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Summary

Using a microsimulation approach, this paper evaluates the distributional consequences of the Covid-19 pandemic in Finland. We use up-to-date administrative data on incomes and employment developments in 2020 at the entire population level. The employment changes for different types of workers are then combined with the dataset underpinning SISU, the Finnish tax-benefit microsimulation model. Finland, as other Nordic countries, is characterized by a generous welfare state offering considerable automatic stabilization. Our results suggest that the welfare state contained the crisis well – even without additional Covid-19-related policies. Inequality, as measured by the Gini index, increased, but only marginally (at one-digit level). The welfare state insured up to 85 per cent of the possible poverty and inequality reduction due to Covid-19**.**

Key words: Covid-19, unemployment, furloughed workers, inequality, poverty, automatic stabilization, microsimulation

Contents

1. Introduction

The coronavirus pandemic has implied, in addition to its grave health consequences, severe economic difficulties. However, the economic implications for the households can be mitigated by public action. Measures may include bespoke policies introduced to counteract the coronavirus shock or more conventional social insurance – automatic stabilization – type of policies. It may be the case that the greater is the extent of automatic stabilization, the less is needed in terms of additional corona-related policies. In this paper, we examine, using a microsimulation approach, how well the social insurance offered by a generous welfare state in a Nordic country, Finland, fares in terms of cushioning the negative income consequences of the first phase of the coronavirus shock.

Covid-19 hit Finland somewhat later than many other European countries. In March 2020, an emergency law was enacted and the country took several steps to contain the virus. These included the closure of schools and restaurants and many public places, such as libraries, concert halls, and public sports facilities. Those who were able to were encouraged – but not mandated to – telecommute. All workplaces, stores, and shopping centres remained, however, open.

These measures helped bring down the number of infections (see Figure 1), but as elsewhere in Europe, the case numbers started to rise again in the autumn.[1] The containment policies, as well as consumer cautiousness, led to severe troubles at the labour market. Finnish labour market institutions allow employers to lay off workers temporarily in a fairly straightforward manner, and this was made even easier during 2020.[2] After declaring a state of emergency, the government extended the temporary layoff scheme to cover also workers on fixed-term contracts, and reduced the periods for notice and negotiation of terms. This is reflected in the sharp rise in the number of furloughed workers starting from week 12 (Figure 2). In the first eight months of the year 2020 over 350,000 furlough spells started, more than nine times the number one year earlier. At the same time the number of new unemployment spells declined by 18 per cent from the previous year. Job losses occurred rather equally across age groups, although younger individuals were slightly over-represented among newly unemployed and furloughed workers (Figure 3). In 2020, the average age of laid-off workers was 40 among both women and men, two years up from the previous year for men, and one year up for women.

[1] The overall infections number in early versus late 2020 are not comparable, as testing became more systematically available in the latter half of the year.

[2] In addition, the waiting period of five days for unemployment benefits was removed.

As a result of the surge in furlough spells, the aggregate wage bill also contracted in the spring of 2020, but returned to earlier levels during the latter half of the year (Figure 4). Naturally, there were great sectoral differences in the furlough and unemployment incidence, with many services suffering the most. While the aggregate wage bill dropped only by 1.3 per cent by August from the previous year, workers in some occupations experienced over five percent or even two-digit declines (Figure 5). According to the Ministry of Finance, the economy is forecast to have contracted by 3.3 per cent and the unemployment rate to reach almost eight per cent in 2020.

This paper evaluates the impacts of the corona crisis on households' income as well as poverty and inequality. To do so, we use population-wide, up-to-date labour market and income information available from the so-called 'Income register' data, which is an administrative database of all Finnish workers' employment and income information at a monthly level. The database was introduced in 2019, which enables us to compare the developments under the corona pandemic with a normal year at the labour market. We use granular information about the incidence of joblessness (by worker age, gender, occupation education and area) during the first eight months of 2020 and combine these data with the dataset that underpins the Finnish microsimulation model, SISU, to predict the household-level gross incomes for 2020. The model is then run to calculate taxes and benefits in order to arrive at estimated disposable incomes for the coronavirus year. This allows us to estimate the poverty and economic inequality implications of the crisis.

The paper is related to similar microsimulation exercises conducted for several other countries, see e.g. the studies by Brewer and Tasseva (2020) for the UK, Figari and Ficario (2020) for Italy, and Jara et al. (2021) for Ecuador. A difference of our approach is that we are able to use population-wide administrative data to characterize employment changes during the coronavirus pandemic. Earlier results for Finland are available in Almeida et al. (2020), but our simulations are based on a much more disaggregated information about the incidence of joblessness.

Our results indicate that while market incomes fell by approximately 4.5 per cent in 2020, the corresponding reduction in disposable income amounted to less than half of that (1.8 per cent). The impact was the largest in the middle of the income distribution, whereas disposable income declines were smaller at the bottom and the top of the distribution. The smaller relative reduction at the bottom of the distribution is due to a higher effective replacement rate – which is a combination of unemployment insurance as well as housing benefits and social assistance – among the households in the first decile. The Gini index did increase, but only marginally (from 0.277 to 0.280), and the at-risk-of-poverty rate worsened as well, from 17.7 to 18.4 per cent. Given the extent of the shock at the labour

market, these increases were, in the end, fortunately fairly moderate, which suggests that the Finnish welfare state fared well in terms of providing cushioning to the households amid the crisis.

The paper proceeds as follows. Section 2 introduces our data and provides some descriptive information. Section 3 presents the methods used, whereas results are reported in Section 4. Section 5 concludes.

2. Data

To estimate the impact of Covid-19 crisis on income distribution, we use two sources of data. Firstly, we calculate the unemployment shock for different groups of workers from the Helsinki GSE Situation Room data.[3] This data is collected from several administrative sources to provide up-to-date information on economic development in Finland during the Covid-19 pandemic. We use group-level information about the change in the number of new unemployment and furlough spells between January to August 2020 and January to August 2019. We do not make a distinction between temporary and permanent layoffs when measuring the increase in the unemployment inflow due to Covid-19. The groups are based on age (ages 16-29, 30-39, 40-49, 50-63), occupation (9 groups), region (19 regions), gender and education (tertiary or no-tertiary degree). The region variable is from year 2019, education from 2018, and occupation from 2017. This causes some mismeasurement as especially for the youngest age group the situation might have changed by 2020. However, we use quite a coarse classification of the background variables mitigating the problem.

Secondly, we use a representative sample of household microdata which is source data in the SISU microsimulation model, which is maintained and developed by Statistics Finland[4] and used in Finland extensively for example by the Ministry of Finance to evaluate the distributional impacts of different policy proposals. This data consists of 800,000 individuals (approximately 15% of Finnish population) and includes a comprehensive collection of individual and household income items and various background information on annual level. The current source data is from year 2018. For the baseline simulation we use this data and the legislation from year 2020. For the counterfactual simulation we match the unemployment shocks from the grouped data to the SISU microdata.

In this microdata we define the employed individuals based on their income. The employed individuals have wage income, no unemployment benefits or study

[3] See https://www.helsinkigse.fi/korona-data/

[4] For more information on SISU, see https://www.stat.fi/tup/mikrosimulointi/index_en.html

benefits. For the counterfactual simulation we modify the microdata by randomly allocating these employed individuals to unemployment based on grouped data. We match the proportional change in unemployment in each group found in the SISU source data.[5] Table 1 presents the descriptive statistics on the employed individuals in the baseline (Column 2). Column 3 depicts the share of new unemployed or furloughed in the counterfactual simulation. On average 7.5% of the target population became either furloughed or unemployed in 2020 due to Covid-19. Among young workers 11.5% lost their job, which is mostly explained by the fact that Covid-19 during the spring 2020 affected industries and occupations where younger workers are more common (services such as restaurant and hotels). Also, the pandemic affected more workers without tertiary degree. All in all, the unemployment risk was unevenly distributed due to the Covid-19 crisis as the low-income households work mainly in industries which were closed down during the first phase of the Covid-19 pandemic.

3. Methodology

We follow the methodology used in Brewer and Tasseva (2020). We combine the household micro data, with and without adjusting for the unemployment shock due to Covid-19, and microsimulation methods to evaluate the effect of the crisis on household disposable income. We also decompose the change in disposable income to evaluate the role of earnings losses and automatic stabilizers, that is, the role of tax-and-transfer policies. Additional Covid-related policy changes are left out from the decomposition as policy changes affecting working household were relatively minor during the spring of 2020.

The SISU microsimulation model simulates income tax liabilities and entitlement for different benefits for each individual and household based on the gross earnings, other sources of income and individual and household characteristics. We run two simulations. In the baseline, let us denote household disposable income by *B*, household gross market income with *y*, paid taxes with *t* and income transfers received with *b*. We then have:

$$B = y - t(y) + b(t, y).$$

In the second simulation we take into account the unemployment shock. Unemployment reduces the labour market earnings to zero but part of these are replaced by unemployment benefits and other benefits. We can denote the gross market income after the unemployment shock by *y*', paid taxes by *t*(*y*') and

[5] In total (applying the population weight), approximately 153 000 employees in the SISU source data are simulated to be newly unemployed or furloughed. This represent approximately 80% of the real number of new unemployed or furloughed workers observed in the register data.

benefits received by $b(t,y')$. This implies that the household disposable income after the shock may be written as

$$D = y' - t(y') + b(t, y').$$

Now we can decompose the change in the household income, *D* - *B*, into earnings changes, changes in taxes and changes in transfers. The last two represent the automatic stabilizers and reveal how much the current tax-and-transfer system softens the burden of the unemployment shock. Using the notation above the decomposition can be written as

$$\begin{aligned} D - B &= y - t(y) + b(t, y) - \left(y' - t(y') + b(t, y')\right) \\ &= (y - y') - \left(t(y) - t(y')\right) + \left(b(t, y) - b(t, y')\right). \end{aligned}$$

The exact measure of household disposable income is cash income, including markets incomes, public pensions, benefits minus the municipal and national income taxes and insurance contributions, adjusted for the household composition. Household composition and economies of scale are taken into account by using the modified OECD equivalence scale where the first adult in a household gets a weight equalling 1, the next adult or over 14 years old child a weight of 0.5 and each child under 14 a weight of 0.3.

4. Results

4.1 Results regarding disposable income

We first discuss the impact of the crisis on household incomes by income deciles. The main analysis is conducted by fixing the deciles on the basis of pre-crisis income ranking. Figure 6 illustrates the impact on all households with labour incomes. This includes both households which were not affected and households experiencing temporary or permanent layoff due to Covid-19. The average decline in earnings was approximately 4.5 per cent, but the households at the bottom experienced larger reductions in market income. The drop in disposable income was much more muted, on average 1.8 per cent. The main cushioning is provided by benefits, especially at the bottom of the distribution, whereas the contribution of lower taxes matters more towards the top of the distribution.

We can compare the drop in market incomes, calculated from the height of the crisis, to overall economy-wide developments over a longer period of time. In comparison to the same time in 2019, the overall wage bill was 2.2 per cent higher in January-February 2020, i.e. before Covid-19 hit the economy. In contrast, the wage bill in 2020 from March onwards was 2.2 less than during a similar period a year earlier. If we assume that earnings in 2020 in the absence of Covid would

have developed as in early 2020, the “difference-in-differences” type of estimate for the earnings reduction due to the coronavirus therefore amounts to 4.5 per cent. This is very close to the aggregate reduction calculated on the basis of micro data above.

When focusing only on households which experienced an unemployment shock (Figure 7), the impacts are much larger. The reduction for earnings was around 45 per cent, and in disposable income 18 per cent. The pattern is similar, with households in the middle of the income distribution facing the greatest relative decrease in disposable income.

If households are re-ordered by the new, 2020, income levels (see Figure 8), the impact of the Covid-19 crisis appears, not surprisingly, regressive. Households in the first decile experienced a 14 per cent drop in disposable income, whereas the reductions at the top are minimal.

The coronavirus crisis hit young workers more than older workers. This is also reflected in a slightly higher reduction of disposable income for households with the youngest household head (Figure 9). As usual when facing shocks, having a spouse provides insurance against income loss. Figure 10 demonstrates this for households experiencing coronavirus-related unemployment: single individuals’ decline in disposable income amounted to 37 per cent, whereas the corresponding number for couples without children was around 20 per cent. Interestingly, the income reduction was the smallest for single parents, whose replacement rate, via a more generous housing benefit and other transfers, is the greatest.

When examining the impacts by educational status, the reductions affected most those households without members with tertiary education (Figure 11). Figure 12, in turn, reports the reduction in disposable income by the gender of the household head. These results indicate that the average reduction was much greater for the male-headed households experiencing unemployment.

4.2 Results on poverty and inequality

We now turn on our results related to income poverty and inequality. The basic results are reported in Table 2. The poverty calculations have been conducted using a fixed, pre-crisis, poverty line (60% of median income). The Covid-19 crisis increased the at-risk-of-poverty rate by 0.7 percentage points, which is equivalent to around 40,000 new low-income persons. The Gini index of inequality increased, but only very marginally (from 0.277 to 0.280).

We have also calculated the poverty and inequality consequences only for those households who have either labour income or whose members are of working age (15-74). The absolute numbers are similar, but the relative changes, especially for wage earners whose poverty rate increased from 7.7 to 9.6, are

greater as the starting point is one with fewer individuals below the poverty line and the shock pertained to this part of the population.

The question about the role of the welfare state in providing social insurance can be examined using a similar approach as Dolls et al. (2012). They note that the stabilization impact on household disposable income can be expressed as

$$\tau_y = 1 - \frac{\sum_i \Delta y_i^D}{\sum_i \Delta y_i^M},$$

where $\sum_i \Delta y_i^D$ denotes the aggregate change in disposable income and $\sum_i \Delta y_i^M$ the aggregate change in market income. The similar idea can be extended to poverty and inequality measures, as applied by Adu-Ababio (2021). Therefore, the stabilization of a poverty or inequality metric can be written as

$$\tau_p = 1 - \frac{\sum_i \Delta p_i^D}{\sum_i \Delta y_i^M},$$

where $\sum_i \Delta p_i^D$ denotes the change in the metric calculated on the basis of disposable income and $\sum_i \Delta p_i^M$ the corresponding change in the space of market income. For example, if the poverty stabilization coefficient equals 0.25, the automatic stabilization by the government cushions 75 per cent of the poverty-increasing impact of the shock.

These stabilization coefficients are reported in Table 3. The results suggest that the extent of automatic stabilization of the corona shock by the Finnish welfare state has been very high: 69 per cent of the poverty impact and 86 per cent of the potential worsening of inequality has been cushioned by the public sector via increased transfers and lower taxes. The impacts of the corona shock on households' income would have been much more serious in the absence of the safety net provided by the system.

5. Conclusions

Using a microsimulation approach and population-wide administrative data on income and labour market developments during 2020, we examined the impact of the coronavirus pandemic on household incomes as well as poverty and inequality. Wage earners' market incomes fell by approximately 4.5 per cent because of the crisis, but the corresponding reduction in disposable income was limited to 1.8 per cent. Poverty and inequality both increased, but the increase would have been much more significant had the welfare state not insured households against the income shock. The results suggest that 70-85 per cent of the poverty and inequality increase was avoided due to the cushioning impact of automatic stabilization via greater transfers and lower taxes.

In this version of the paper, we only included the conventional, pre-crisis, policies when conducting the microsimulation exercise. The results in this paper serve, therefore, to assess how the automatic stabilization and social insurance offered by the Finnish system was able to contain the effect of the crisis on household incomes. In fact, in comparison to many other countries, Finland only introduced few new policies in 2020 because of the coronavirus pandemic. These included making unemployment assistance more readily available to the self-employed and a reduction in the waiting period until the benefits can be claimed for all unemployed. While we plan to also model these additional policies in further work, we consider their additional impact fairly small in comparison to what the standard Finnish welfare system already offers.

Another extension we plan to carry out is to also include an analysis of the impact on the self-employed, who were now excluded from the analysis. While the impacts on their incomes could be partly tracked in a similar manner as those of the wage earners, the simulation of their benefit eligibility requires more work. Information about the longer-term impacts on their capital incomes (i.e. firm profits, expected to be severely hit in certain sectors) will only became available after a longer delay. And as the data on earnings and employment for the entire year become available, the analysis will be extended to take into account the entire year of 2020.

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Figure 1: Covid-19 cases in Finland, 2020

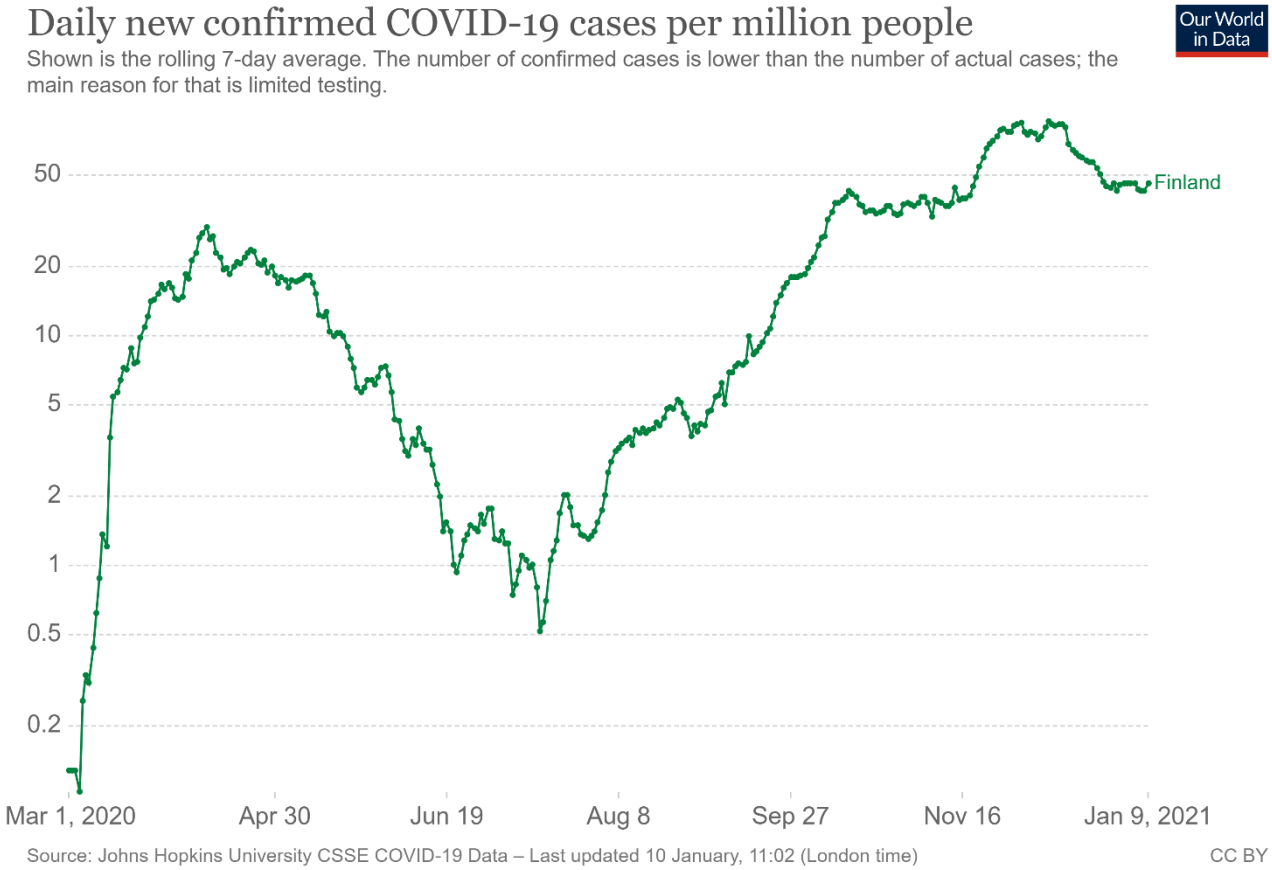
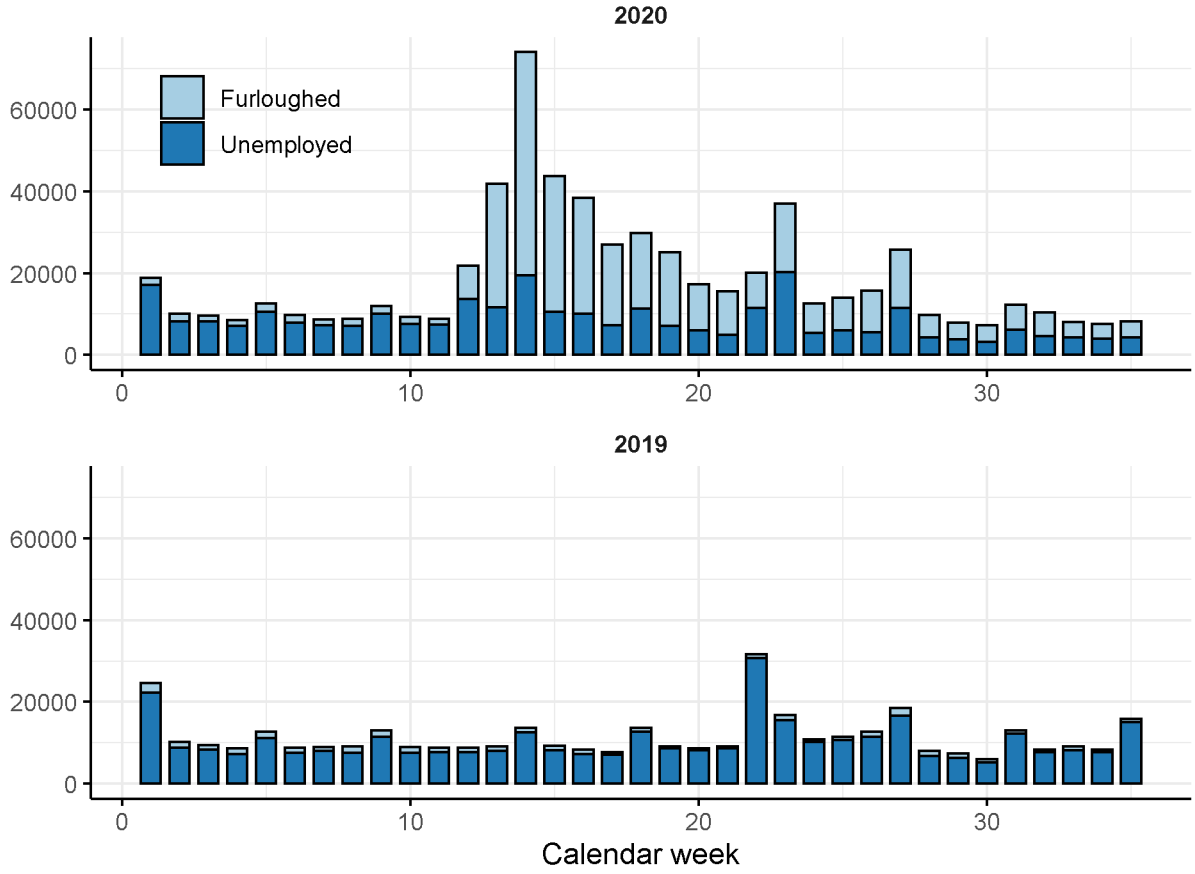
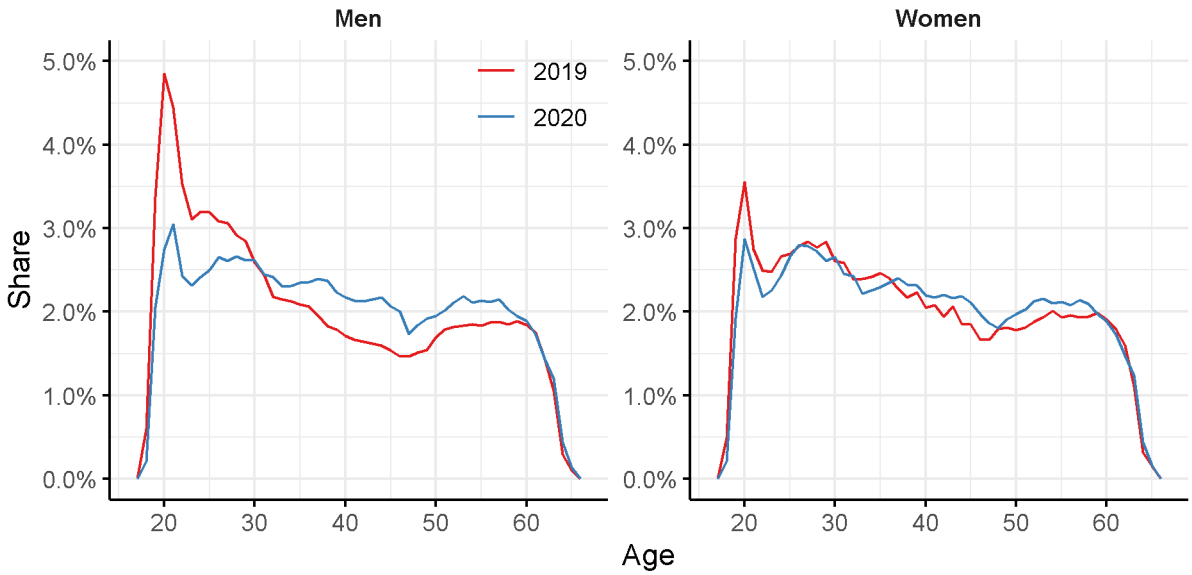


Figure 2: New unemployment and furlough spells by week



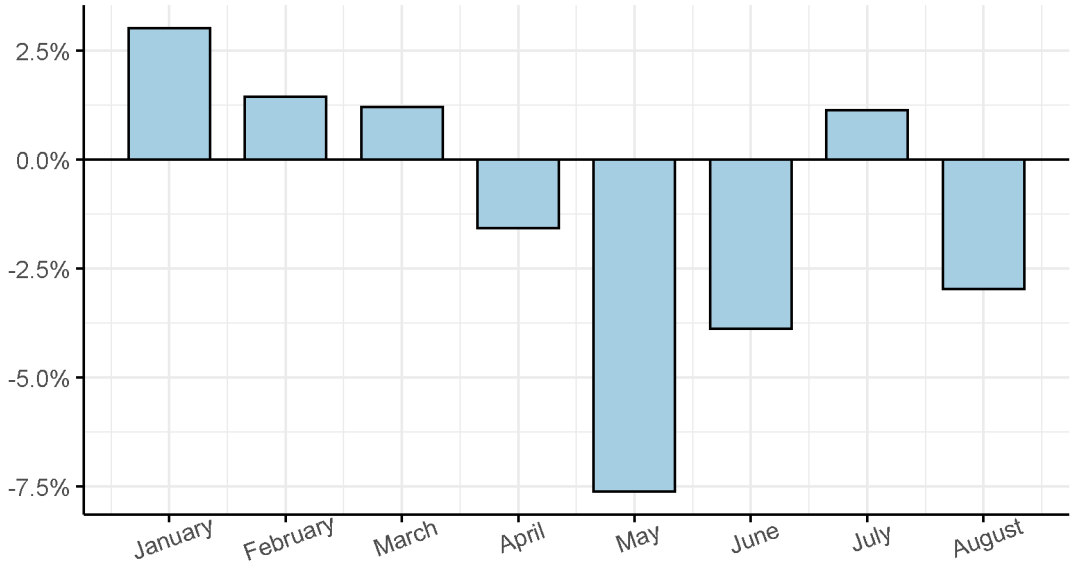
Source: Authors' calculations on the basis of Helsinki GSE situation room data.

Figure 3: Age distributions of newly furloughed and unemployed workers



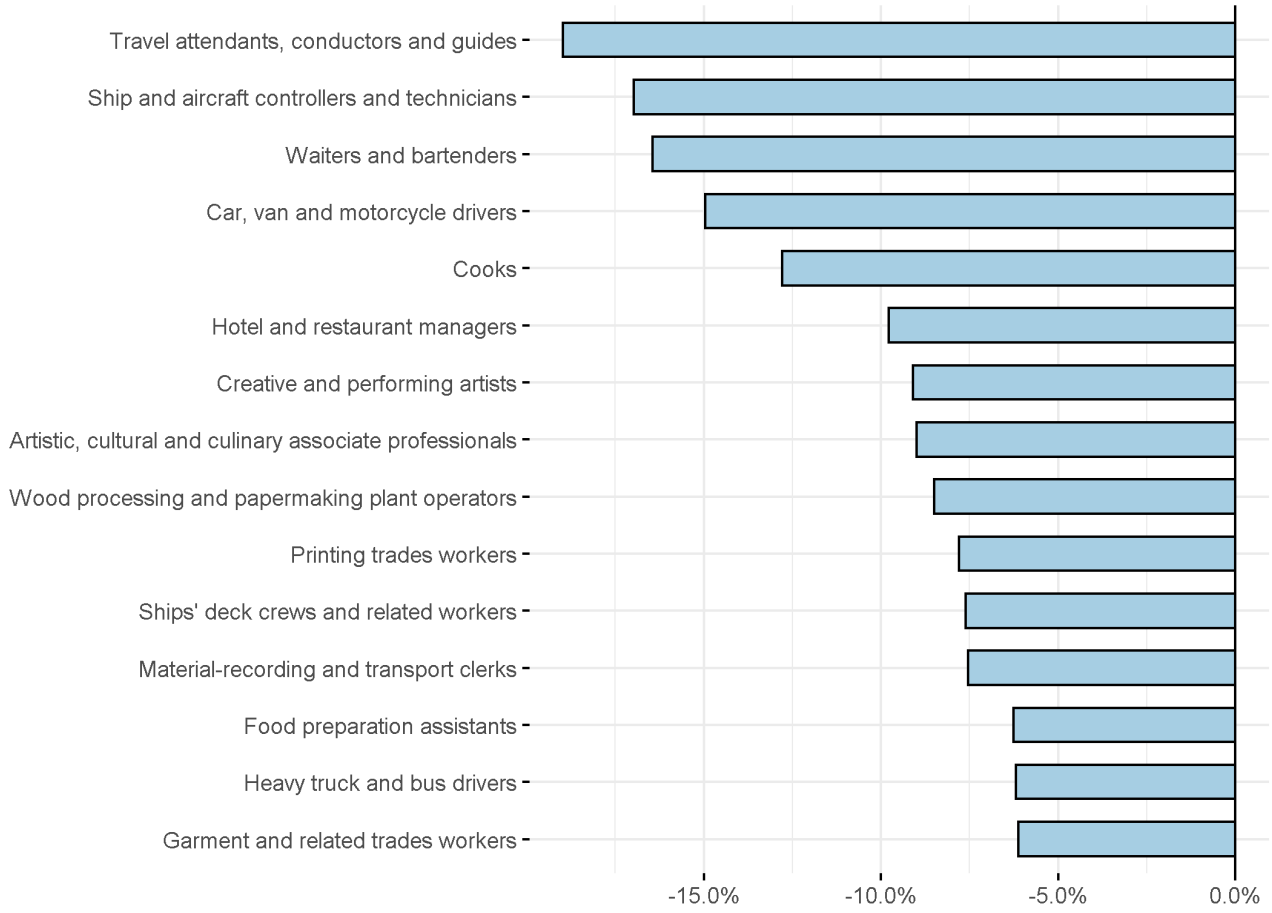
Source: Authors' calculations on the basis of Helsinki GSE situation room data.

Figure 4: Year-over-year changes in wage bill, 2019-2020



Source: Authors' calculations on the basis of Helsinki GSE situation room data.

Figure 5: Occupations with the largest wage losses



Note: Year-over-year change in wage bill between January and August, 2019 and 2020.
Source: Authors' calculations on the basis of Helsinki GSE situation room data.

Figure 6: Impact on all households by household income decile

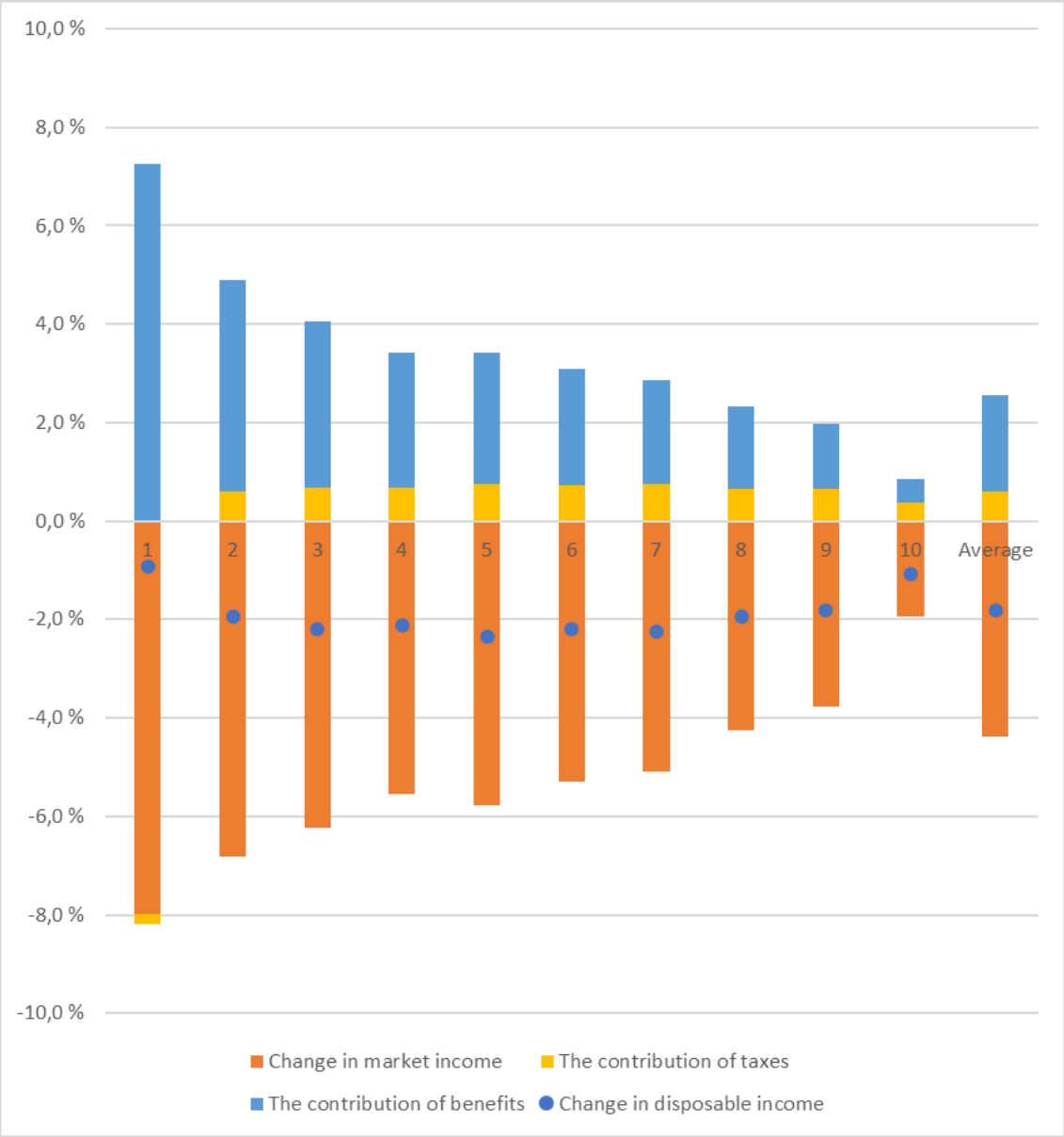


Figure 7: Impact on households which faced unemployment by household income decile

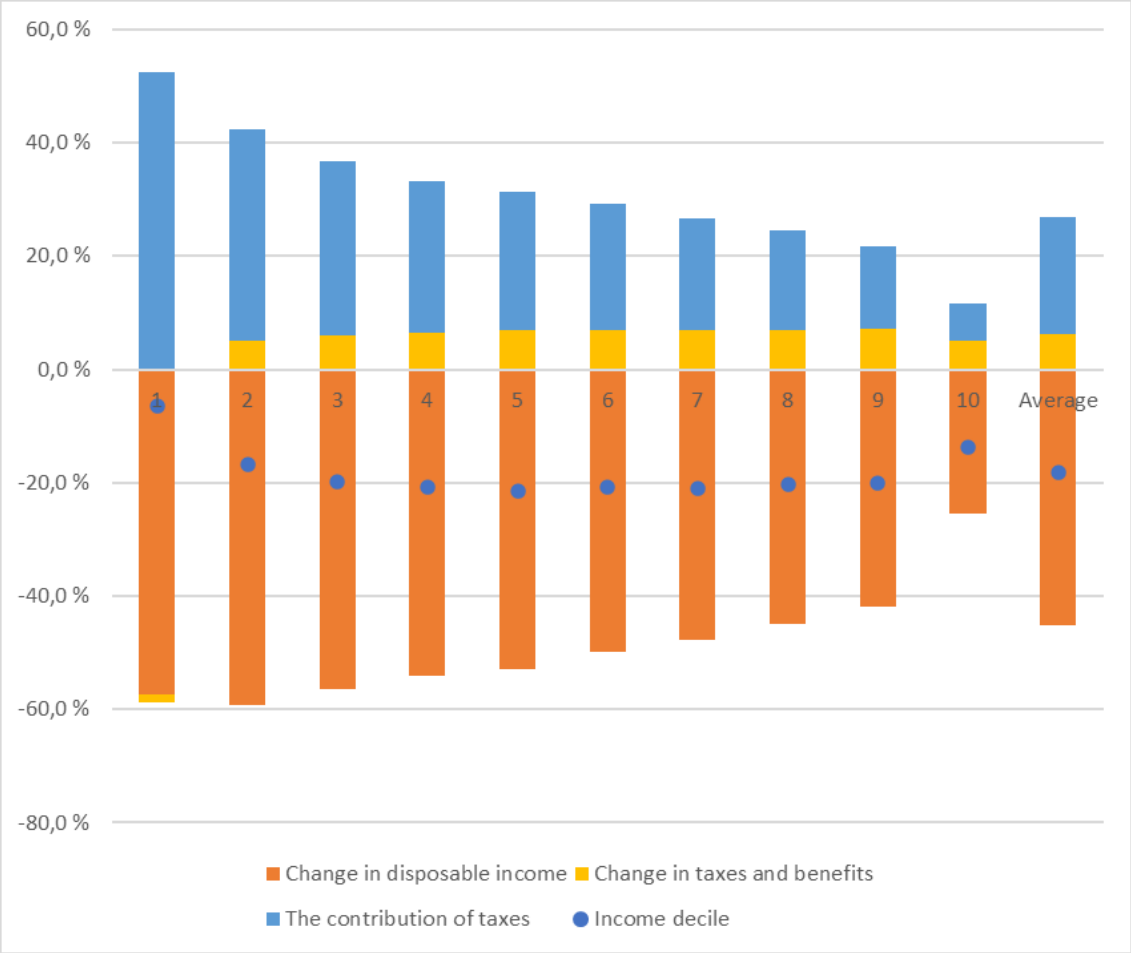


Figure 8: Impact on all households, reranked deciles

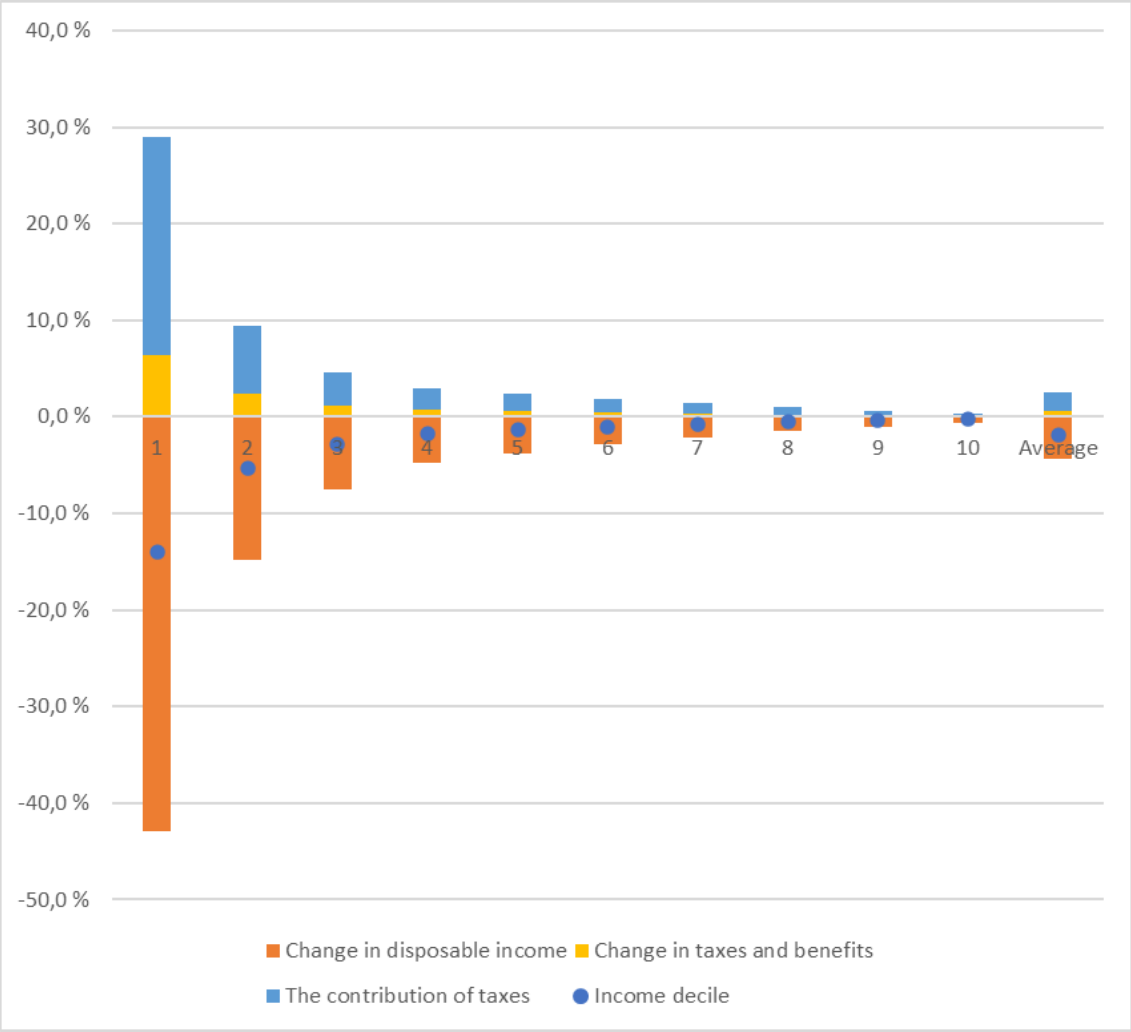


Figure 9: Impact on household which faced unemployment, by age of household head

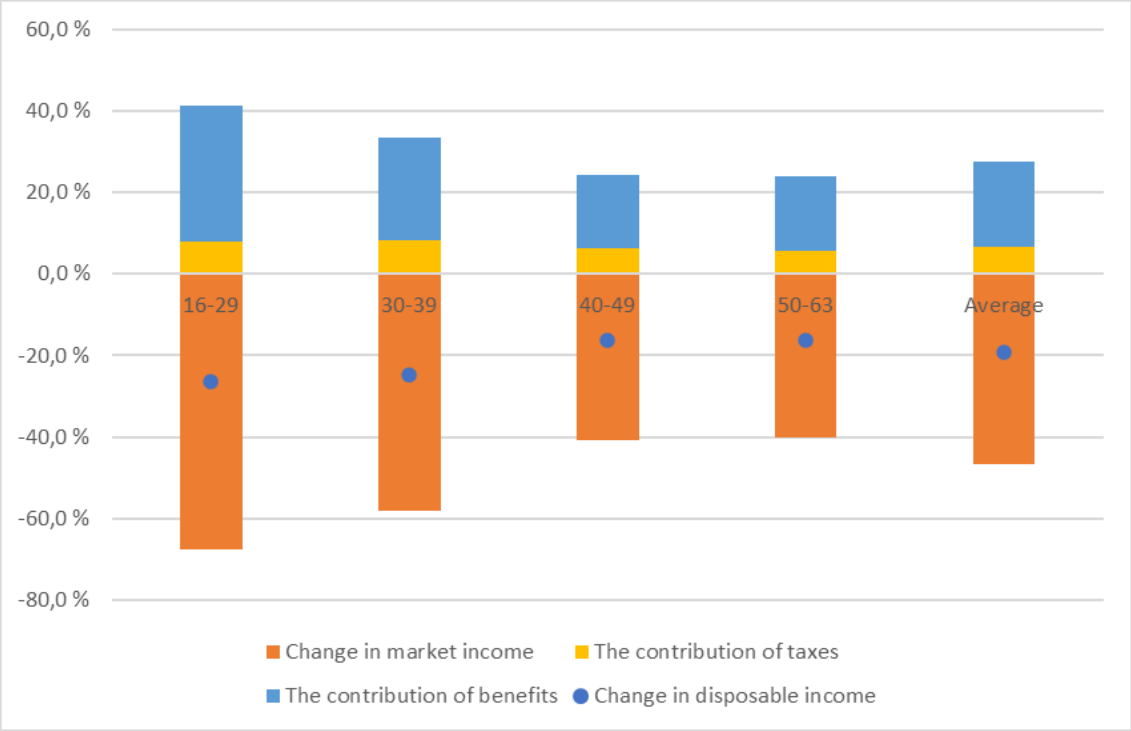


Figure 10: Impact on households which experienced unemployment, by family situation

Figure 11: Impact on households which experienced unemployment, by education

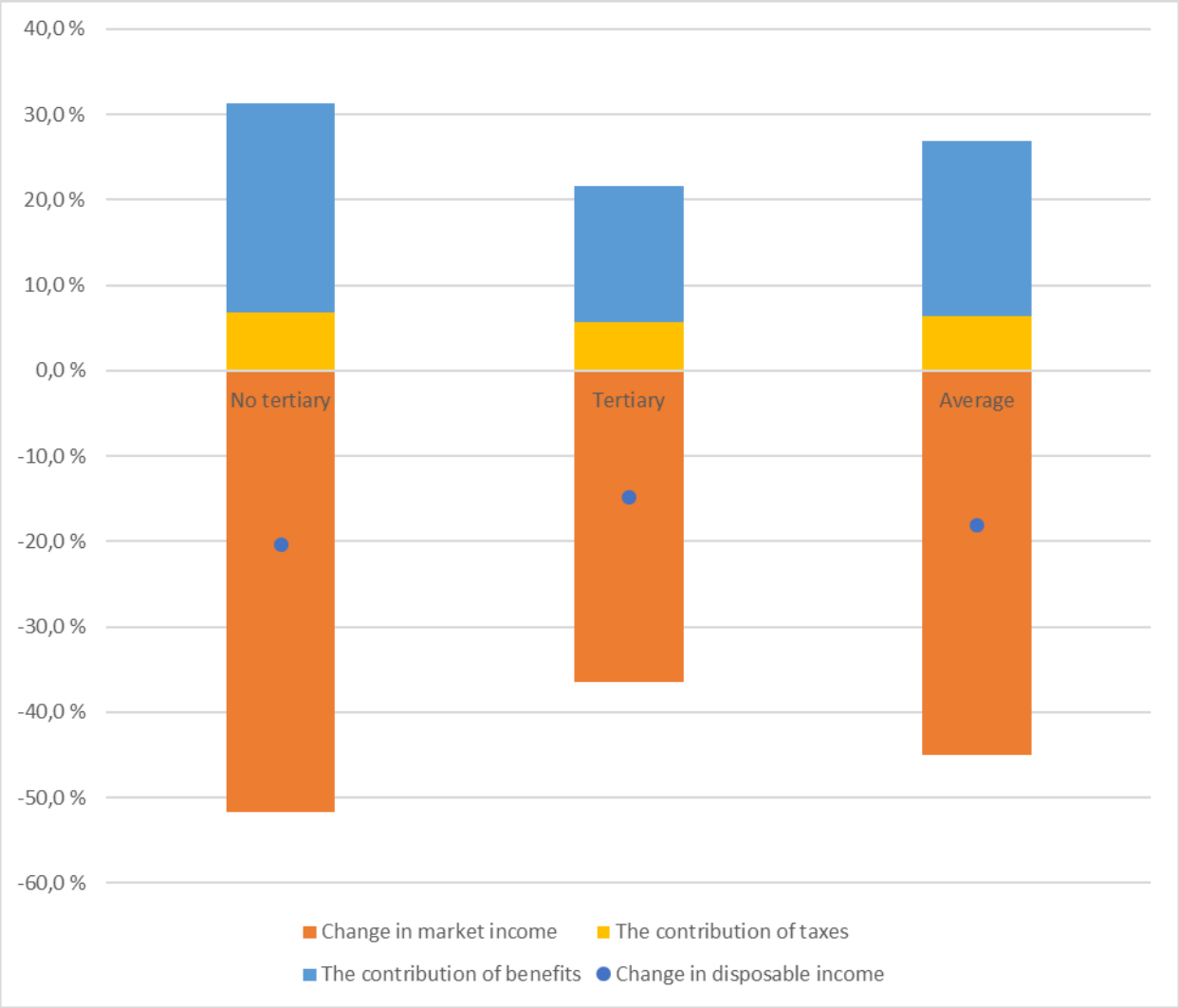


Figure 12: Change in disposable income, by gender and household income decile

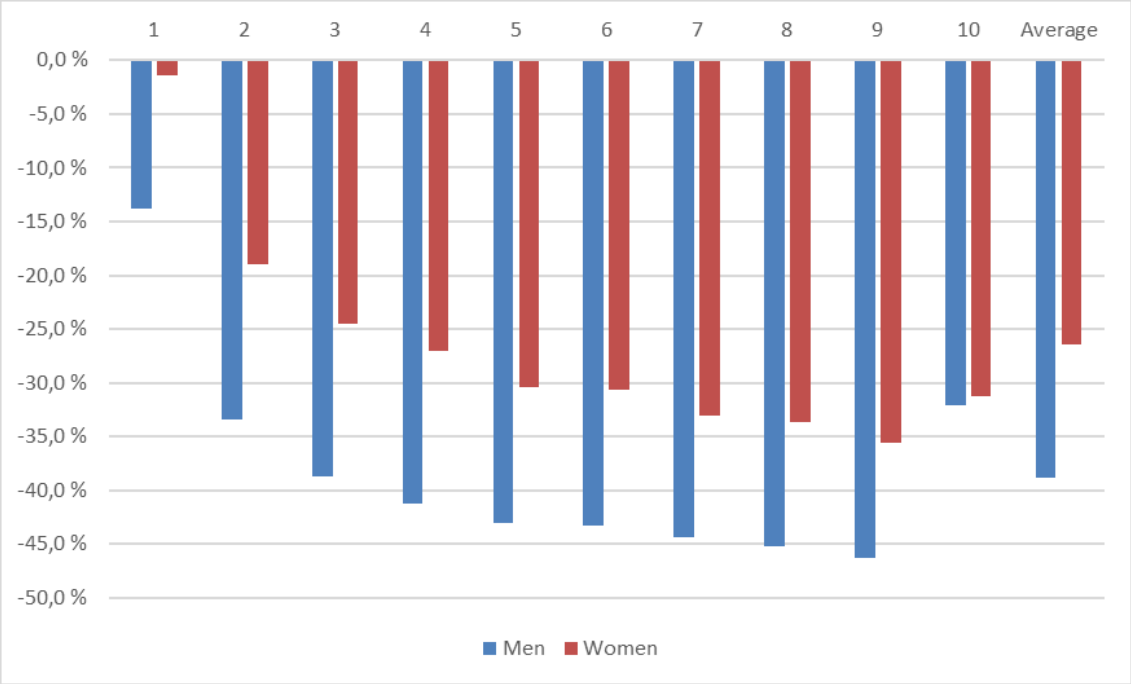


Table 1: Descriptive statistics

	(1)	(2)	(3)
		Employed	**Share of new unemployed/furloughed**
	All	2 044 062	7.5 %
Age	16-29	434 877	11.5 %
	30-39	483 435	7.2 %
	40-49	473 890	6.1 %
	50+	651 859	6.2 %
Gender	Men	1 045 849	7.3 %
	Women	998 212	7.8 %
Household type	Single	390 935	7.0 %
	Single parent	86 697	9.6 %
	Couple, no kids	527 957	6.5 %
	Couple, with kids	732 199	8.0 %
	Other households	306 273	8.2 %
Education	No tertiary degree	1 161 847	10.2 %
	Tertiary degree	882 214	4.0 %
Household income	1	165 036	13.0 %
decile	2	176 655	9.4 %
	3	185 459	8.6 %
	4	191 849	7.8 %
	5	199 093	7.9 %
	6	207 864	7.4 %
	7	218 369	7.1 %
	8	226 913	6.1 %
	9	234 871	5.6 %
	10	237 952	4.7 %

Table 2: Results on poverty and inequality

	Baseline	Covid-19	Difference
Total population			
Number of individuals	5 517 919	5 517 919	
Gini	0.277	0.280	0.003
Poverty line, 60% of median income	15 016	15 016	
Persons below the poverty line	720 161	758 798	38 637
Headcount ratio	13.05	13.75	0.7
Wage earners only			
Number of individuals	2 044 294	2 044 294	
Gini	0.242	0.249	0.01
Poverty line, 60% of median income	18 431	18 431	
Persons below the poverty line	157 483	196 754	39 271
Headcount ratio	7.70	9.62	1.92
Working-age population			
Number of individuals	4 071 578	4 071 578	
Gini	0.283	0.285	0.00
Poverty line, 60% of median income	15 665	15 315	
Persons below the poverty line	608 780	640 966	32 186
Headcount ratio	14.95	15.74	0.79

Table 3: Automatic stabilization

	Baseline	COVID-19	Difference
Inequality			
Gini market income	0.528	0.543	0.015
Gini disposable income	0.278	0.280	0.002
Stabilization coefficient	0.864		
Poverty			
Headcount ratio, market income	0.381	0.404	0.023
Headcount ratio, disposable income	0.1305	0.1375	0.007
Stabilization coefficient	0.691		