changes more quickly.

At the same time, it is important to pay attention to the interrelationships between different characteristics of labour markets and employees in terms of education, economic sector, and remote work. The comparison of 2019 and 2020 revealed significant changes in economic sectors and their impact on income losses. Since the field of activity and the level of education might be closely related, this topic needs further investigation in the future to find the separate and combined effects of all these characteristics. In addition, in the context of future work, remote work and other new ways of working are being introduced, and this is resulting in new demands on human capital and its ability to adapt to change, as well as new digital opportunities.

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Appendix 1. Multinomial logistic regression analysis, RRR, 95% confidence intervals and standard errors for the estimates.

	2019				2020			
	RRR	95% Confidence intervals		Std.Err	RRR	95% Confidence intervals		Std.Err
Partial loss of income								
Primary or lower secondary education	1,110	1,081	1,140	7,68	1,129	1,101	1,157	9,59
Secondary education	1,064	1,043	1,085	6,23	1,124	1,104	1,145	12,82
Vocational education	1,073	1,053	1,093	7,43	1,135	1,116	1,155	14,59
Clerical support workers	1,113	1,085	1,142	8,19	1,095	1,069	1,121	7,54
Service and sales workers	1,490	1,458	1,523	35,52	1,359	1,331	1,387	29,09
Craft and related trade workers, elementary occupations	1,147	1,125	1,169	13,98	1,043	1,025	1,061	4,67
Total loss of income								
Primary or lower secondary education	1,370	1,285	1,460	9,67	1,444	1,378	1,514	15,3
Secondary education	1,123	1,066	1,183	4,34	1,298	1,250	1,348	13,59
Vocational education	1,008	0,958	1,062	0,32	1,115	1,074	1,158	5,73
Clerical support workers	1,209	1,127	1,296	5,32	1,252	1,190	1,317	8,69
Service and sales workers	1,798	1,697	1,905	19,85	1,976	1,896	2,059	32,39
Craft and related trade workers, elementary occupations	1,867	1,774	1,966	23,85	1,876	1,808	1,946	33,53

Source: authors’ calculations based on detailed administrative data