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The Distributional Impact of the COVID-19 Shock on Household Incomes in Belgium

COVIVAT Working Paper 2

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CSB Centrum voor Sociaal Beleid Herman Deleeck
Universiteit Antwerpen
CeSO
CENTRUM VOOR SOCIOLOGISCH ONDERZOEK
CENTRE FOR SOCIOLOGICAL RESEARCH
KU LEUVEN
FACULTEIT ECONOMIE EN BEDRIJFSWETENSCHAPPEN

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The distributional impact of the COVID-19 shock and policy responses on household incomes in Belgium[1]

Sarah Marchal[1], Jonas Vanderkelen[2], Bea Cantillon[1], Koen Decancq[1], André Decoster[2], Sarah Kuypers[1], Ive Marx[1], Johannes Spinnewijn[2], Wim Van Lancker[3], Lena Van Meensel[1] and Gerlinde Verbist[1]

[1] Centrum voor Sociaal Beleid Herman Deleeck, Universiteit Antwerpen
[2] Onderzoekseenheid Economie, KU Leuven
[3] Centrum voor Sociologisch Onderzoek, KU Leuven

Executive summary

The economic shock following the COVID-19 pandemic and the subsequent partial lockdowns have considerable consequences for household incomes. This paper looks at two aspects of that impact in Belgium. First, it gauges the impact on monthly household incomes in April of the partial lockdown that started mid-March. Second, it estimates the impact of some of the most important compensating measures that the Belgian (federal) government took to safeguard household living standards: the extension of the temporary unemployment scheme and the bridging right for the self-employed. Importantly, the aim of our paper is also to discuss a method that can be used to monitor the impact of the crisis as it unfolds. We focus on first-order effects, i.e., the day after the shock and the start of the measures, without considering long-term consequences or behavioural reactions. We use the Belgian version of the microsimulation tax-benefit model EUROMOD, which runs on a representative sample of Belgian households, the EU-SILC. We recalibrate the EU-SILC to reflect the labour market impact of the COVID-19 shock by modelling the probabilities of individuals to experience a transition to temporary unemployment or the bridging right. These probabilities are based on a real-time non-probability survey conducted in April. The probabilities were calibrated against administrative recipiency statistics. We describe in detail the distribution of our (modelled) shock, and simulate its impact on the income distribution. We find that the impact of the shock on monthly disposable incomes was substantially mitigated by additional incomes in the household and by the workings of the tax benefit system. The latter worked especially well in mitigating the short term impact for wage earners in the second and third wage quintile. It is important to note that we model the COVID-19 shock based on the administrative recipiency numbers of persons falling back on temporary unemployment and the bridging right for the self-employed. This means that we model the impact on the incomes of labour

[1] Corresponding authors: Sarah Marchal (sarah.marchal@uantwerpen.be) and Jonas Vanderkelen (jonas.vanderkelen@uantwerpen.be).

market insiders with access to support measures. We therefore only provide a partial assessment of the impact of the shock and the policy measures.

Key findings

- The shock predominantly affected employees with low wages. In the lowest wage quintile, 40% of employees was affected by temporary unemployment, whereas this was only 17% of employees in the highest quintile. Self-employed were more equally affected throughout the income distribution;
- Market incomes of affected employees decreased on average with 1950 euro in April, i.e. a decrease of 64%.
- The tax and benefit system mitigated the income shock substantially: after taking account of the temporary unemployment benefit and mechanical decreases in social insurance contributions and the withholding tax, disposable incomes of affected employees decreased on average with 382 euro, or 17% in relative terms.
- The tax benefit system worked especially well for employees in the second and third pre-COVID wage quintile: their disposable income decreased on average by 12% and 12.6% (as opposed to 16% in the first wage quintile, and 17.4% and 25.8% in the fourth and fifth quintile). Affected employees in the second and third pre-COVID wage quintile benefited from the relatively generous replacement rate in the temporary unemployment scheme for wages under the wage ceiling, while they also ended up in lower withholding tax bands. Affected employees in the lowest pre-COVID wage quintile already benefited from the lowest withholding tax band. When they were affected by temporary unemployment, they did not benefit from a reduced withholding tax liability. In contrast, due to the fixed rate withholding tax applied on the temporary unemployment benefit, they could no longer benefit from fiscal reductions that are awarded on a monthly basis when in work.
- The relative impact on disposable household incomes among households with an affected employee or self-employed was higher for households in lower household income quintiles. As affected households in the lower income quintiles are more often one-earner households, the impact of the lockdown was only buffered through policies, and not through the presence of additional incomes in the household.
- The average impact over the total population was relatively limited: the average household income decreased by 4%, or with 122 euro in absolute terms.

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1 Introduction

The COVID-19 pandemic affects people's health and the health care system in an unprecedented way. It also has a major impact on living standards. In Belgium, the most immediate effect was brought about by the shock of the lockdown starting mid-March 2020. During that lockdown, several "non-essential" economic sectors were shut down. This affected the employment situation of over a million Belgians. The different governments (federal and regional) responded quickly by taking support measures, the most important ones being an extension of the system of temporary unemployment and of the bridging right for the self-employed. At the peak of the lockdown in April over 1 million people were on temporary unemployment, with especially the sectors of accommodation and food services, of wholesale and non-food retail, and of arts, entertainment and recreation being severely hit (Decoster, Van Lancker, Vanderkelen, & Vanheukelom, 2020).

In this paper we examine the short-term impact of the shock and the accompanying support measures on the disposable income of Belgian households and asses how this impact is distributed over the population. Because we do not have real-time data on household incomes, we use nowcasting techniques and the Belgian version of the tax-benefit microsimulation model EUROMOD to simulate changes in individual employment status and earnings, as well as changes in household income tax and benefit levels. We focus on the impact of the shock on individual earnings and household disposable incomes in the month of April. It is important to note that we only model the COVID-19 shock based on the numbers of persons falling back on temporary unemployment and the bridging right for the self-employed. This means that we build our analysis around the impact on the incomes of labour market insiders with access to support measures. We therefore only provide a partial assessment of the impact of the shock and the policy measures on the incomes of the Belgian population.

This paper adds to earlier analyses for other European countries, such as Brewer and Tasseva (2020) and Bronka, Collado, and Richiardi (2020) for the United Kingdom, Figari and Fiorio (2020) for Italy, and Beirne, Doorley, Regan, Roantree, and Tuda (2020) and O'Donoghue, Sologon, Kyzyma, and McHale (2020) for Ireland. These studies model the short-term impact of the COVID-19 shock on disposable income of households. They show that loss of market income after the lockdown is substantial, with on average 30% of individual earnings losses in Italy and up to 15% in Ireland and the United Kingdom. Government schemes partially compensated for these losses (e.g. through the Wage Supplementation Scheme in Italy; the Earnings Subsidy in the United Kingdom and the Temporary Wage Subsidy in Ireland). All studies found that this support was more substantial for those at the bottom of the disposable income distribution.

The aim of this paper is to look into the distributional impact of COVID-19, but also to introduce a method that allows to monitor the change and distribution of disposable incomes during subsequent stages of the pandemic. The current analysis looks at the impact for one month, comparing pre-COVID-19 incomes with those in the month of April 2020, thus showing the immediate effect of the shock. This analysis will be extended in the future with comparisons of the ensuing months, thereby also including policies that took effect in later months.

2 The early COVID-19 shock in Belgium

As COVID-19 reached Europe and started to wreak havoc in countries like Italy, it became clear that far-reaching actions were necessary to prevent a collapse of the care system. The federal government[2] announced a set of stringent social distancing measures on March 12th. From midnight March 13th, schools, bars and restaurants, museums and theme parks were closed, and public events were cancelled. Non-essential shops had to close during the weekend. These measures were initially foreseen to last until April 3rd (Crisis Center and Federal Public Service Public Health, 2020).

On March 18th, these measures were further tightened into a semi-lockdown. Non-essential shops fully closed and remote work became mandatory. Essential shops remained open, but under strict requirements: clients had to shop alone, keep distance, and shops had to make sure there was only one customer per 10 m². All non-essential traffic was forbidden, except for outdoor walking, cycling and running. Non-essential international travel was prohibited (Belgische Federale Overheidsdiensten, 2020a). On March 20th, the borders were closed. Initially the measures were foreseen to last until April 5th, but were soon extended until Easter (April 19), and eventually until May 3rd. Afterwards, measures were gradually relaxed. The first relaxation was already implemented on April 18th, when garden and DIY-shops could reopen (Belgische Federale Overheidsdiensten, 2020b). (A description of the social distancing measures (and their relaxations) in May and consecutive months, will be provided in future working papers.)

The closure of large parts of the economy had a profound impact. In June 2020, the Organisation for Economic Co-operation and Development (OECD) projected a 8.9% decline in annual economic output (gross domestic product) for Belgium relative to 2019 in a single hit scenario. If, as is currently the case, a second lockdown became necessary, the projected decline would increase further to 11.2% (OECD, 2020). The European Commission spring forecast expected a 7% drop in real GDP in 2020, due to the impact of the lockdown measures on household consumption and low consumer and investor confidence, mainly in the first two quarters of 2020 and partially compensated by a rebound afterwards. Real GDP was expected

[2] This section focuses on the federal measures. In addition, the regional governments took adjacent measures, e.g. relating to the allowed number of visitors in retirement homes. However, these adjacent measures were not always communicated at the same time as the "safety council" (a government body representing the federal caretaker government and the regional governments).

to increase again with 6.75% in 2021, but to remain below 2019 levels. The Commission also projected a growth in unemployment, from 5.4% to 6.5% (European Commission, 2020b). The Autumn forecast, taking account of the further unfolding of the COVID19 containment measures and their consequences up to October 22nd, projects a decline of real GDP of 8.4% in 2020, with an increase of 4.1% in 2021 and 3.5% in 2022. Total investment is expected to be down by 13.7% (European Commission, 2020a).

Also the Federal Planning Bureau (FPB) has published economic forecasts since the start of the COVID-19 crisis. In its forecasts published in June 2020, the FPB reported a substantial decrease of economic activity in the first quarter of 2020, driven by the lockdown that also spanned the two last weeks of March. The second quarter, when the brunt of the (first) lockdown occurred, saw a far steeper decrease. It was expected that the third quarter would show signs of a recovery, with catch-up growth in the following quarters. Still, in June, the Planning Bureau expected Belgian GDP to decrease by 10.5% in 2020. Until mid-2022, quarterly growth is expected to be higher than usual, although even then, losses of economic activity in the Belgian private sector would still represent 4% as compared to a situation without pandemic. Only in the period 2023 – 2025 does the Planning Bureau expect the Belgian economy to match trends from the past. These forecasts assumed that a second lockdown would be unnecessary, as new contaminations would be quickly identified and isolated (Federal Planning Bureau, 2020).

3 Policy responses

Together with the lockdown, the federal and regional governments announced important support measures. The federal government announced an extension of both the bridging right for the self-employed, and of the temporary unemployment scheme (the Belgian short-time work scheme). The regional governments announced important support measures to companies, as well as income supplements to households. The scope of our exercise is limited to measures that have an immediate effect on net disposable incomes. For this reason, we do not include the measures to support companies, such as the Flemish corona premium. We do include regional measures that are targeted at individuals or households, such as the energy premia implemented by both the Flemish and the Walloon region, or the social supplements within the child benefits in Wallonia, Flanders and Brussels. We intend to include these measures from the month onwards in which they could at the earliest be received, which for most of these regional measures is May or later (these will be the subject of a follow-up COVIVAT report). The present paper focuses on the impact of the lockdown and the subsequent support measures on the monthly income distribution in April.

Table 1 below provides an overview of the federal income support measures applicable (and paid out) in April 2020. The quantitatively most important measures are the extension of the temporary unemployment scheme, and the extension of the bridging right for the self-employed. Below, we sketch these measures in more detail. At the start of April, the federal government also announced a temporary halt to the degressivity of unemployment benefits, and a slight tightening of access conditions. We do not include the impact of this measure in our analysis.

Table 1. Federal income support measures paid in April 2020

		Number of users	Budgetary cost (in euro)
Measures for employees	Temporary unemployment (extended, federal)	1,170,461	1,307,656,683
Measures for self-employed	“bridging right” (extended, federal)	405,231	569,070,450[a]

[a]: The budget for the bridging right is based on statistics of the number of users by category in April 2020, multiplied by the lump sum benefit applicable to each category, rather than on a directly reported budget.

Source: (RVA, 2020a) and communication with RSVZ

Access to temporary unemployment was extended during the lockdown (in a first instance until end of June, later this was further extended to the end of August).[3] In normal times, employers can only apply for temporary unemployment for their employees under force majeure or for economic conditions. Temporary unemployment due to force majeure is accessible to all employees of the employer who is forced to temporarily shut down (for reasons such as a flood or fire). When the temporary unemployment is requested because of economic conditions, only employees with a sufficient contribution record are eligible.

Temporary unemployment – COVID-19 uses a far broader definition of force majeure and a simplified application procedure, causing most employees from impacted employers to be eligible (RVA, 2020b). In addition, the benefit was increased, from 65 to 70% of the previous wage (up to a ceiling of 2754.76 euro), and with a daily supplement of 5.63 euro. The daily benefit ranges between a minimum of 55.59 euros and a maximum of 74.17 euros. Benefits are paid out according to a 6-day work week. A withholding tax for the personal income tax of 26.75% is withheld at the base. The temporary unemployment benefit can be combined with continued part-time employment. The benefit only depends on the previous monthly wage and the number of days of unemployment. Sectoral or employer-specific supplements are possible (RVA, 2020c). In April 2020, 1,170,461 individuals filed an application for the system (in contrast to a total of 104,404 cases in April 2019). Around 40% of these temporarily unemployed were 20 days or more in the system, while 16% were in the system for less than 6 days (Working Group Social Impact COVID-19, 2020). The budgetary cost of the system for this month amounted to 1.308 billion euro.

Moreover, the bridging right for the self-employed was made (far) more accessible during the lockdown. Usually it is only accessible for one year over the entire career, and only in cases of

[3] From September onwards, access to temporary unemployment was tightened, though still nowhere near pre-lockdown regulation.

bankruptcy, a collective debt procedure, force majeure and economic difficulties (i.e. a very low income in the last year of self-employed activity) (Sociale zekerheid zelfstandige ondernemers, 2020). Due to COVID-19, access was broadened to all forced closures in the framework of the lockdown, and to all self-employed who voluntarily shut down their businesses for at least 7 consecutive days because their activity was not profitable due to COVID-19. The contributory condition was relaxed. The premium amounts to 1291.69 euros per month for self-employed persons without dependent family members and 1614.10 euros for those with dependent family members (amounts for those whose self-employment activity is the main one or the secondary activity with a yearly income of minimum 13993.77 euros). Amounts are halved for those self-employed whose activity is a secondary one and whose yearly income ranges between 6996.89 euros and 13993.77 euros (Agentschap innoveren en ondernemen, 2020). The benefit will be taxed in the personal income tax at 16.5%, or included in the general tax base, whichever is more favourable. 405,231 self-employed filed for this bridging right in April, only 9,701 of them applying for the partial premium (communication with RSVZ).

4 The socio-economic impact of COVID-19 in Belgium

Federal institutions started to trace the socio-economic impact of the COVID19 crisis as soon as they could, using the scarce data that was available. Our own research consortium COVIVAT also started monitoring the socio-economic impact of the lockdown and the government response from an early stage. As data were lacking, research for Belgium so far centred on 1) non-probability surveys among employers, local welfare agencies and other relevant actors, such as food banks; 2) tracing of the administrative statistics on support measures recipiency; and 3) tracking (the characteristics of) the most affected sectors and the employees who work there, or a combination thereof.

COVIVAT policy note 1 for instance reports on the findings of two surveys fielded immediately after the start of the lockdown in local welfare agencies and in food banks (De Wilde, Hermans, & Cantillon, 2020). Both institutions report an increased demand for their services. The federal Public Planning Service Social Integration (POD MI) implemented a parallel survey among local welfare agencies, aimed at quickly gathering information on the number and characteristics of new claimants at the local welfare agencies. The results show that local welfare agencies do report an increase in new claims, and this from a clientele that previously did not resort to help, such as freelance workers (POD Maatschappelijke Integratie, 2020).

The National Bank of Belgium coordinates together with the Federation of Enterprises in Belgium (VBO) a survey among enterprises and the self-employed in order to track the economic impact of the unfolding of the COVID crisis (National Bank of Belgium, 2020). Table 1 presents three indicators based on this survey to show which sectors have been affected most severely by the lockdown. These indicators are (1) loss of revenue as compared to the previous year, (2) the share of the temporary unemployed and (3) the risk of bankruptcy as reported by respondents (see also COVIVAT policy note 2). The most strongly affected sectors, as in other countries, are accommodation and food service activities, the arts, entertainment and recreation sector and the non-food retail sector, with around or over 80% of firms reporting loss of revenue and with over 70% of employees on temporary unemployment in the month of April. Firms in these sectors also reported the highest share of expected bankruptcy. Indicators are lower for the medium affected sectors, but still substantial, with e.g. almost half of employees on temporary unemployment in the transportation and storage sectors. Often the lockdown was less severe for these sectors, with e.g. an earlier restart of activities in the construction sectors. Least affected sectors include retail food, as these shops did not close during the lockdown.

Table 2: Economic Impact per sector (in %, ranked on the basis of loss of revenues)

	Loss of revenue compared to previous year	Share of temporary unemployed	Risk of bankruptcy	Number of employees
Source	(%) ERMG*	(%) ERMG*	(%) ERMG*	(x1000) RSZ**
Strongly affected sectors:				
Accommodation, food service activities	-88	83	19	117
Arts, entertainment, recreation	-85	80	26	39
Trade - Retail non-food	*-79*	*71*	*11*	*145*
Medium affected sectors:				
Transportation and storage	-48	49	15	235
Trade***	-47	40	8	497
Trade – wholesale	*-47*	*35*	*7*	*243*
Construction	-42	30	5	207
Manufacturing	-28	21	8	531
Real estate, Prof., Scient. & Admin. support	-24	21	8	617
Slightly affected sectors:				
Information & communication	-21	12	8	111
Agriculture	-17	3	5	30
Fin. and insurance activ	-12	3	1	119
Trade - Retail food	*-4*	*9*	*7*	*108*
Education				397
Public Administration				466
Care				560
Other				77
Overall	*-33*	*28*	*8*	*4003*

* Survey ERMG uses another division of sectors. Specific sectors have been aggregated into categories as above, with number of employees as weighting factor. ** Share of unemployed is number of temporary unemployed on 21 April (RVA) divided by number of employees in third quarter 2019 (RSZ). *** Division of Trade sector (NACE-sectors 45, 46 & 47): Wholesale includes all employees in NACE-sectors 45 & 46, retail food encompasses 43% and non-food 57% of employees in NACE-sector 47 (Steunpunt Werk).
Source: RSZ, ERMG, Steunpunt Werk

The Working Group Social Impact (WGSI) of the COVID-19 crisis, under the auspices of the Federal Public Service (FPS) Social Security, regularly updates a report that summarizes all known currently available administrative data on support measure recipients and available labour market indicators. Through an intensive collaboration between different administrations, they have succeeded in sketching the impact of the first three phases of the crisis, the lockdown phase, the gradual reopening in May – June, and the stability phase in the Summer. We focus here on their findings on the socio-economic impact of the lockdown in March and April (Working Group Social Impact COVID-19, 2020).

Building on data provided by three social secretariats, the WGSI report shows the impact of the lockdown on the hours worked. They find that labour activity (in terms of total amount of work hours in the private sector) reduced by nearly 60%. This concurs with findings from the Belgian Statistical Office (Statbel) based on data drawn from the quarterly Labour Force Survey (LFS): 44.2% of the working population indicates that they worked less hours than usual. This reduction in labour volume was mainly mitigated by the extension of the temporary unemployment scheme (see also Lens, Marx, & Mussche, 2020). Combining the information of the social secretariats with administrative data from *inter alia* the unemployment office, the report tracks the daily increase in temporary unemployment applications. The administrative data furthermore allow to track the number of days of temporary unemployment and to show the distribution by gender and sector. Men are more often temporary unemployed than women. The sectors of construction (63.8%), food service activities (72%) and art, amusement and recreation (51%) were the sectors with the highest levels of temporary unemployment, as well as with the highest numbers of days of temporary unemployment. Importantly, the administrative data show that the closure also impacts a number of people that will likely not appear in the temporary unemployment and bridging right statistics. Interim work substantially reduced. Employment of so-called flexi-jobbers[4] in the food services came to a halt, whereas also in other sectors this type of employment fell back. There are indications that a similar trend occurred for student employment, but as employers usually declare student employment well before the actual dates, the administrative data are less likely to reflect the real reduction. For these groups, it is unclear whether they had access to support schemes. The WGSI report also gauges the impact of the lockdown on the self-employed by scrutinizing the administrative data on bridging right applications and payments and the demands for postponed payment of social contributions. Around 50% of the full-time self-employed received a bridging right in the period March – May 2020; 45% of them were mandatorily closed. The self-employed receiving a bridging right are mainly found in the sectors Trade, Free professions and Industry and crafts. The mandatorily closed are mainly found in the Trade sector, whereas those receiving a bridging right due to a voluntary halting of activities for 7 days in a row are mainly found in the other two sectors.

[4] 'Flexijobbers' refers to a specific labour contract type in Belgium, that allows employees with a steady employment of at least 4/5th of regular working time to take-up an additional part-time job under a favourable tax and social insurance regime.

The number of self-employed demanding postponed payment of social contributions increased to 160,000 in April.

Finally, a number of papers have appeared that aim to link the available information on the differential impact between sectors with microdata in order to gauge the likely profile of the employees and self-employed impacted by the lockdown. Decoster et al. (2020) find that in the most severely hit sectors, people with a vulnerable socio-economic profile are overrepresented. They are more often young, low educated, single, part-time and temporary workers, tenants and self-employed. Also, wages in these sectors are generally lower. Horemans, Kuypers, Marchal, and Marx (2020) report similar findings, based on analyses of the EU-SILC and the HFCS data. They show that vulnerable workers in the hardest hit sectors have fewer assets to bridge periods of income loss, increasing their risk of becoming poor. In addition, they highlight the precarious situation of the vulnerable workers already before the start of the COVID-19 lockdown.

Our knowledge on the adequacy and the distributional impact of the support measures remains so far limited. The National Bank of Belgium has published a note on the net incomes and the income replacement levels guaranteed by the temporary unemployment scheme for a number of hypothetical individuals (NBB, 2020). They found that gross replacement rates for low wage earners were rather high on a monthly basis, but due to the application of the uniform withholding tax of 26.75%, the net replacement rate was only just above 70%. Hypothetical individuals with an average income enjoyed a net replacement rate of just under 70%. On an annual basis, the progressive personal income tax limits the income loss. Also the Federal Planning Bureau analyses hypothetical household simulations showing the income loss for typical households on an annual basis, under different assumptions of temporary unemployment duration, previous wage and sectoral supplements (Thuy, Van Camp, & Vandelannoote, 2020). They find that replacement rates on an annual basis are generally higher than 90% for a limited unemployment duration (with a return to the previous wage level after the unemployment spell). These replacement rates decrease as the unemployment spell lengthens. Due to the maximum benefit, they are also lower for high wage earners. The COVIVAT consortium (Cantillon, Marchal, Peeters, Penne, & Storms, 2020; Marchal, Penne, & Storms, 2020) has released simulation results for hypothetical households that became temporary unemployed. Rather than focusing on replacement rates, these papers compared the guaranteed net (monthly) disposable incomes with reference budgets and the at-risk-of-poverty threshold in order to gauge the extent to which they protect against poverty. Both COVIVAT-studies found that single-person households, as well as households in which an additional income from employment is present are well protected by the temporary unemployment extension. One temporary unemployment benefit, even for those who previously earned a relatively high wage, does not suffice to protect against poverty when there are children or other dependents present in the household. An annual assessment would likely mitigate these findings to some extent. Still, for low income families, the monthly income loss is likely to be highly relevant.

The actual impact of these schemes on poverty rates and on the overall income distribution remains so far unknown. Linked administrative data that show the household income before and after the onset of the lockdown and the support measures are not yet available. The income concept of net disposable household income that is used in the literature to gauge distributional consequences is not available in the register data included in the *Datawarehouse Labour Market & Social Protection* (DWH LM&SP). The Datawarehouse interlinks all register data from the different social security institutions in Belgium, but includes only gross (taxable) incomes. Moreover, although basic administrative data on the COVID-19 impact was made rapidly available, not all relevant information is currently available to observe the distributional consequences of the COVID-19 shocks on incomes.

Hence, the current approach to track the distributive impact of the socio-economic lockdown and the policy measures is to “simulate” the shock on already available microdata. The Joint Research Centre of the European Commission (JRC) has published in August a technical report on the cushioning impact of fiscal measures in the EU Member States throughout the shock based on the EU-SILC and EUROMOD. They reweighted the EU-SILC and fiscal measures based on the European Commission’s Spring forecast, and found fiscal measures to have a large role in cushioning the shock. For Belgium, they report a 4% decrease in total equivalised household incomes in a no-policy scenario, an impact that is more than halved by policy measures. A 3 ppt increase in anchored poverty decreases to less than 1 ppt thanks to the fiscal measures taken (Almeida et al., 2020).

In what follows, we present our own nowcasting exercise on the 2018 EU-SILC sample, aiming to show the impact on monthly available incomes and their distribution in the month of April. We present our approach in order to obtain these monthly outcomes. In following papers, we aim to further track the distributional impact of the COVID-19 crisis for subsequent months.

5 Methodology

The empirical analysis is conducted on the Belgian data of the European Union Statistics of Income and Living Conditions (EU-SILC), which is the underlying database of the tax-benefit microsimulation model EUROMOD. The EU-SILC is a yearly survey carried out in all EU member states on the income and living conditions of private households. It contains a representative sample of private households in each country.

One of the challenges of our exercise is that the most recent data of EU-SILC refer to 2018, and do not include any information on the impact of COVID-19 on individuals' labour status or income. We remedy this through techniques of nowcasting, which we introduce in section 5.1, where we also describe the dataset that is used for this purpose (the *Corona Study*) (Universiteit Antwerpen & Universiteit Hasselt, 2020). This data is used to predict changes in labour market status due to the COVID-19 shock, as discussed in section 5.2. In section 5.3 we describe in detail how the outcomes of these predictive models are used to simulate changes in labour market status for employees and self-employed in the EU-SILC 2018 database. The nowcasted data are then used in combination with the microsimulation tax-benefit model EUROMOD to estimate the impact of both the change in earnings as well as of the policy responses; in section 5.4 we explain the changes made in EUROMOD to present results on a monthly basis, as well as the simulated scenarios for which results are presented in the empirical analysis in section 6.

5.1 Nowcasting the impact on employment and earnings

The studies for other European countries mentioned earlier used various techniques to model the effect of the labour market shock due to COVID-19. We can roughly distinguish two approaches. On the one hand, Figari and Fiorio (2020) start from available macroeconomic statistics on the impact of the lockdown in Italy across different economic sectors, and then randomly select individuals in the EUROMOD dataset working in these specific sectors who are assumed to lose their earnings (both for self-employed and employees in the private sector). Beirne et al. (2020) take a similar approach. On the other hand, Brewer and Tasseva (2020) use microeconomic information from the Understanding Society COVID-19 study conducted by the University of Essex, to estimate two multinomial logit models (for employed and self-employed respectively), in order to predict for each individual in the EU-SILC dataset the probability of being affected by the shock. Bronka et al. (2020) use Labour Force Survey data to arrive at similar probabilities. In addition, the authors first use an input-output model to differentiate the employment effect of the lockdown by industry on a more aggregate level.

In our study, we use a combination of these two approaches. For our analysis, we need to know which individuals are affected in their employment situation and earnings, i.e., who became (temporary) unemployed in the case of employees and who resorted to the bridging right for self-employed. As discussed, this information in not (yet) available in existing survey data such as the EU-SILC, which is the standard source for distributive analysis at the micro level in Belgium. Hence, we developed a predictive model of changes in the employment status of individuals, which allows the identification of respondents in EU-SILC who are likely to suffer from temporary unemployment of other changes in their employment status, even if this cannot be observed directly.

To this end we have used the Corona Study, a Belgian nonprobability online survey organised by the University of Antwerp, Hasselt University and KU Leuven. It has been specifically designed to evaluate how households are affected in a medical, economic and social sense by and responding to the COVID-19 outbreak and lockdown measures, to get a better understanding of the further evolution of the epidemic and to monitor the overall well-being of the population. The survey was initially organised on a weekly basis. The data used here are those of the seventh wave, which was fielded on April 28th and has a sample size of 119,634 respondents. There are two important caveats about the data collected by the Corona Study. First, the survey makes use of nonprobability sampling, which means that the sample is not established by random selection based on determined probabilities, but rather consists of all individuals who are willing to participate in the study. We can therefore not know whether the sample is representative of the Belgian population at large, which hinders inference from the sample to the general population. Second, while the Corona Study collects information on whether respondents experienced a change in income due to COVID-19, it does not include data on household income before the pandemic nor the magnitude of the potential change in income.

The information included in this dataset is used to model the probability of becoming temporarily unemployed (or, similarly, taking up the bridging right for the self-employed) by taking into account a set of individual and household characteristics. The estimated model can in turn be used to impute predicted temporary unemployment in the Belgian EU-SILC dataset of 2018, which allows the estimation of the distributive effects of COVID-19 and both support measures.

It is important to note that, given the potential unrepresentative character of the Corona Study, it is possible that the predictive model systematically under- or overestimates the probability of experiencing a labour market shock, which ultimately results in too few or too many individuals being classified as such in the EU-SILC dataset. To remedy this, we make use of aggregate statistics provided by RVA and RSVZ on the share of employees that have become temporary unemployed and the share of self-employed that have resorted to the bridging right, respectively.[5] These data allow us to reweigh the estimated probabilities; as a result, the number of individuals classified as experiencing a labour shock will be calibrated to the macroeconomic situation.

[5] The data are retrieved on November 2020

5.2 Estimation of the nowcasting model

We estimate two binomial logit models, one for employees and one for self-employed, of the following form:

$$L_i = \log\left(\frac{P(Y_i = 1)}{P(Y_i = 0)}\right) = \log\left(\frac{\pi_i}{1 - \pi_i}\right) = \beta_1 X_i, \tag{1}$$

With:

- i the unit of observation;
- Y_i is the labour status of individual i after the COVID-19, which takes the value of 0 is the labour status remain unchanged and 1 otherwise;
- π_i the probability of individual i having an unchanged labour status;
- $X_i = (1, x_{i,1}, \dots, x_{i,t}, \dots, x_{i,T})$ a set of $T + 1$ covariates of an individual i, including a constant term; and
- $\beta_1 = (\beta_{1,0}, \beta_{1,1}, \dots, \beta_{1,t}, \dots, \beta_{1,T})$ a set of $T + 1$ parameters, one associated with each covariate t.[6]

It is important to note that the logistic regression formulated above expresses the average propensity of experiencing a change in labour status for individual i with covariates X_i. The individual propensity of individual i will be $\beta_1 X_i + e_{i,1}$. The random term $e_{i,1}$ captures factors which influence individual i's propensity of experiencing a change in labour status, but which are not included in the model. In logit models, this random term is assumed to follow an Extreme Value I distribution.

We estimate the probabilities for each state based on the data collected in the 7th wave of the Corona Study. For our analysis, we do not include all 119,634 respondents, but only those that were active on the labour market (and not unemployed) before the COVID-19 outbreak. We include a total of 67,752 respondents, which are divided into two subsamples for the estimation of the two logit models: one subsample of 62,260 employees and one subsample of 5,492 self-employed individuals.

For determining the respondents' labour status Y, the primary question of interest is *'Is your current employment situation different from before the Corona crisis (since 13 March)?'*. There are five possible answers: (1) *No*, (2) *Yes, temporary unemployed,* (3) *Yes, unemployed,* (4) *Yes, I had to close my own business*, (5) *Yes, new job*. Based on this question, we construct the status variable Y_i as follows (see ***Table 3***).

For an employee, the two possible states are:

[6] Note that binomial logit models express the propensity of $Y = 1$ relative to the propensity of $Y = 0$; hence, they are normalised with $\beta_0 = 0$. Considering that a binomial model only evaluates two states, the subscript of β is therefore redundant. However, we keep the subscript for clarification purposes of our later steps.

- $Y_i^{(ee)} = 0$: Unchanged status compared to March 13, still employed (answered *'No'* to our question of interest);
- $Y_i^{(ee)} = 1$: temporary unemployed (answered *'Yes, temporary unemployed'* to our question of interest).

For a self-employed individual, the two possible states are:

- $Y_i^{(se)} = 0$: Unchanged status compared to March 13, and not making use of bridging right (answered *'No'* to our question of interest);
- $Y_i^{(se)} = 1$: Receiving bridging right (answered *'Yes, temporary unemployed'* or *'Yes, I had to close my own* business' to our question of interest).[7]

Table 3: Subsamples of interest

		Employees	Self-employed
Status	Unchanged	53,540	3,104
	Temporary unemployed	8,720	-
	Bridging right	-	2,388
Total		62,260	5,492

Source: Authors' calculations based on *Corona Study*.

We include six explanatory variables and a constant term:

- $Female$: dummy variable for sex of the respondent;
- Age: dummy variable indicating whether the respondent is 35 years or younger;
- $Education$: dummy variable indicating whether the respondent's highest level of education completed is secondary education or lower;
- $Parttime$: dummy variable indicating whether the respondent worked part-time before the pandemic;
- $Occupation$: main activity of the respondent before the pandemic, categorised as manager, white-collar worker, blue-collar worker or self-employed;
- $Sector$: sector in which the respondent was active before the pandemic according to NACE 1.

Some descriptive statistics about these explanatory variables are included in Table 4. The distribution of demographic characteristics reinforces the concerns of the unrepresentative character of the Corona Study; the sample disproportionately consists of women (76% for employees and 58% for self-employed), younger (67% for employees and 77% for self-employed) and high-educated (80% for employees and self-employed). Moreover, since the distribution of respondents across sectors is very uneven, certain sectors contain only a (very)

[7] For self-employed, both answer possibilities *'Yes, temporary unemployed'* or '*Yes, I had to close my own business'* will be considered as the respondent having received a bridging right. In theory, self-employed are not eligible for temporary unemployment benefits, which would make this answer possibility redundant for them. However, we choose to not emit self-employed who have reported to have become temporary unemployed, as the answer possibility has possibly been interpreted by self-employed as having to halt their activities due to force majeure, which would mean they are eligible for the receipt of a bridging right.

low number of observations. This increases the degree of uncertainty of our estimated coefficients and is an important limitation of the presented methodology.

Table 4: Descriptive statistics of the subsamples of interest in Corona Study

		Employees	Self-employed
Sex	Male	16,522	2,316
	Female	45,738	3,176
Age	> 35	41,551	4,244
	<= 35	20,709	1,248
Education	High-educated	49,938	4,408
	Low- or middle-educated	12,322	1,084
Sector	Agriculture and forestry	247	110
	Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	7,103	231
	Construction	1,817	745
	Wholesale and retail	3,519	720
	Transport and storage; information and communication	1,596	68
	Accommodation and food service activities	533	312
	Financial and insurance activities	3,156	233
	Real estate; services to businesses	6,732	1,747
	Public administration and defence	7,841	25
	Education	15,062	70
	Human health and social work activities	12,723	880
	Arts, entertainment and recreation; personal service activities	1,931	351
Part-time	Full-time	45,312	4,782
	Part-time	16,948	710
Occupation	Managers	5,402	-
	White-collar workers	54,187	-
	Blue-collar workers	2,671	-
	Self-employed	-	5,492
Total		62,260	5,492

Source: Authors' calculations based on *Corona Study*.

The two logit models and the estimated coefficients are presented in ***Table 5***. To interpret these coefficients more easily, we also present odds ratios. These odds ratios are calculated by taking the exponent of the regression coefficients; they express the ratio of two odds corresponding to a specific value of an explanatory variable and the reference group.

Table 5: Change in labour market status for employees (compared to March 13, coefficients of two estimated binomial logit models and odds

	β_1 coefficients		Odds ratios	
	Employees	**Self-employed**	**Employees**	**Self-employed**
Female	0.312***	0.266***	1.366	1.305
	(0.032)	(0.068)	(0.436)	(0.088)
35 and younger	0.127***	0.031	1.135	1.031
	(0.029)	(0.077)	(0.328)	(0.080)
Low- or middle-educated	0.469***	0.764***	1.598	2.147
	(0.033)	(0.086)	(0.052)	(0.184)
Part-time employment	0.247***	-	1.280	-
	(0.032)		(0.041)	
Sector (reference: A. Agriculture and forestry)				
Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	0.760***	0.794	2.138	2.212
	(0.204)	(0.426)	(0.436)	(0.943)
Construction	1.732***	1.786***	5.652	5.966
	(0.207)	(0.380)	(1.172)	(2.268)
Wholesale and retail	2.204***	3.327***	9.061	27.855
	(0.205)	(0.379)	(1.853)	(10.542)
Transport and storage; information and communication	0.526*	0.337	1.692	1.401
	(0.213)	(0.568)	(0.360)	(0.795)
Accommodation and food service activities	4.229***	4.938***	68.649	139.491
	(0.257)	(0.419)	(17.667)	(58.419)
Financial and insurance activities	-0.847***	0.896*	0.429	2.450
	(0.221)	(0.423)	(0.095)	(1.037)
Real estate; services to businesses	1.187***	1.910***	3.277	6.753
	(0.204)	(0.376)	(0.667)	(2.541)
Public administration and defense	-2.122***	1.742**	0.120	5.709
	(0.225)	(0.601)	(0.027)	(3.433)
Education	-0.999***	3.275***	0.368	26.443
	(0.206)	(0.446)	(0.076)	(11.778)
Human health and social work activities	-0.438*	3.751***	0.645	42.564
	(0.204)	(0.380)	(0.132)	(16.163)
Arts, entertainment and recreation; personal service activities	1.217***	3.582***	3.377	35.945
	(0.208)	(0.389)	(0.703)	(13.977)
Occupation (reference: Manager)				
White-collar workers	0.198***	-	1.219	-
	(0.045)		(0.055)	
Blue-collar workers	1.164***	-	3.203	-
	(0.065)		(0.209)	
Self-employed	-	-	-	-
Constant	-2.880***	-3.152***	0.056	0.043
	(0.207)	(0.377)	(0.012)	(0.016)
Observations	62,260	5,492	62,260	5,492
McFadden Pseudo R2	0.2317	0.2076		

Source: Authors' calculations based on *Corona Study*.

5.3 Simulation with binomial models

5.3.1 *Estimation of probabilities in EU-SILC*

In the EU-SILC 2018 survey data, we can identify two subsamples for which we estimate probabilities for a change in their labour market status: one with individuals with labour market status as employee and one with individuals with labour market status as self-employed. The probability to a change in labour status is calculated for all respondents within these groups, using the model estimated with the Corona Study. Table 6 describes the two subsamples of interest in EU-SILC 2018. The distribution of demographic variables in EU-SILC 2018 differs significantly from that of the Corona Study, with a more equal distribution across gender, age groups and education levels. However, EU-SILC 2018 has a considerably smaller sample size compared to the Corona Study, which further exacerbates the problem of limited observations in certain sectors.

Table 6: Descriptive statistics of subsamples of interest in EU-SILC 2018

		Employees	Self-employed
Sex	Male	2354	475
	Female	2267	261
Age	> 35	3208	583
	<= 35	1413	153
Education	High-educated	2247	381
	Low- or middle-educated	2125	329
	Unknown	249	26
Sector	Agriculture and forestry	8	39
	Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	643	36
	Construction	220	91
	Wholesale and retail	440	99
	Transport and storage; information and communication	397	43
	Accommodation and food service activities	106	51
	Financial and insurance activities	165	20
	Real estate; services to businesses	430	152
	Public administration and defence	538	5
	Education	573	20
	Human health and social work activities	649	94
	Arts, entertainment and recreation; personal service activities	184	31
	Unknown	268	55
Part-time	Full-time	3392	612
	Part-time	1229	91
	Unknown	0	33
Occupation	Managers	295	-
	White-collar workers	3174	-
	Blue-collar workers	1107	-
	Self-employed	-	734
	Unknown	45	2
Total		4621	736

Source: Authors' calculations based on *EU-SILC 2018*.

5.3.2 *Determination of predicted labour status*

Once the estimated probabilities are calculated, we need to determine the predicted labour status $\hat{Y}_i$ of each respondent i. We determine that an individual i is predicted to have experienced a change in labour status, thus $\hat{Y}_i = 1$, if their individual propensity for a change in labour status is greater than or equal to their individual propensity for an unchanged labour status. Hence, individual i will be assigned $\hat{Y}_i = 1$ if

$$\beta_1 X_i + e_{i,1} \geq \beta_0 X_i + e_{i,0}. \qquad (2)$$

Recall that logit models are normalised with $\beta_0 = 0$. The condition therefore simplifies to

$$e_{i,1} - e_{i,0} \geq -\beta_1 X_i. \qquad (3)$$

As mentioned, the terms $e_{i,1}$ and $e_{i,0}$ follow an Extreme Value I distribution. As a result, the difference between both is logistically distributed.[8] It thus suffices to draw only one random term u_i from the logistic distribution, and determine $\hat{Y} = 1$ if

$$u_i \geq -\beta_1 X_i. \tag{4}$$

Furthermore, it can be noted that, since u_i is random, the occurrence of $\hat{Y}_i = 1$ is random too. The probability that this occurs, π_i, is therefore

$$\pi_i = P(u_i \geq -\beta_1 X_i). \tag{5}$$

Since u is logistically distributed, and the logistic distribution is symmetric around zero, this equals to

$$\pi_i = 1 - L(-\beta_1 X_i) = L(\beta_1 X_i). \tag{6}$$

Applying the definition of the logistic regression $L(.)$,

$$\pi_i = \frac{\exp(\beta_1 X_i)}{1 + \exp(\beta_1 X_i)}. \tag{7}$$

5.3.3 *Rescaling of estimated probabilities*

The Corona Study is likely to be unrepresentative of the general population due to its nonprobability sampling. As a result, the probabilities estimated with the logistic model be systematically under- of overestimated, which would lead to too little or too many respondents of EU-SILC being identified as having experienced a labour market shock, i.e. being assigned $\hat{Y}_i = 1$. To remedy this, the estimated probabilities are rescaled such that they reflect the macroeconomic situation as closely as possible.

First, we calculate the average occurrence Π_G. The average occurrence expresses the share of employees (self-employed) that are identified as becoming temporary unemployed (receiving the bridging right) in EU-SILC according to the original predicted probabilities, within a specific sector, gender and age group. G indexes the various combinations these variables can take. The average occurrence Π_G is calculated as follows:

$$\Pi_{G,1} = \sum_{i \in G} \omega_i \pi_{i1}, \tag{8}$$

where ω_i is the normalised population weight of i (normalised means here that the sum of the weights of the observations i belonging to group G should equal one).

Second, the target occurrence z_G is calculated. The target occurrence z_G expresses the actual share of individuals within group G that have experienced a change in labour status, according

[8] The logistic distribution is defined as $\mathrm{L}(.) = \frac{\exp(.)}{1+\exp(.)}$.

to macroeconomic statistics. For its calculation, we rely on data provided by RVA, RSZ and RSVZ.[9]

For employees, the target occurrence $z_G^{(ee)}$ is defined as the share of employees in group G that were temporary unemployment in April and is calculated as follows:

$$z_G^{(ee)} = \frac{N_G^{TU}}{N_G^{E}}, \qquad (9)$$

with N_G^{TU} the absolute number of temporary unemployed employees in group G in April (as derived from the website of RVA)[10] and N_G^{E} the absolute number of employees in group G at the end of the first quarter of 2020 (as derived from the website of RSVZ)[11].

For the self-employed, RSVZ has provided us with data to calculate $z_G^{(se)}$, defined as the share of self-employed in primary activity in group G that have received a bridging right in April:

$$z_G^{(se)} = \frac{N_G^{BR}}{N_G^{SE}}, \qquad (10)$$

with, for each group $_G$, N_G^{BR} the number of self-employed in primary activity that have received a bridging right in April and N_G^{SE} the total number of self-employed in primary activity at the end of March 2020.

Table 7 and Table 8 respectively present the average occurrence Π_G and the target occurrence z_G for all groups G. Two important observations can be made. First, the target occurrence generally exceeds the average occurrence for a group G, with the exception of the sectors 'Accommodation and food services' and 'Public administration and defence'. This means that the probabilities estimated with the logistic model are generally underestimated, which further motivates the rescaling of probabilities. Second, when looking at the target occurrences, there is a clear gender and age effect; younger individuals and men are more likely to be impacted than older individuals and women, respectively. While a similar age effect can be found across the average occurrences as well, the gender effect is reversed.[12]

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[9] Consulted on November 2020

[10]https://www.rva.be/nl/documentatie/statistieken/tijdelijke-werkloosheid-wegens-coronavirus-covid-19/cijfers

[11]https://www.rsz.fgov.be/nl/statistieken/publicaties/loontrekkende-tewerkstelling

[12] The gender and age effect in the average occurrence can also be retrieved from Table 5, where the estimated coefficients corresponding to being 35 years old or younger and being female are indicated as significantly positive.

Table 7: Overview of average occurrence in the sample

	Employees				Self-employed			
	Female, old	**Female, young**	**Male, old**	**Male, young**	**Female, old**	**Female, young**	**Male, old**	**Male, young**
Agriculture and forestry	9,60%	11,80%	-	21,85%	9,58%	-	7,90%	8,66%
Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	26,16%	27,55%	24,31%	29,84%	19,06%	11,30%	14,74%	16,39%
Construction	46,61%	41,24%	53,75%	58,51%	34,99%	25,26%	32,50%	32,35%
Wholesale and retail	56,73%	59,90%	52,79%	56,71%	69,10%	75,05%	65,93%	69,10%
Transport and storage; information and communication	19,02%	20,19%	19,79%	21,26%	11,13%	7,47%	7,86%	9,08%
Accommodation and food service activities	92,11%	92,38%	89,65%	89,56%	93,09%	92,83%	91,84%	91,36%
Financial and insurance activities	4,88%	4,78%	3,26%	3,67%	12,03%	12,36%	10,53%	-
Real estate; services to businesses	41,97%	38,54%	29,65%	27,88%	28,02%	30,97%	24,25%	27,26%
Public administration and defence	2,13%	1,77%	1,39%	1,56%	-	24,74%	19,62%	-
Education	4,50%	4,17%	3,08%	3,16%	60,38%	60,35%	59,07%	-
Human health and social work activities	10,47%	9,92%	7,42%	7,78%	72,11%	74,33%	65,77%	62,25%
Arts, entertainment and recreation; personal service activities	33,07%	39,36%	24,67%	29,23%	77,57%	80,52%	70,25%	69,52%

Source: Authors' calculation based on *EU-SILC 2018*

Table 8: Overview of target occurrence

	Employees				Self-employed			
	Female, old	**Female, young**	**Male, old**	**Male, young**	**Female, old**	**Female, young**	**Male, old**	**Male, young**
Agriculture and forestry	11.37%	10.90%	10.74%	8.63%	21.36%	50.67%	23.67%	37.68%
Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	38.08%	38.49%	41.25%	45.71%	43.01%	60.51%	54.16%	63.83%
Construction	59.15%	65.17%	61.92%	68.21%	48.34%	59.81%	59.71%	70.20%
Wholesale and retail	42.22%	51.31%	46.10%	53.81%	48.77%	68.37%	53.45%	69.80%
Transport and storage; information and communication	23.11%	29.70%	23.46%	25.59%	66.35%	81.94%	73.29%	85.46%
Accommodation and food service activities	73.96%	83.22%	77.36%	84.18%	39.63%	53.66%	50.78%	57.88%
Financial and insurance activities	10.97%	17.28%	7.86%	15.78%	28.23%	54.95%	30.84%	54.52%
Real estate; services to businesses	52.58%	49.60%	33.26%	35.80%	42.92%	53.19%	40.01%	52.25%
Public administration and defence	0.15%	0.21%	0.06%	0.06%	0.00%	0.00%	0.00%	0.00%
Education	3.19%	2.71%	3.75%	3.60%	55.83%	36.89%	68.72%	47.06%
Human health and social work activities	10.70%	10.21%	21.16%	19.13%	50.37%	78.00%	58.66%	87.40%
Arts, entertainment and recreation; personal service activities	31.79%	52.16%	32.10%	49.17%	61.72%	75.05%	63.31%	74.14%

Source: Authors' calculation based on *RVA, RSVZ, RSZ* data

Once the average occurrence Π_G and the target occurrence z_G are calculated, we can reweigh the estimated probabilities. The rescaling factor s_G is defined as:

$$s_G = \frac{z_G}{\Pi_G}. \tag{11}$$

The estimated probabilities π_i of an individual i belonging to group G will be thus be rescaled to $s_G\pi_i$.

Finally, the condition for determining individuals' labour status needs to be adapted, to take into account their rescaled probabilities. More specifically, with the individual probabilities being rescaled to $s_G\pi_i$, individual i will be assigned $\hat{Y}_i = 1$ if

$$u_i < \ln(s_G\pi_i) - \ln(1 - s_G\pi_i), \tag{12}$$

with u_i being a random term drawn from the logistic distribution. The calculation of the new identification condition is documented in Appendix (9.2).

5.3.4 *Missing values*

As can be seen from Table 6, there are missing values for some of the variables. If values of explanatory variables are missing, the estimated probabilities cannot be calculated for a respondent and the respondent cannot be classified to a state on the basis of the simulation technique described above. Omitting respondents with missing values from our nowcasting model would result in an underestimation of temporary unemployment and the receipt of a bridging right, which we deem highly undesirable considering that we are performing a poverty and inequality analysis. Therefore, we opt for a random allocation of respondents with missing values in which we take the overall share of temporary unemployed or recipients of a bridging right into account when the value of the sector is unknown. In case gender, age and sector is known but one of the other explanatory variables is unknown, we use the target shares as presented in Table 8. More specifically, employees with missing values will be assigned to the state of temporary unemployment with a chance of 29.57% and self-employed with missing values will be assigned to the state of receiving a bridging right with a chance of 51.88%.

5.3.5 *Validation of nowcasting results*

In the following tables, we present the results of the nowcasting exercise in EU-SILC 2018 and compare them to the macroeconomic data provided by RVA, RSZ and RSVZ. Table 9 presents a comparison of the target occurrence z_G and the simulated occurrence of temporary unemployed amongst employees, per group G. Table 10 presents the same comparison for the receipt of bridging rights amongst self-employed. Due to the rescaling of the probabilities, which can be seen as a calibration to the macroeconomic data, the simulated occurrence approaches the target occurrence asymptotically, i.e. if the sample is sufficiently large. However, as some groups G only have a (very) limited number of observations, disparities between the two may arise. Table 11 presents the percentage of temporary unemployment and the receipt of bridging rights across subgroups and compares this percentage to the aggregate statistics. From these tables, it can be concluded that the nowcasting exercise approaches the macroeconomic situation reasonably well. Significant disparities can be found in the sector ‘Agriculture’, which are likely caused by the limited number of observations within the group.

Table 9: Weighted percentage of employees in temporary unemployment

	Female, old			Female, young			Male, old			Male, young			Total		
	Ext. Stat.	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**
Agriculture	11.37%	0.00%	2	10.90%	0.00%	1	10.74%	-	0	8.63%	37.18%	5	10.20%	24.78%	8
Mining, Manifact. And Utilities	38.08%	34.79%	88	38.49%	29.00%	51	41.25%	40.69%	361	45.71%	47.04%	143	41.46%	40.50%	643
Construction	59.15%	75.62%	17	65.17%	63.11%	5	61.92%	57.73%	130	68.21%	64.03%	68	63.96%	61.13%	220
Wholesale and retail	42.22%	37.81%	136	51.31%	63.64%	80	46.10%	46.87%	134	53.81%	56.59%	90	47.29%	49.25%	440
Transport and communication	23.11%	25.50%	63	29.70%	46.61%	28	23.46%	24.17%	205	25.59%	16.67%	101	24.40%	23.97%	397
Hotels and restaurants	73.96%	71.21%	33	83.22%	95.52%	21	77.36%	83.08%	30	84.18%	81.56%	22	79.28%	81.77%	106
Financial intermediation	10.97%	10.03%	57	17.28%	18.53%	17	7.86%	10.21%	72	15.78%	11.26%	19	11.25%	11.14%	165
Real estate and business	52.58%	58.36%	180	49.60%	60.01%	80	33.26%	40.39%	104	35.80%	17.35%	66	44.03%	48.19%	430
Public administration and defense	0.15%	0.00%	208	0.21%	0.00%	63	0.06%	0.00%	204	0.06%	0.00%	63	0.12%	0.00%	538
Education	3.19%	2.95%	278	2.71%	4.29%	119	3.75%	2.37%	128	3.60%	4.55%	48	3.24%	3.25%	573
Health and social work	10.70%	12.12%	361	10.21%	7.06%	154	21.16%	27.28%	94	19.13%	29.15%	40	12.59%	14.48%	649
Other	31.79%	32.64%	64	52.16%	54.26%	26	32.10%	33.10%	71	49.17%	66.26%	23	38.86%	40.95%	184
Total	23.38%	22.02%	1487	28.87%	28.11%	645	31.50%	29.98%	1533	39.13%	34.81%	688	29.57%	27.86%	4353

Source: Authors' calculations based on *EU-SILC* and *RVA, RSZ, RSVZ* data

Table 10: Weighted percentage of self-employed receiving a bridging right

	Female, old			**Female, young**			**Male, old**			**Male, young**			**Total**		
	Ext. Stat.	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**	**Ext. Stat.**	**EU-SILC**	**N**
Agriculture	21.36%	22.24%	12	50.67%	-	0	23.67%	30.41%	26	37.68%	0.00%	1	26.46%	27.43%	39
Mining, Manifact. And Utilities	43.01%	48.50%	7	60.51%	0.00%	1	54.16%	52.59%	22	63.83%	80.15%	6	53.41%	55.74%	36
Construction	48.34%	57.36%	7	59.81%	0.00%	1	59.71%	59.02%	64	70.20%	62.90%	19	61.29%	59.46%	91
Wholesale and retail	48.77%	51.39%	28	68.37%	67.43%	5	53.45%	55.16%	57	69.80%	42.69%	9	53.90%	53.84%	99
Transport and communication	39.63%	100.00%	4	53.66%	100.00%	2	50.78%	41.83%	30	57.88%	50.78%	7	50.48%	48.97%	43
Hotels and restaurants	66.35%	54.59%	18	81.94%	84.74%	6	73.29%	73.50%	19	85.46%	77.37%	8	73.17%	69.62%	51
Financial intermediation	28.23%	44.91%	4	54.95%	71.11%	3	30.84%	21.76%	13	54.52%	-	0	32.04%	33.95%	20
Real estate and business	42.92%	27.99%	34	53.19%	51.88%	19	40.01%	37.04%	76	52.25%	58.03%	23	43.16%	39.82%	152
Public administration and defense	0.00%	-	0	0.00%	0.00%	3	0.00%	0.00%	2	0.00%	-	0	0.00%	0.00%	5
Education	55.83%	66.92%	11	36.89%	0.00%	2	68.72%	82.19%	7	47.06%	-	0	55.93%	68.85%	20
Health and social work	50.37%	47.85%	39	78.00%	63.97%	20	58.66%	57.35%	30	87.40%	89.65%	5	59.90%	56.57%	94
Other	61.72%	74.01%	12	75.05%	83.05%	7	63.31%	87.31%	9	74.14%	100.00%	3	65.03%	81.43%	31
Total	51.96%	45.86%	176	61.99%	66.50%	69	56.84%	48.82%	355	59.94%	64.89%	81	51.88%	51.21%	681

Source: Authors' calculations based on *EU-SILC* and *RVA, RSZ, RSVZ* data

Table 11: Relative share of changed labour status per subgroup

		Employees		Self-employed	
		EU-SILC	External Statistics	EU-SILC	External Statistics
Gender	Male	31.52%	33.95%	51.48%	52.35%
	Female	23.93%	25.10%	50.70%	51.00%
Age	36 and older	26.12%	27.46%	47.88%	49.95%
	35 and younger	31.12%	34.12%	65.11%	60.51%
Sector	Agriculture and forestry	24.78%	10.20%	27.43%	61.29%
	Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	40.50%	41.46%	55.74%	53.90%
	Construction	61.13%	63.96%	59.46%	50.48%
	Wholesale and retail	49.25%	47.29%	53.84%	73.17%
	Transport and storage; information and communication	23.97%	24.40%	48.97%	43.16%
	Accommodation and restaurants	81.77%	79.28%	69.62%	73.17%
	Financial and insurance activities	11.14%	11.25%	33.95%	22.69%
	Real estate; services to businesses	48.19%	44.03%	39.82%	28.27%
	Public administration and defense	0.00%	0.12%	0.00%	0.00%
	Education	3.25%	3.24%	68.85%	55.93%
	Human health and social work activities	14.48%	12.59%	56.57%	59.90%
	Arts, entertainment and recreation; personal service activities	40.95%	38.86%	81.43%	65.03%
Total		27.86%	29.57%	51.21%	51.88%

Source: Authors' calculations based on *EU-SILC* and *RVA, RSZ, RSVZ* data

5.3.6 *Days of temporary unemployment*

For all individuals that are classified as temporary unemployed, we determine the days of temporary unemployment in April in order to calculate their change in labour income. We make use of publicly available data of RVA on how the days of temporary unemployment are distributed per sector. More specifically, the data present the share of temporary unemployed individuals in a sector that belongs to each of the following categories: less than 6 days, 6 to 12 days, 13 to 19 days, 20 to 25 days, and 26 days or more. From this data, we thus know how many temporary unemployed individuals should be assigned to each category per sector.

We do not assign respondents that have become temporary unemployed to a category randomly, as this may lead to respondents being considered to have become temporary unemployed for more days than he or she usually works in a month.

Rather, we take the following approach. First, the maximum amount of days that a respondent is eligible for temporary unemployment is calculated. To this end, the RVA adopts the following formula:

$$\frac{hours\ worked\ per\ month\ \times 6}{standard\ hours\ worked\ per\ week\ in\ sector} \tag{13}$$

We adopt the same formula but, due to data limitations, have to make additional assumptions. Since EU-SILC only contains respondents' average hours of work per week, we assume that one month consists of 4.33 weeks:

$$hours\ worked\ per\ month\ = hours\ worked\ per\ week \times 4.33. \tag{14}$$

Furthermore, we assume that a standard full-time regime consists of 38 hours per week. Consequentially, the maximum amount of days that a respondent can be temporary unemployed is calculated using the formula:

$$\frac{hours\ worked\ per\ week \times 4.33\ \times 6}{38} \tag{15}$$

Once the maximum days of temporary unemployment are calculated, the respondents are ranked in descending order. The respondents with the highest maximum days of temporary unemployment are assigned to the highest category of '26 days or more', until the number of individuals in this category corresponds to that of the data provided by the RVA. The following respondents are assigned to the category '20 to 25 days', until this category is also full. This process is repeated until all respondents are assigned to a category.

Once all respondents are assigned to a category, we need to fix the number of days that each respondent has become temporary unemployed. We choose the maximum of the category to which a respondent belongs. This means that days of temporary unemployment will be put at 6 for respondents in the category 'less than 6 days', at 12 for respondents in the category '6 to 12 days', and so on. Respondents in the category 'more than 26 days' will be considered to have become temporary unemployed for 26 days. Finally, if the days of temporary unemployment assigned to a respondent by the process described above exceeds the maximum amount of days for which he can become temporary unemployed, the former will be replaced by the latter.

5.4 Simulation with microsimulation model EUROMOD

EUROMOD simulates tax liabilities (direct taxes and social insurance contributions) and cash benefit entitlements on the basis of the tax-benefit rules in place and information available in the underlying dataset. The components of the tax-benefit system which are not simulated due to lack of information in the survey data (e.g. on previous employment) and which are used as input for EUROMOD (e.g. for the calculation of contributory benefits), as well as market incomes, are taken directly from the data. EUROMOD is a static model: the arithmetic simulation of taxes and benefits disregards potential behavioural reactions of individuals (see Sutherland and Figari (2013) for further information on EUROMOD in general, and Derboven, Rongé, Van Houtven, and Vanheukelom (2019) for information on the most recent version of the Belgian part). We use the 2018 national version of the EU-SILC data provided by STATBEL. Monetary variables relating to 2017 are uprated in EUROMOD to 2020 price levels, using relevant uprating factors for different income components as described in Derboven et al. (2020). No adjustment is made for changes in population composition between 2018 and 2020, apart from the changes in employment as described in the previous section.

Our aim is to analyse the impact of the shock and to stress-test the tax-benefit system, i.e., in what way does the tax-benefit system protect households and individuals against a macroeconomic shock (see Atkinson, 2009; Fernandez Salgado, Figari, Sutherland, & Tumino, 2014). In line with studies of the current and earlier shocks, we compare different counterfactual scenarios (see e.g. Figari & Fiorio, 2020). Microsimulation techniques are well-suited for this type of analysis, as it combines detailed microdata on households' living standards and other characteristics with a model that can simulate actual and alternative policy measures. The different scenarios can refer to changes in the underlying population characteristics (e.g. loss in earnings), as well as to changes in tax-benefit policy rules (e.g. new benefits for those who lost their earnings), thereby taking account of possible interactions between tax-benefit measures.

We focus on two main counterfactual scenarios, notably the baseline pre-COVID-19 scenario and the simulated post-COVID-19 scenario. The baseline pre-COVID-19 scenario is based on the EU-SILC data for Belgium for 2018 uprated to 2020 price levels and the policy system of 2020.

The post-COVID-19 scenario includes the impact of the shock, as estimated by our nowcasting scenario, as well as the impact of automatic stabilizing policies that were already in place and the discretionary policies that were installed because of COVID-19. In principle, it would be possible to distinguish between the effect of the policies already in place and those that were introduced because of COVID-19, as is done in Brewer and Tasseva (2020). This is, however, not straightforward for the Belgian case, as one of the major policies taken was the extension of eligibility for existing temporary unemployment measures. As we cannot simulate pre-COVID-19 eligibility for temporary unemployment, we decided not to distinguish between already existing and new policies, but show the stabilizing effect of tax-benefit policies as a whole. To show the magnitude of the stabilizing effect of tax-benefit policies, we also show outcomes for an intermediate counterfactual scenario, i.e. one in which we show the impact of losses in earnings due to COVID-19 in April 2020, without compensation through government policy measures. Clearly, this is a purely fictional scenario, as in reality, unemployment benefits and social assistance would have been available for many affected workers. However, this fictional scenario allows us to demonstrate the pure impact on market incomes.

We look at the impact of the shock on a monthly basis, i.e. we compare household disposable income as defined in the baseline (pre-COVID-19) with a counterfactual scenario referring to April 2020, where temporary unemployment was at its peak. This way, the impact will be shown more sharply than in the standard case of using yearly incomes. In principle, EUROMOD calculates annual incomes based on the annual policy systems and annual data.

For our monthly approach, we made two changes.

First, we adapted EUROMOD in order to apply tax benefit measures on a monthly basis. Our policy system combines a number of different logics. Personal income tax liabilities are calculated on annual incomes, social insurance contributions are based on current monthly incomes, means-tested child benefits are calculated on annual income from previous years, while social assistance benefits are based on current income. EUROMOD usually takes the shortcut of applying all policies on annual incomes,[13] as provided by the EU-SILC and further simulated through the EUROMOD policies. Hence, the progressive impact of the personal income tax, with its tax credits and allowances, is immediately included in the calculation of net disposable income. A monthly assessment of incomes could be done by just assuming that the new monthly income is relevant for the entire year. EUROMOD would then calculate the personal income tax, the child benefits and social assistance benefits in line with this lower annual income. This would very likely be a good enough approximation of what happened to monthly incomes in more stable times, i.e. without a shock of the magnitude experienced in Spring 2020. For this paper we took a different approach. Rather than applying the "annualized" EUROMOD policy system on a lower monthly income, assumed to be the same for 12 months, we aimed for an approximation of monthly incomes based on the withholding tax. The withholding tax is an advance levy on monthly employment income, that is assessed against the personal income tax due for the entire year afterwards. In principle, this should be (nearly) equal to the final personal income tax, but since the 2001 personal income tax reform there is some discrepancy as the lower tax liability following from this reform has not been integrated in the withholding tax rules. In addition, for replacement incomes, the usual reductions and allowances are not applied. Instead, a fixed rate is withheld from replacement incomes. This rate can differ substantially from the final personal income tax rate. In times of quickly changing incomes, this difference likely matters for experienced hardship. This is all the more so as replacement incomes could be below the income threshold applied for social assistance eligibility when taking account of the withholding tax, while based on the final personal income tax net replacement incomes would be above this threshold. In reality, social assistance eligibility depends on the actual income in pocket, i.e.,

[13] There are some exceptions. The programming of the workbonus within social insurance contributions for instance does correct the wage variable for the number of months worked, so that it is applied on the best possible approximation of monthly income.

after the withholding tax. Hence, this difference is likely relevant in order to track monthly incomes[14].

Second, we calculated a monthly income distribution based on the annual EU-SILC income data. This means that annual income combinations exist that in principle are exclusive in a given month (e.g. employment income below the minimum wage at full-time employment, wage income combined with unemployment income, …). In addition, and importantly, the temporary unemployment scheme provides benefits that are a percentage of previous monthly incomes, between certain minima and maxima. We calculate the previous monthly income by dividing the annually observed wage income by the number of months in employment. However, if we would only do this in order to calculate the monthly benefits, and leave the income distribution as is (i.e. based on annual incomes), our monthly benefits would be too high in relation to the income distribution. If we would calculate the benefits based on unchanged annual incomes, the applicable minimum benefits would still ensure a relative generosity of the temporary unemployment benefit. Hence, in order to show changes from baseline – shock – policies month by month, we chose to construct a real monthly baseline. The next point describes more fully our approach to build a monthly baseline scenario. Next, we describe the decisions made for the shock and policy scenario.

5.4.1 *Creation of the monthly baseline scenario*

We changed the EUROMOD policies slightly in order to reflect monthly disposable incomes throughout the lockdown. Relevant changes to EUROMOD in this respect were an update of the withholding tax policy and using this adjusted net concept for social assistance eligibility. Other benefits remain based on the annual EU-SILC pre-COVID-19 income, as also in reality, these types of benefits do not react quickly to changes in incomes. Basing these on adjusted monthly incomes or on the current COVID-19-affected income, would likely lead to too high social supplements. In future updates of this paper, we intend to include unforeseeable COVID-19 related policy measures in the months they can at the earliest be expected to be received. Regular (and hence foreseeable) annual benefits or taxes (e.g. new school year supplements, or the Flemish care premium) remain in line with usual practice in EUROMOD, i.e. as the annual value divided by 12, included in each month. There is one important caveat: the withholding tax in principle does not apply to the self-employed, who are expected to predict their total person income tax due, and to transfer each three months an advance of this amount. Shortfalls are punished. For pragmatic reasons, we apply the withholding tax rules for employees also on the self-employed. There is one exception: we tax the bridging right at the final personal income tax rate of 16.5%. As a support measure, the COVID-19

[14] In addition, our aim here is to set up a research infrastructure that allows to track the progression of the lockdown and the impact of the different policy measures taken in order to support incomes. One of these measures is the reduction of the withholding tax on temporary unemployment benefits from 26.75% to 15% in May.

bridging right will be taxed in the personal income tax system at a favorable rate of 16.5%, instead of being included in the overall tax base (except if the latter would turn out to be more advantageous). For this reason, we already apply this tax rate as a withholding tax.

In addition, we changed the annual EU-SILC input data to such an extent that they better reflect the situation in a single month, by aligning the reported labour market status in that month with the related income types. We take for this exercise the labour market status that was reported for March in the EU-SILC in March (2018).[15]

As a general rule, we keep the income that is in line with the main employment status in March (e.g. employment income if mainly employed). Note that this income is the monthly average of all income earned throughout the year, regardless of the number of months than one held this labour market status. In order to let this income reflect the likely monthly income in March (rather than the monthly average) we correct this income with a factor **12/number of months mainly in this labour market status*.

Other incomes are set equal to zero if they align with a main labour market status reported for a (number of) different month(s) (e.g. we assume that someone who is mainly employed in March will not combine his or her employment income with a sickness allowance, if he or she reported "sick" as main activity status in a different month). If for no other month the related labour market status was reported, we leave this income as is (i.e. as a monthly average of annual income) and hence implicitly assume that this income is received constantly throughout the year.

We make an exception for combinations with the unemployment benefit. Legislation makes it rather hard to combine unemployment benefits with other (labour market or replacement) incomes. Therefore, if one reports unemployment as their main labour market status *and* receives an unemployment benefit, we put other labour market or replacement incomes equal to zero for that month, also when the related labour market status was not reported in a different month. We let a symmetrical reasoning apply to put the unemployment benefit equal to zero when the main labour market status is not unemployment, and when unemployment is never repeated as the main labour market status[16].

A summary of these rules that we apply to convert annual incomes to monthly incomes, is provided in Appendix (9.3).

Table 10 below compares the monthly incomes we obtain in this way with the EU-SILC incomes (divided by 12). As we would expect, the monthly incomes are slightly higher than

[15] A perhaps more intuitive option would be to base the monthly incomes on the situation in April. However, in following working papers, we would like to show the unfolding of the social impact of the crisis. A fixed baseline will then aid in interpreting results. Because of the timing of the COVID-19 lockdown, we take March as baseline already in this paper.

[16] This affects 225 observations that report an "orphan" unemployment benefit. In section 9.6 in appendix, we compare our current approach with an alternative approach in which we convert the unemployment benefit in line with the adopted practice for the other income components.

the annual incomes simply divided by 12, and refer to a slightly smaller number of observations. All in all, differences remain limited for employment income and self-employment income. They are more substantial for unemployment benefits, where more fluctuations are reported in the EU-SILC throughout the year, and where we also observed some unemployment benefits without related labour market status (see also footnote 15).

Table 12: Comparison of annual EU-SILC incomes and monthly incomes

	Original EU-SILC incomes (divided by 12)			Adapted monthly incomes		
	Mean	Median	N	Mean	Median	N
Employment income	3120.1	2929	5021	3527.9	3177.6	4347
Self-employment income	2560.9	1983.9	735	2751.2	2071.6	710
Unemployment benefit	893.6	530	764	1030.4	1081.9	452

Source: Authors' calculations

A final change to the baseline has to do with low reported income in the EU-SILC. We noted that some employees experienced increases in disposable income upon entering the temporary unemployment scheme, as they received wages that were substantially below the national minimum wage, even when taking account of their actual working time. For this reason, we activated the minimum wage correction included in EUROMOD. This correction replaces employment income lower than the hourly minimum wage by the minimum wage applicable for each individual's age and level of experience, for those with employment incomes higher than zero and a reported labour market status as employee. We encountered a similar – and more pressing – problem with the self-employment incomes reported in the EU-SILC. Self-employment incomes reported in the EU-SILC are often very low, and even negative. In order for EUROMOD to run, we replaced the negative self-employment incomes by zero. However, we have no objective measure to further adjust the self-employment incomes reported in the EU-SILC. Hence, the impact of the shock and policies for the self-employed are calculated on relatively low baseline incomes. This has its impact on the results which should be interpreted with care[17].

5.4.2 ***Shock***

Our nowcasting exercise identified the temporary unemployed and the self-employed that take up a bridging right. In the shock scenario, we use this information to simulate the shock on self-employment incomes and employee earnings.

For those identified to be temporary unemployed in April, we change their monthly employment income in line with the number of days they are predicted to become

[17] This is all the more so as self-employed are likely underrepresented in the EU-SILC. We found the (weighted) number of self-employed according to the EU-SILC to be substantially lower than the numbers reported by the RSVZ.

unemployed. Similarly, we also change the number of weekly working hours in line with the number of days they are predicted to become unemployed, relative to their total number of work days. We hereby take account of the assumptions we made to predict the days of temporary unemployment (see section 5.3.5). This is necessary, since the number of hours worked per week or month (and the level of the hourly wage) are important for certain policy measures in the Belgian tax benefit system, such as the (fiscal) work bonus. Other incomes are unaffected.

For those identified to take up a bridging right as self-employed, we set their monthly income from self-employment to zero. Note that this is a very strong assumption. Some businesses that were mandatorily closed down for the entire month were allowed to undertake related, social-distancing-proof services (e.g. takeaway meals). It is unclear (and perhaps also unlikely) whether these side-activities were profitable, or to what extent. The monthly bridging right was however also awarded to those who only closed their business for seven consecutive days. It is likely that some of these self-employed still raised an income from their self-employment activity in the remainder of the month. As for the temporary unemployed, other incomes are assumed to be unaffected.

We do not change the incomes of individuals not predicted to become temporary unemployed or taking up a bridging right. Therefore we underestimate the real impact of the shock: we only change the incomes of those we know to have been covered by the system[18]. From the research cited above (see section 4), we know that this is an unlikely assumption. Likely, employed students or people employed in atypical employment were hit. However, given the availability of data we currently have access to, it is not possible to take these groups into consideration. In the future, we will deliver an adjacent exercise that aims to chart the (post-)lockdown labour market trajectories of these groups.

In the shock scenario, we only change the earnings in line with the predicted change in employment status. We disregard the reaction of the (standard or extended) policy system that would in reality occur. Clearly, this is a purely fictional scenario that solely serves to demonstrate the pure impact on market incomes. (In practice, we do this by keeping benefits constant between the baseline and the shock scenario.)

5.4.3 ***COVID-19 compensation policies***

In our analysis we consider the effect of the following COVID-19 policy measures, relevant for the month of April:

- The (extension of the) system of temporary unemployment;
- The federal bridging right for self-employed individuals;

[18] Also other labour market responses, such as a possible increase in (paid) overtime in the care and retail food sectors, are not taken into consideration.

Section 3 supra summarized the COVID-19 temporary unemployment scheme. The calculation of this benefit is based on reported earnings of the month defined in the baseline as prior to the crisis (see section construction of the monthly baseline). We assume that all those that are temporary unemployed in April 2020 receive the temporary unemployment – COVID-19 benefit, and hence receive the supplement of 5.63 euro per day. In contrast, we have no information on eligibility for sectoral or company level supplements, which can be quite sizeable. We assume for all those becoming temporary unemployed that they do not receive these supplements.

We also include the bridging right for self-employed. We did not need to make additional assumptions in order to simulate this policy. However, for pragmatic reasons, we apply the withholding tax for employees also on the self-employed in order to calculate their monthly disposable income. We make one exception: we tax the bridging right already at the final 16.5% rate introduced in the personal income tax as a COVID-19 support measure (see section 3). Note that this is a deviation from reality.

In addition, from April 1st onwards, the degressivity of regular unemployment benefits is relaxed. We do not take this policy change explicitly on board. As we have no information on how long people were already receiving an unemployment benefit at the onset of the lockdown, we are unable to include the impact of this measure. In our simulation scenarios the unemployment benefits are kept constant between our baseline and policy scenario, so our outcomes will not reflect the impact of suspending the degressivity of unemployment benefits.

6 Empirical results

In this section we describe the main results of the simulation of the economic shock caused by Covid-19 and the containment measures taken. We also show how well the policy response was able to cushion the shock.

6.1 Overall impact of the economic shock

We first describe how the economic shock affected the employment status and earnings. Table 13 presents the prevalence of different labour market positions across the total population in the pre-COVID situation and compares it to the situation after the shock. The figures refer to the main employment status; in practice of course different positions can be combined. In the pre-COVID period slightly more than 40% of the population was economically active, about 35.5% worked mainly as an employee and 4.8% was self-employed in their main profession. Due to the COVID-induced economic shock 9.9% of Belgians became temporarily unemployed, representing about 27.9% of all employees. 1.4% of the population became temporarily unemployed for the entire month of April (about 5.1% of employees or 14.2% of all temporarily unemployed) and 8.5% of the population became temporarily unemployed for less than a month. Over half of the self-employed were forced to or voluntarily shut down their activities (2.5% of the total population). Because of our strategy of modelling the shock (i.e. through a parametric model calibrated by administrative recipiency data of the temporary unemployed and the bridging right), we do not see an impact on unemployment and on inactivity. This is not to say such changes did not occur in April 2020, but as this was not reflected (yet) in administrative caseload data, we did not account for it in our modelling. (It is of course fully conceivable, and even likely, that people ended up being unemployed or inactive without receiving a benefit, hence not appearing in the administrative data.)

Table 13. Estimated change in main employment status due to COVID-shock, April 2020

	Baseline	**Shock**
Employee	35.5%	35.5%
Fully employed		25.6%
Parttime temporarily unemployed		8.5%
Fulltime temporarily unemployed		1.4%
Self-employed	4.8%	4.8%
Activities not shut down		2.3%
Activities shut down		2.5%
Unemployed	3.5%	3.5%
Retired	20.3%	20.3%
Inactive (including <18 years old)	35.9%	35.9%

Source: Authors' calculations

This large labour market shock was self-evidently reflected in a large decrease in earnings. Table 14 shows the average and total decrease in earnings at the individual level among both the active population (self-employed and employees) and the affected active population. We further subdivide the latter group into affected employees on the one hand and affected self-employed on the other.

Table 14. Estimated changes in individual earnings due to COVID-19–shock

	Baseline	Shock	Difference shock - baseline	
			Absolute	Relative
Mean				
All active individuals	3460.6	2797.6	-663.0	-19.2%
All affected active individuals	3052.1	888.0	-2164.1	-70.9%
All affected employees	3069.0	1108.5	-1960.5	-63.9%
All affected self-employed	2984.1	0.0	-2984.1	-100.0%
Total (in millions)				
All active individuals	15755.1	12736.6	-3018.5	-19.2%
All affected active individuals	4257.1	1238.6	-3018.5	-70.9%
All affected employees	3429.0	1238.6	-2190.5	-63.9%
All affected self-employed	828.0	0.0	-828.0	-100.0%

Source: Authors' calculations

We find that total earnings of the active population decreased by 19.2%. Of course, when we zoom in on the affected population (i.e. the population that we estimated to become temporary unemployed or to receive a bridging right, according to our nowcasting model), the drop in total earnings is far larger, and amounts to 70.9%. Among affected employees, the drop in total earnings was 63.9%, whereas it amounted to 100% for the affected self-employed. Note that this large decrease is due to our assumption that self-employed see their income fall back to zero when they claim a bridging right, whereas for the temporary employed, we reduce their monthly wage in line with the number of days they become unemployed. Since a large part of the temporary unemployed are only part-time temporary unemployed (see Table 13), their reduction in income is more limited. In updates for consecutive months, we will include alternative scenarios to assess the impact for the self-employed under different drops in income scenarios. Especially for subsequent months, it is rather unrealistic that they would see their incomes drop to zero.

Ideally, we would compare this decrease in total earnings with external sources on the decrease of the total wage mass in April 2020. Unfortunately, the available projections are mainly for the entire year. The Federal Planning Bureau for instance projects a drop in total wage mass of -7.8%, which is a less severe drop than the drop in total individual earnings of -19.2% that we find for April 2020. As the Federal Planning Bureau includes the impact of the expected recovery in the remainder of the year, this is of course unsurprising. Statbel has published the quarterly drop in total wage mass, by sector. The sectors reported by Statbel do not fully overlap with the sector identifiers in the EU-SILC. Below we compare the reduction in earnings with the quarterly decrease reported by Statbel for those sectors where we can expect a reasonable overlap. Again, the Statbel data, that include the gradual reopening of the economy in May and June, show less severe reductions than we find for the month of April. Alternatively, for the sector of Accommodation and restaurants, that was only allowed to reopen late in the quarter, we do find our estimated drop in total earnings to be closer to the reduction reported by Statbel.

Table 15. Comparison decrease in wage mass and estimated decrease in total earnings, by sector

Statbel sector	Decrease in wage mass	EU-SILC sector	Simulated decrease in total earnings
Manufacturing (NACE C)	-8%	Mining, manufacturing or utilities	-22%
Construction (NACE F)	-11%	Construction	-42%
Wholesale and retail trade; repair of motor vehicles and motorcycles (NACE G)	-11%	Wholesale and retail	-39%
Transporting and storage (NACE H)	-10%	Transport and communication	-17%
Information and communication (NACE J)	-3%		
Services in sections H to N of NACE Rev. 2 (NACE H_N)	-19%	Real estate and financial intermediation	-26%
Accommodation and food service activities (NACE I)	-61%	Accomodation and restaurants	-72%

Source: https://statbelpr.belgium.be/nl/themas/conjunctuurindicatoren/werk/loonmassa#figures. Author's calculation on EU-SILC.

Table 16 shows the impact of the shock on labour earnings at the household level. Self-evidently, the shock does not only affect living conditions at the individual level, but also the living conditions of those living with affected workers. In addition, other household members' income can have a cushioning role by protecting the household against a severe fall in living standards. We present our findings as follows: First, changes in earnings are shown for all households with at least one active individual (an employee or self-employed). Secondly, we show the impact on earnings only for the households affected by the shock (i.e. households with at least one affected employee or self-employed). Thirdly, we further distinguish between the impact for the affected employees and self-employed. If a household has both an affected employee and an affected self-employed, it is included under 'HH with an affected self-employed person'. The change in household earnings is presented in both absolute and relative (as a percentage of the pre-COVID earnings) terms. In the pre-COVID period average household earnings amounted to 6,223 euros. Because of the economic shock these decreased to 5,008 euros, representing a decline of 19.5%. The total household earnings of the entire Belgian population decreased by 3 billion euros from almost 15.8 billion euros to 12.8 billion euros in April. Among the affected population, mean household earnings decreased by 42.3%. The decrease is larger for households with affected self-employed than for households with solely affected employees. This is due to the fact that we set the earnings of the self-employed receiving the bridging right to zero (see above).

Table 16. Estimated change in household earnings due to COVID-19 shock

	Baseline	Shock	Difference shock - baseline	
			Absolute	Relative
Mean				
HH with an active individual	6223.4	5007.9	-1215.6	-19.5%
HH with an affected active individual	6047.1	3489.4	-2557.6	-42.3%
HH with an affected employee	6075.6	3825.4	-2250.2	-37.0%
HH with an affected self-employed	5944.8	2286.3	-3658.6	-61.5%
Total (in millions)				
HH with an active individual	15797.3	12778.8	-3018.5	-19.1%
HH with an affected active individual	6635.3	3616.8	-3018.5	-45.5%
HH with an affected employee	5209.1	3113.1	-2096.0	-40.2%
HH with an affected self-employed	1426.2	503.7	-922.5	-64.7%

Note: HH: household. Source: Authors' calculations

Decreases in household earnings among the affected population (in terms of having an affected household member) are less severe than the decreases experienced at the individual level (and reported in section 6.1). This is due to the cushioning effect of other incomes in the household, for instance from a partner whose employment was not affected by the lockdown. This raises the question to what extent it actually happens that multiple individuals in the same household are affected by the COVID-induced economic shock. Therefore, Table 17 presents the share of households with one, two or more affected individuals. In 21% of all households one active individual was affected by the shock, and in 4.1% of all households at least two active individuals were affected. For households with only one active individual, we see that in 30.5% of the households this one individual was affected in April. Among households with at least two active individuals, we see that more than 50% contains one affected individual.

Table 17. Distribution of affected individuals across households

	Number of active individuals in the household			**All households**
	0	1	2 or more	
Number of affected individuals in household				
0	100.0%	69.5%	47.7%	75.4%
1	-	30.5%	40.1%	21.0%
2 or more	-	-	12.2%	4.1%

Source: Authors' calculations

6.2 Who was affected? Distribution of the economic shock

The previous section provided a general overview of the economic shock. In this section we zoom in on who exactly is affected, describing their socio-demographic characteristics as well as their position in the pre-COVID income distribution. First we focus on the subpopulation of active individuals. Next, we situate the affected individuals in the total population.

Table 18 provides an overview of the socio-demographic characteristics of the affected population. For each group (affected employees, affected self-employed, unaffected employees and self-employed and all active individuals), the share of individuals with a specific socio-demographic characteristic is shown, summing to 100% over each type of socio-demographic characteristic. The fourth column shows the distribution of the relevant population over the socio-demographic characteristics to serve as a benchmark for comparing the affected population.

Table 18. Socio-demographic characteristics of the estimated affected population and total population of employees and self-employed

	Affected employee (%)	Affected self-employed (%)	Unaffected employees and self-employed (%)	All employees and self-employed (%)
Age group				
16-29	18.8	9.7	14.6	15.4
30-39	29.8	23.5	26.1	26.9
40-49	23.8	27.6	26.0	25.6
50-59	24.0	28.3	27.9	26.9
60+	3.6	10.9	5.3	5.2
Gender				
Women	41.5	33.4	49.5	46.5
Men	58.5	66.6	50.5	53.5
Education				
No or primary	8.2	6.7	6.1	6.7
Secondary	65.8	49.3	36.1	44.2
Tertiary	26.0	44.0	57.7	49.1
Household type				
Single	13.1	13.3	14.5	14.1
Single parent	2.3	1.7	2.3	2.3
Couple	33.4	38.3	33.6	33.9
Couple with children	35.0	39.6	37.8	37.2
Other	16.2	7.2	11.8	12.6
Tenure status				
Owner	51.9	48.1	58.8	56.5
Tenant	48.1	51.9	41.2	43.5
Sector				
Lightly hit	12.9	22.9	54.1	42.1
Medium hit	74.8	60.9	41.8	51.1
Severely hit	12.2	16.3	4.1	6.9

Source: Authors' calculations

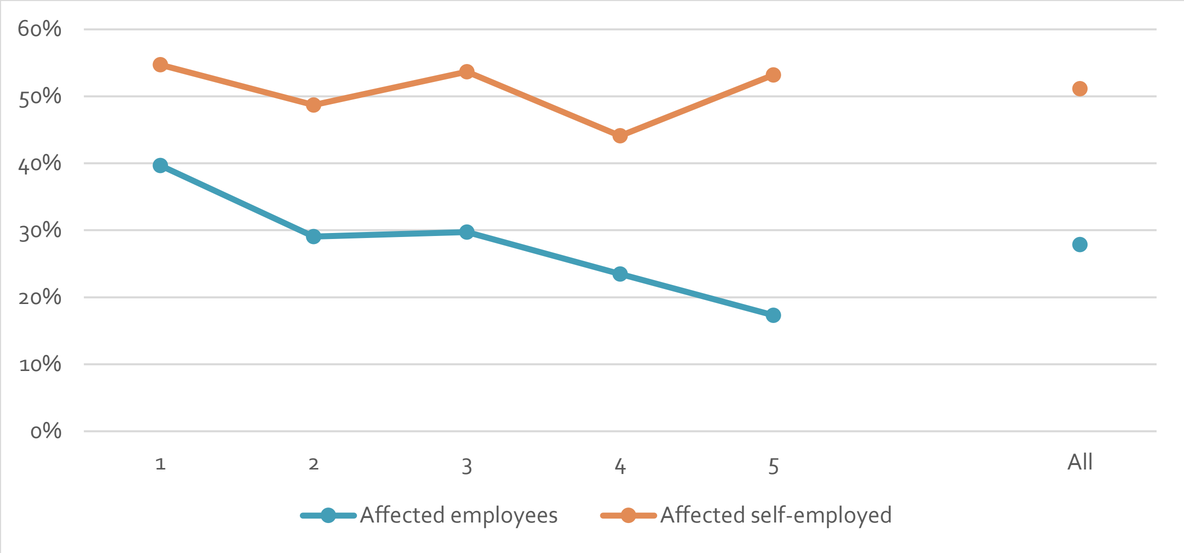
Comparing the shares within each subgroup with the share in the total population of employees and self-employed, we find that affected employees are more often aged between 30 and 39 years old, male, low-educated, and tenants. The affected self-employed are more often older men, in a relationship and tenants than the general profile of employees and self-employed. Unsurprisingly, both affected employees and self-employed work substantially more often in medium and severely hit sectors.

Figure 1 presents the share of all (self-)employed experiencing a change in employment status by quintiles of pre-COVID individual earnings. Here we distinguish between the employees and the self-employed. We present the share of affected employees over pre-COVID wage quintiles, and the share of affected self-employed over pre-COVID self-employment incomes. Therefore, each quintile in Figure 1 contains respectively 20% of the employees and 20% of the self-employed individuals[19].

We find that among the employees, those affected are mainly found in the lower wage quintiles: in the lowest quintile, 40% of the employees became temporary unemployed and this share decreased to around 30% in the second and third quintile and to less than 20% in the highest quintile. According to the distribution of affected self-employed over the pre-COVID self-employment income, self-employed are affected relatively equally over the self-employment income distribution.

Figure 1. Estimated share of employees and self-employed experiencing a change in employment status to temporary unemployment among the employees, by quintiles of pre-COVID individual wages and to bridging right among the self-employed, by quintiles of pre-COVID individual self-employment incomes

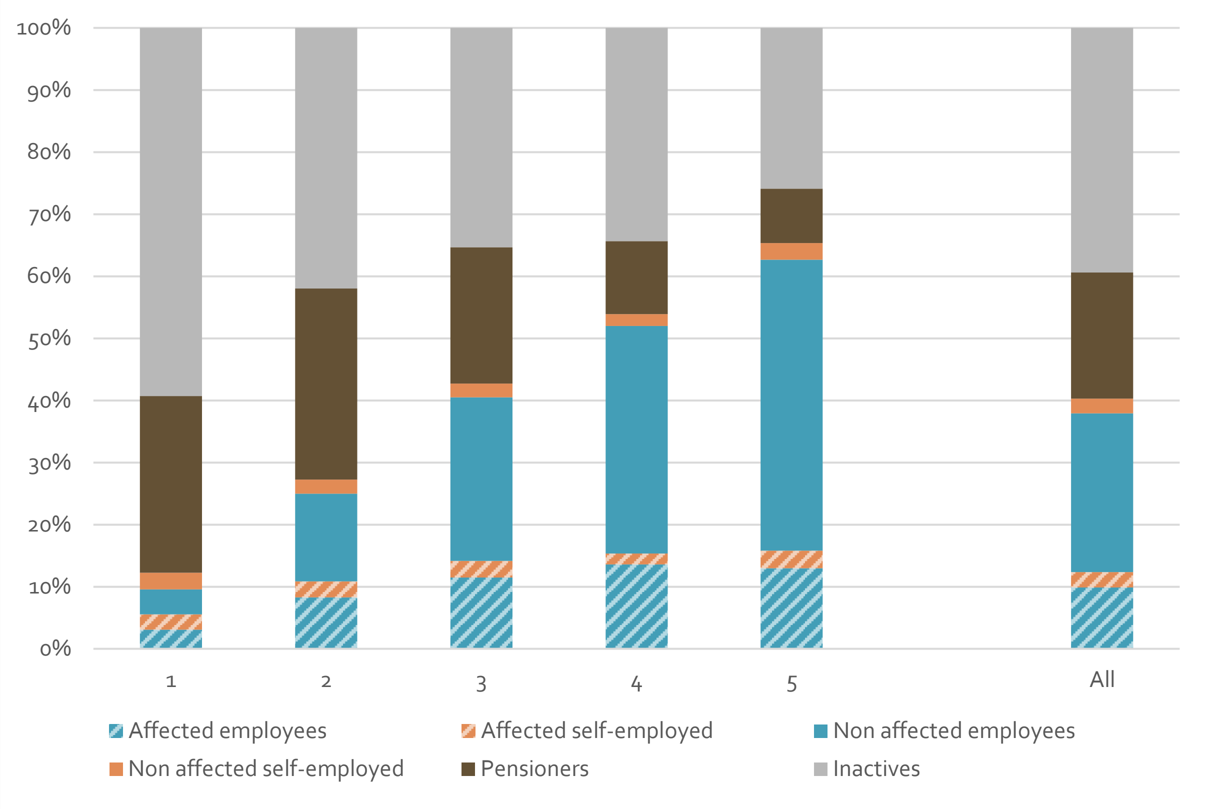
[19] As the self-employment incomes reported in the EU-SILC cluster around certain values, the quintiles for self-employed contain respectively 23%, 21%, 20%, 17% and 20% of self-employed. This does not have an impact on the overall image.



Note: For employees, quintiles are based on pre-COVID employment wages; For self-employed individuals, quintiles are based on pre-COVID self-employment incomes. Source: Authors' calculations

Figure 2 shows that active individuals are more concentrated in the higher quintiles if we rank all individuals of the total population on their pre-COVID equivalised disposable household income. Only 12% of the individuals in the lowest equivalised disposable household income quintile are (self-)employed and this share increases over the quintiles to about 66% of active individuals in the highest decile. By consequence, when looking at the shares of affected active individuals, we observe the same pattern of increasing shares over the quintiles. We can conclude that Figure 2 puts our findings on the subpopulation of active individuals (as shown in Figure 1) in perspective: while Figure 1 showed that the active individuals with lower earnings were more affected, we see that affected individuals mainly find themselves in the upper three disposable household income quintiles when looking at the total population.

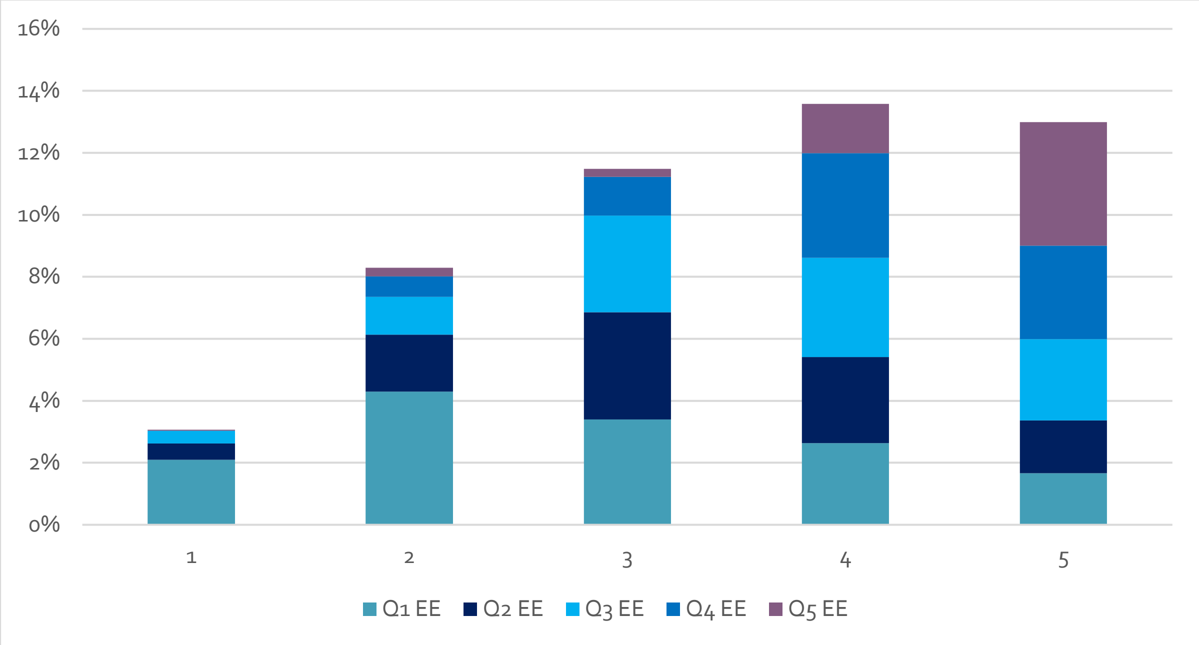
Figure 2. Estimated share of individuals with a specific activity status among the total population, by quintiles of pre-COVID equivalised disposable household income



Note: 'Inactives' include the unemployed, sick, invalid, student or other.
Source: Authors' calculations

In Figure 3 we zoom in on this observation. Figure 3 offers a breakdown of the affected employees as a percentage of the entire population (the shaded blue bars in Figure 2) by their pre-COVID wage decile. Whereas affected low wage employees are unsurprisingly also overrepresented among the lower disposable household income quintiles, affected low wage employees are also present in the higher income quintiles. Alternatively, affected employees with higher wages may also find themselves in lower household income quintiles. Clearly, the impact of other household members, and other incomes in the household, matters a lot for the position of affected employees in the overall (household disposable) income distribution.

Figure 3. Breakdown of affected employees by pre-COVID individual wage quintile, over quintiles of pre-COVID equivalised disposable household income



Note: Q1-5 EE: quintile 1 – 5 of pre-COVID wage distribution. Source: Authors' calculations

6.3 Impact of shock and policy response on the affected population

In what follows we estimate the extent to which the policy measures taken by the governments cushioned the economic shock. In other words, to which extent do the changes in earnings described in the previous sections also translate into changes in *actual* net disposable incomes, if we take into account the decrease of the withholding tax liabilities and social insurance contributions[20] driven by lower earnings, as well as the benefits granted under the form of the temporary unemployment scheme and the bridging right for the self-employed (these benefits then increase the liabilities for the withholding tax again[21]). In this section we focus on the subpopulation of affected active individuals. In section 6.4, we contextualize our results found for the affected population by showing the impact of the shock, after policy responses, on the total population.

6.3.1 *Impact at the individual level*

6.3.1.1 Temporary unemployed employees

We start with the changes in disposable incomes for affected employees. Figure 4 shows the estimated difference in disposable income between the baseline and the post-COVID policies scenario. In addition, it shows the changes in the different income components, that together explain the change in disposable incomes. As we focus here on individuals, we include the

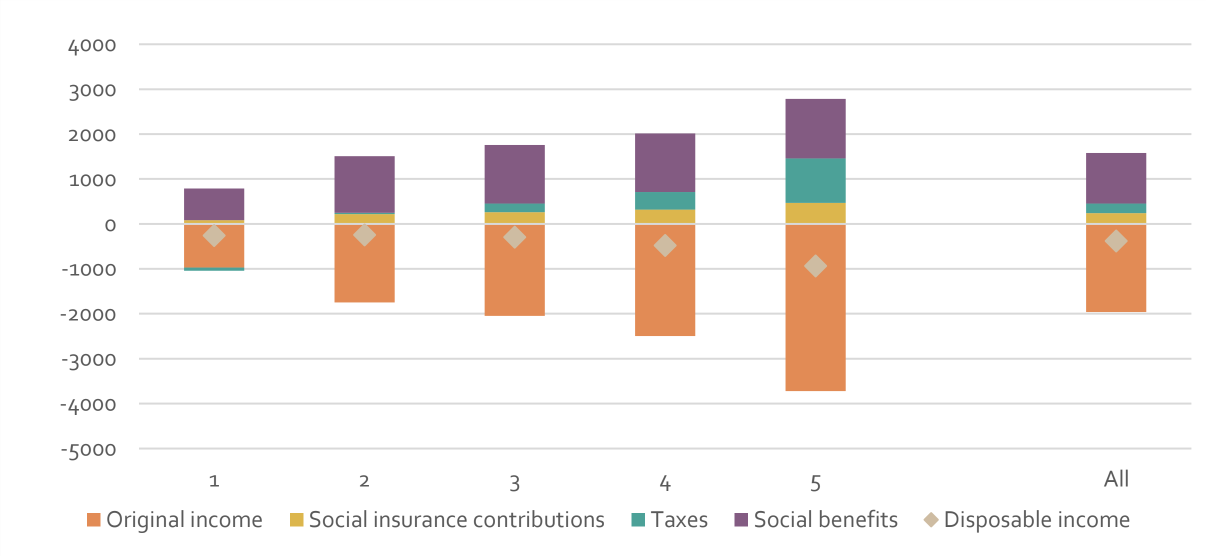
[20] These are employee and self-employed social contributions; employer contributions are not considered here.
[21] See section 5.4.3 on the underlying assumptions regarding the application of the withholding tax on the bridging right and incomes of the self-employed.

following in the individual disposable income concept: original incomes (mainly wages for employees, resp. self-employment income), the withholding tax, social insurance contributions and temporary unemployment and social assistance benefits as social benefits. We only include those benefits that can change between the baseline and policy (April) scenario, and hence can provide an explanation for the change in disposable individual income. We distinguish between employees and self-employed, and show the change in disposable income over their respective earnings quintiles (based on wages for employees, based on self-employment income for the self-employed). In Figure 4 below, we show the estimated average change in disposable income among affected employees.

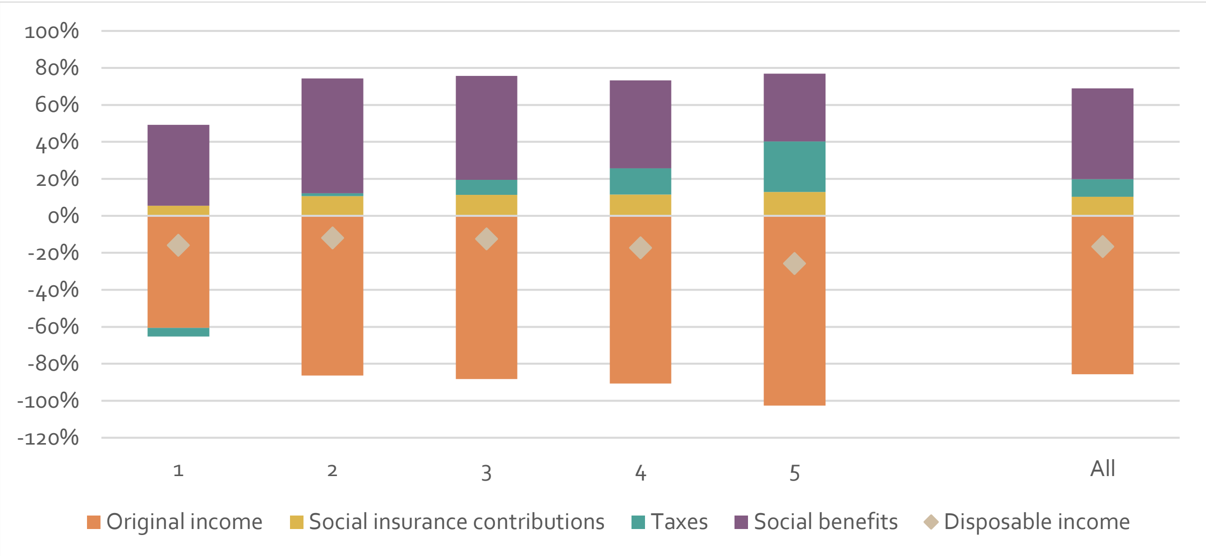
Panel A of Figure 4 shows that individual disposable incomes among the affected employees decreased on average by 382.3 euro monthly, or 16.7% of pre-COVID disposable income in panel B. However, this is nowhere near the drop in original income of 1960,5 euro. The difference is due to the reduction in social insurance contributions and withholding tax (the yellow and green bars in Figure 4, depicted above the x-axis as their decrease contributes positively to the change in disposable income), and to the social benefits that were awarded. Social benefits in Figure 4 mainly include the gross temporary unemployment benefit, that on average increased with 1126.1 euro relative to the pre-COVID scenario. Panel A shows that as the original income decreases more sharply in higher wage quintiles, also the absolute amount of the (proportional) social insurance contributions decreases. The withholding tax reacts far more strongly to decreases in original income, contributing substantially to decreasing the impact of the earnings shock on disposable incomes in the higher wage quintiles. The contribution of the change in average social benefits towards the change in disposable income reacts far less heavily to the drop in original income, as the maximum temporary unemployment benefit is quite quickly reached.

Figure 4. Estimated average change in disposable income and income components of affected employees, over pre-COVID wage quintiles

Panel A. Absolute changes



Panel B. Relative changes



Note: Relative changes are expressed as a percentage of pre-COVID disposable income for each quintile. Quintiles are based on pre-COVID wage incomes. Source: Authors' calculations

This becomes even more clear when we look at the relative decrease in average disposable income, and the relative contribution of changes in the underlying income components to the change in average disposable income (panel B of Figure 4) per quintile. The diamonds in panel B represent the change in disposable income relative to pre-COVID disposable income. The bars in panel B represent the change in each income component reative to pre-COVID average disposable income in each quintile. In the first (pre-COVID) wage quintile, we observe an estimated decrease in disposable income of 16%. The large decreases in original (i.e. mainly wage) income are partially balanced by the positive impact of a (small) decrease in social insurance contributions, but mainly by gross social benefits. Note that, other than in the other quintiles, the change in withholding tax has a negative impact on the change in disposable income in the first quintile: affected employees in the lower earnings quintiles pay on average a larger withholding tax on their replacement income than they do on their wage income.

Whereas both wage income and the temporary unemployment benefit are in April taxed at the lowest rate (26.75%), wage income is recuced by professional costs before the withholding tax is levied. In addition, tax breaks for low wage employees or family situation are applied on the wage income, but not on the temporary unemployment benefit. This stands in stark contrast to the impact of social benefits and the withholding tax in higher wage quintiles. In the second quintile, the decrease in disposable income is less pronounced than it is in the first, as the temporary unemployment benefit, combined with the RVA supplement, provides a relatively generous replacement rate. The mitigating impact of social benefits decreases in higher wage quintiles, as the maximum benefit is reached at a previous income of around 2750 euro. Affected employees who previously earned higher incomes hence face a less generous replacement rate. However, under a blind application of the withholding tax regulation on their remaining wage income, these employees face a substantial reduction in withholding tax liabilities. The temporary unemployment benefit is taxed separately at the lowest band. Their remaining income hence often falls in a lower withholding tax band, mitigating the large decrease in income. Self-evidently, both withholding tax effects, the more negative effect at the bottom and the more positive impact at the top, will be mitigated after the application of the personal income tax. Affected employees in the lowest quintiles will receive the tax credits they are entitled to, whereas higher income earners will have to compensate the tax reductions they benefited from. Our aim here is to show the real impact of the shock and policy measures on monthly disposable income in the month of April, so to show how the shock at that time was actually felt by affected employees and self-employed. At that time, the correction by the personal income tax was still far away[22].

6.3.1.2 Self-employed individuals and the impact of the bridging right

For the affected self-employed, we observe a somewhat different policy impact on disposable incomes. Several issues are at play here: First, self-employed incomes reported in the EU-SILC are notoriously low. Second, the bridging right for the self-employed is a lump-sum benefit, independent of prior incomes. Third, we make the assumption that self-employed who receive a monthly bridging right do not gain income from their self-employment activity for the entire month, which means that all affected self-employed experience the same relative reduction in income. We will relax this assumption in analyses for consecutive months. Fourth, self-employed do not fall under the withholding tax schedule, but should pay quarterly advances on their personal income tax, with penalties if these advances cover too little of the final tax liability due. However, for pragmatic reasons, we apply the withholding tax schedule also on self-employment income. We tax the bridging right at the more advantageous 16.5% rate that will be applied in the personal income tax. We make abstraction of the possibilities to postpone or forego the payment of social contributions. Of

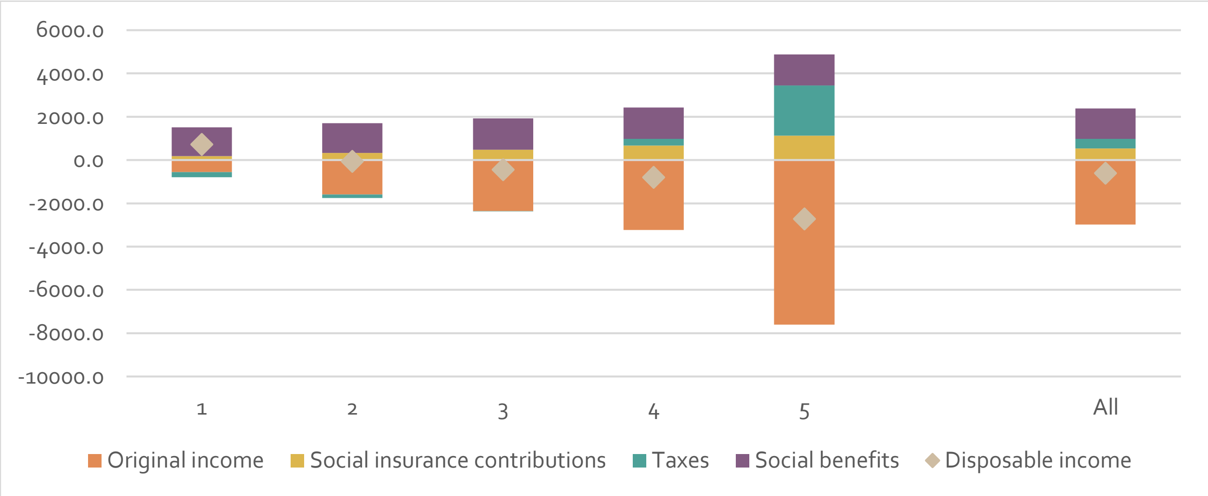
[22] In section 9.5 of the annex, we show the estimated change for the affected employees under the personal income tax regime, under the assumption that their new situation lasted a full year.

course, all these issues combined mean that we should interpret the results for self-employed with great care.

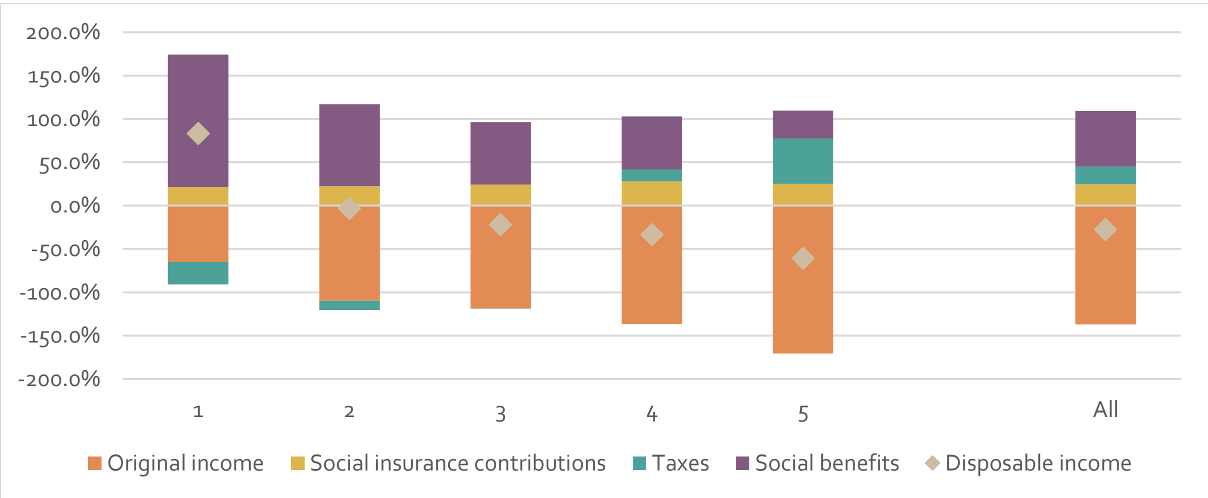
Panel A of Figure 5 shows the absolute changes in disposable income of affected self-employed, and their income components. On average, affected self-employed lost 605.6 euro in terms of disposable income. This amount is self-evidently not representative of the losses businesses have experienced, but only refers to personal disposable incomes. This was caused by a drop in original income of 2984 euro, cushioned by a decrease in social contributions and withholding tax representing 977 euro, and an increase in social benefits of 1402 euro on average.

Figure 5. Estimated change in disposable income and income components of affected self-employed, over pre-COVID self-employment income quintiles

Panel A. Absolute changes



Panel B. Relative changes



Note: Relative changes are expressed as a percentage of pre-COVID disposable income. Quintiles are based on pre-COVID self-employment incomes. Source: Authors' calculations

Whereas for employees, the relative decrease in disposable income ranged from -12% to -26% over the different pre-COVID wage quintiles, the variation in disposable income decreases is far more outspoken for the self-employed. For the first quintile we observe an increase in average disposable income, as the lump-sum bridging right overcompensates the loss in original income, who – as mentioned above – are very low for self-employed in the EU-SILC. At the other end of the spectrum, we observe a decrease in disposable income by 61%. This is self-evidently driven by our assumption that self-employed do not succeed in maintaining income from their self-employment activity when they receive a bridging right. As is the case for the employees, in the higher quintiles, the social benefits no longer succeed in cushioning the shock to original income. This is even more so the case with the self-employed, as the benefit is a lump-sum benefit, and is lower than the maximum temporary unemployment benefit.

6.3.1.3 Winners and losers

For the self-employed, we noted that the first quintile experienced an average increase in net disposable income. Even though not visible in the average change in disposable incomes for affected employees, also for employees slight increases in monthly disposable income were a possibility for some groups. Based on typical cases, the NBB (2020) has for instance identified a slight increase in net disposable income after withholding tax for employees with a wage at 67% of the average wage, as the benefit is quite generous at 70% of the previous wage, plus the RVA supplement. For this wage level, the maximum ceiling of 2754 euro does not yet apply. On the other hand, the withholding tax levied on the benefit is lower than the total of withholding tax and social contributions levied on the former wage. This effect may also play at higher wages, if one is only part time temporary unemployed (Marchal et al. 2020). Again, it is important to note that, even though this impact on the monthly net disposable income is very real, this will to large extent be compensated by the personal income tax in the next year. In this sense, speaking of winners and losers is not fully correct. In table 20, we therefore distinguish between those experiencing no loss in their monthly disposable income, and those that do experience a decrease.

In Table 19, we distinguish those individuals and show where they are located in the earnings distribution with for employees (self-employed individuals) quintiles based on pre-COVID employment wages (pre-COVID self-employment incomes). As mentioned previously, results for the self-employed come with a lot of warnings. This is also the case when identifying those experiencing an increase in monthly disposable incomes in April. In fact, Table 19 shows a high share of “winners” in the first two (pre-COVID self-employment income) quintiles, as can be expected, in a context of (very) low reported EU-SILC self-employment incomes and lump-sum benefits. As neither the lump-sum benefit, nor its minimal access condition (being self-employed as main activity, without income condition[23]) depend on previous incomes, this leads to high shares of "winners" when zooming in on lower income quintiles. Higher up, there were no "winners" whatsoever, as the lump sum benefit did not fully compensate for all earnings losses.

A temporary increase in monthly disposable income among the employees is far less common, partially as reported incomes are higher, and as we enforced the minimum wage legislation in our modelling (see section 5.4.1). Overall, we mainly find "winners" among the employees in the 2nd and 3rd pre-COVID wage quintile, which concurs with the explanations offered above.

Table 19. Estimated winners and losers by quintiles of pre-COVID earnings

	1	2	3	4	5	All
Affected employees						
No loss	7.8%	14.2%	20.6%	0.0%	0.0%	9.2%
Loss	92.2%	85.8%	79.4%	100.0%	100.0%	90.4%
Affected self-employed						
No loss	100.0%	36.1%	1.5%	0.0%	0.0%	31.5%
Loss	0.0%	63.9%	98.5%	100.0%	100.0%	68.5%

Note: For employees, quintiles are based on pre-COVID employment wages; For self-employed individuals, quintiles are based on pre-COVID self-employment incomes. Source: Authors' calculations

6.3.1.4 Characteristics of the (most) affected individuals

Finally, we zoom in on the characteristics of the individuals most affected by the shock. Table 20 shows the characteristics of the affected individuals over three different subgroups: employees and self-employed with (i) no loss or a loss up to 10% of their pre-COVID disposable income, (ii) a loss between 10% and 25% of their pre-COVID disposable income and (iii) a loss of more than 25% of the pre-COVID disposable income. The same characteristics are presented in Table 21 but over three subgroups divided by the absolute loss in individual disposable income. In the last two columns, we added the shares over all affected individuals - in order to assess how the composition of the least and the most affected differs from the general group of affected – and the shares over all active individuals.

Those who experience the largest relative income losses are more often male, whereas women more often experience a loss between 10 and 25% of their previous individual disposable income. Heavily affected are more often higher educated and self-employed. The latter is in line with our expectations: a lump sum benefit will protect those with high incomes less well. This effect is amplified by the large income inequalities among the self-employed. Both singles and couples without children are overrepresented among those who experience the largest relative losses in relative terms. We do not observe large differences in tenure status between the different groups. When we zoom in on the pre-COVID wage or self-

[23] There was an income condition for self-employed whose self-employment is a secondary activity. For the main status to be considered as self-employed, one has to pay minimal social insurance contributions. However, these are not levied proportional to income.

employment income quintile of those affected, we find (rather unsurprisingly) that those formerly present in the highest earnings quintiles are overrepresented among the largest losers.

This effect that the more well-off among the affected experienced the largest losses is all the more evident when we consider absolute losses, since, clearly, in order to lose a large amount, one has to usually receive a large sum in the first place. Generally, as compared to the profile of those who lost substantially in relative terms, in absolute terms, in addition, we observe an overrepresentation of owners. The overrepresentation of single persons disappears, only couples are substantially overrepresented. In addition, those affected with large absolute losses are more often aged between 40 and 59 years.

Table 20. Characteristics of affected self-employed and employees, by extent of their relative loss

	No loss - 10% loss	10%-25% loss	>25% loss	All affected individuals	All active individuals
Share of all affected	**37%**	**33%**	**29%**	**100%**	**-**
Share of all actives	11%	10%	9%	**31%**	**100%**
Age group					
16-29	18%	18%	14%	17%	**15%**
30-39	28%	29%	29%	29%	**27%**
40-49	23%	25%	25%	25%	**26%**
50-59	24%	24%	27%	25%	**27%**
60+	7%	3%	5%	5%	**5%**
Gender					
Women	37%	47%	35%	40%	**47%**
Men	63%	53%	65%	60%	**53%**
Education					
No or primary	9%	8%	6%	8%	**7%**
Secondary	65%	67%	54%	63%	**44%**
Tertiary	26%	25%	39%	30%	**49%**
Labour status					
Employee	80%	90%	69%	80%	**88%**
Self-employed	20%	10%	31%	20%	**12%**
Household type					
Single	12%	9%	18%	13%	**14%**
Single parent	3%	2%	1%	2%	**2%**
Couple	34%	32%	37%	34%	**34%**
Couple with children	34%	41%	32%	36%	**37%**
Other	17%	15%	11%	14%	**13%**
Tenure status					
Owner	49%	54%	51%	51%	**56%**
Tennant	51%	46%	49%	49%	**44%**
Quintile employees (pre-COVID employment wages)					
1	20%	38%	27%	29%	**20%**
2	25%	26%	7%	21%	**20%**
3	25%	21%	17%	21%	**20%**
4	20%	8%	26%	17%	**20%**
5	11%	7%	24%	12%	**20%**
Quintile self-employed (pre-COVID self-employment incomes)					
1	56%	0%	5%	24%	**23%**
2	37%	35%	0%	20%	**21%**
3	7%	48%	23%	21%	**20%**
4	0%	17%	27%	15%	**17%**
5	0%	0%	45%	21%	**20%**

Note: groups identified based on individual relative losses in individual disposable income. Source: Authors' calculations

Table 21. Characteristics of affected self-employed and employees, by extent of their absolute loss (in euros)

	No loss - 250	250 – 750	> 750	All affected individuals	Not active individuals
Share of all affected	**45%**	**38%**	**16%**	**100%**	**-**
Share of all actives	14%	12%	5%	**31%**	**100%**
Age group					
16-29	19%	20%	5%	17%	**15%**
30-39	28%	30%	28%	29%	**27%**
40-49	21%	26%	30%	25%	**26%**
50-59	26%	22%	30%	25%	**27%**
60+	7%	2%	6%	5%	**5%**
Gender					
Women	42%	43%	25%	40%	**47%**
Men	58%	57%	75%	60%	**53%**
Education					
No or primary	9%	8%	5%	8%	**7%**
Secondary	66%	67%	41%	63%	**44%**
Tertiary	25%	25%	54%	30%	**49%**
Labour status					
Employee	80%	87%	64%	80%	**88%**
Self-employed	20%	13%	36%	20%	**12%**
Household type					
Single	12%	15%	13%	13%	**14%**
Single parent	2%	2%	1%	2%	**2%**
Couple	36%	30%	40%	34%	**34%**
Couple with children	33%	37%	40%	36%	**37%**
Other	17%	15%	6%	14%	**13%**
Tenure status					
Owner	50%	49%	60%	51%	**56%**
Tennant	50%	51%	40%	49%	**44%**
Quintile employees (pre-COVID employment wages)					
1	32%	33%	1%	29%	**20%**
2	23%	25%	2%	21%	**20%**
3	23%	25%	5%	21%	**20%**
4	16%	10%	43%	17%	**20%**
5	6%	8%	49%	12%	**20%**
Quintile self-employed (pre-COVID self-employment incomes)					
1	53%	0%	0%	24%	**23%**
2	37%	11%	0%	20%	**21%**
3	9%	66%	1%	21%	**20%**
4	0%	24%	30%	15%	**17%**
5	0%	0%	70%	21%	**20%**

Note: groups identified based on individual absolute losses in individual disposable income. Source: Authors' calculations

6.3.2 *Impact at the household level*

We now turn towards discussing the combined impact of the shock and the policy responses at the household level. We consider all other household incomes, including benefits, such as pensions or child benefits, that were unaffected.

First, in order to make the comparison with the previous graphs at the individual level, we show in Table 22 the impact on disposable income (both at the individual and household level) by quintile groups based on pre-COVID wages for employees and on self-employment income for the self-employed. We see that the impact on disposable income is mitigated at the household level. This is in line with the findings discussed in section 6.1, where we showed that also the impact on earnings was mitigated at the household level thanks to the presence of additional earners (and incomes) in the household **Error! Reference source not found.**.

Table 22. Estimated relative change in disposable income by quintiles of pre-COVID individual earnings

	1	2	3	4	5	All
Affected employees						
Individual disposable income	-16.3%	-12.1%	-12.4%	-16.9%	-26.4%	-16.7%
Household disposable income	-9.5%	-8.3%	-8.6%	-11.2%	-18.8%	-12.9%
Affected self-employed						
Individual disposable income	88.4%	-2.0%	-22.3%	-33.1%	-60.5%	-27.8%
Household disposable income	18.0%	-5.0%	-12.4%	-20.7%	-42.5%	-22.0%

Note: Quintile groups based on pre-COVID wages for employees and on self-employment income for the self-employed.
Source: Authors' calculations

6.3.2.1 Households with affected employee(s)

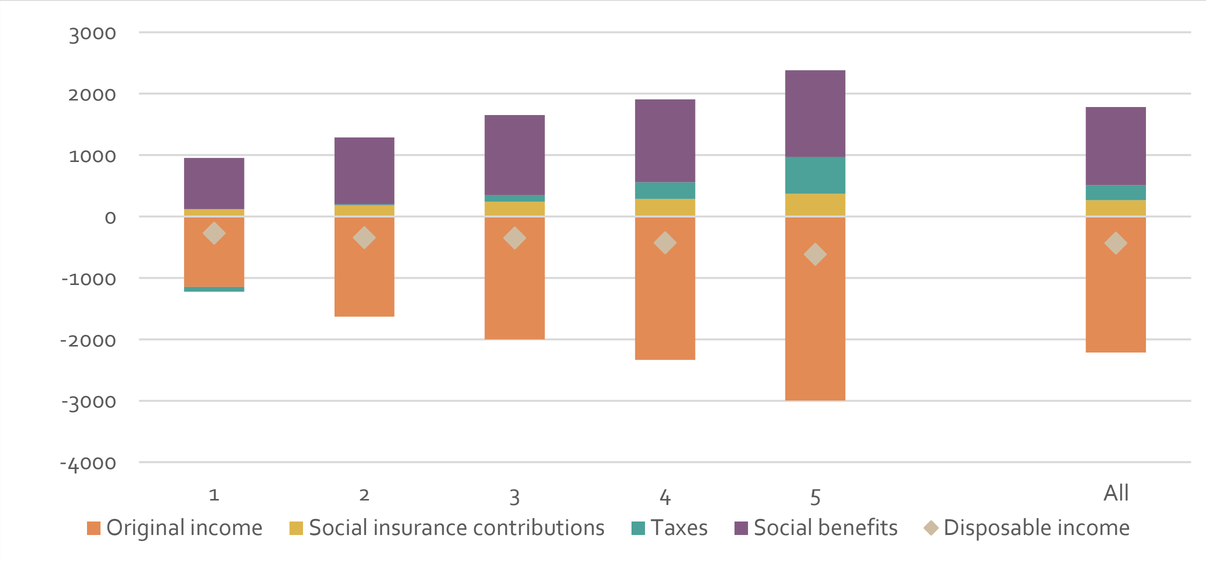
Figure 6 shows the average change in disposable income at the household level for households with affected employees. The average impact on (non-equivalized) disposable income and other income components at the household level are shown over quintiles based on (pre-COVID) equivalized disposable household income. We look at households with affected employees only, households with both affected self-employed and affected employees are included in Figure 7.

Among all households with affected employees, (non-equivalized) disposable household income decreased on average with 430 euros. The decrease in original incomes of 2214 euros was mainly compensated by social benefits, but also by the decrease in withholding tax and social insurance contributions.

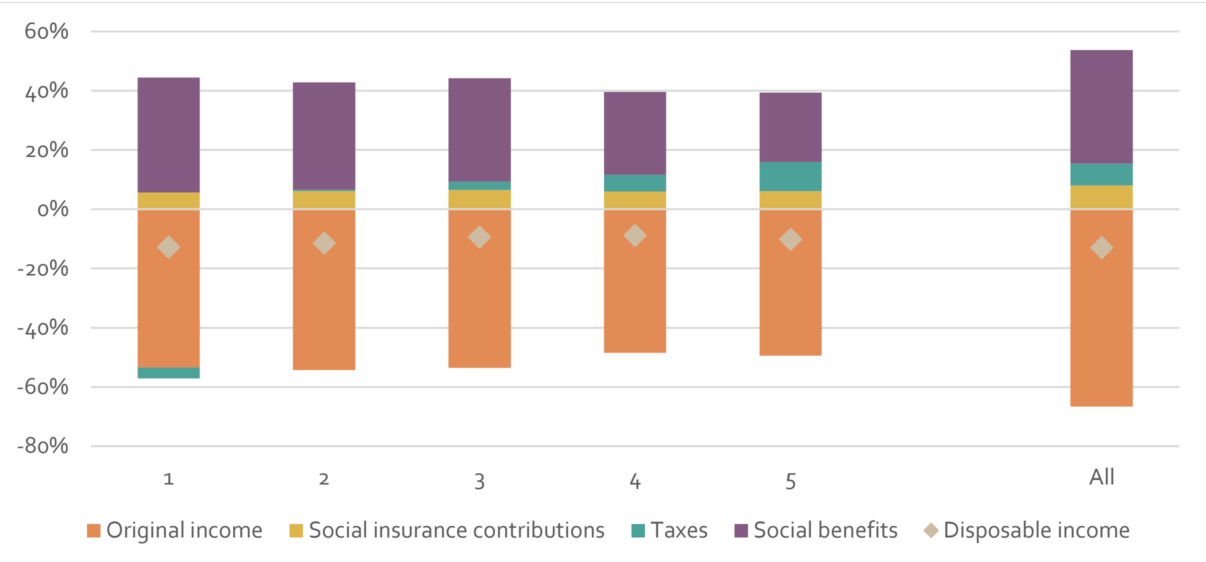
In absolute terms, the decrease in disposable income grows over the quintiles. This is not the case in relative terms (panel B of Figure 6), where up until the 4th quintile, the decrease in disposable income becomes smaller. In the first quintile, the fixed withholding tax rate levied on the temporary unemployment benefit works against the disposable income of the affected employees. Whereas the temporary unemployment benefit compensates to large extent the losses in market income, it is (on average) taxed at a higher rate than the wages these groups earned on the labour market (see also section 6.3.1). From the second quintile onwards, the fixed withholding tax rate on the temporary unemployment benefit offers an additional boost to the monthly disposable income of the affected employees, causing the relative decrease in monthly disposable income to be the lowest in the 4th quintile. It is in the 5th household income quintile that the combined effect of social benefits and withholding tax reactions no longer compensate for the large decreases in market incomes.

Figure 6. Estimated change in disposable income and income components of households with affected employees, over pre-COVID equivalized disposable household quintiles

Panel A. Absolute changes



Panel B. Relative changes



Note: Quintiles are calculated based on the distribution of equivalised household disposable income for the total population. Changes are calculated on non-equivalised household incomes, for households with only affected employees.
Source: Authors' calculations

In section 6.3.1 we showed the impact of the shock on individual disposable income by individual pre-COVID earnings quintile. We found the lowest decrease in disposable income around the 2nd individual earnings quintile, due to the interplay of social benefits who provided a fairly good replacement rate for a prior income up to 2750 euro per month, with a fixed withholding tax rate that was more disadvantageous for those with (very) low prior wages. Absolute and relative losses in disposable income increased steadily from the 2nd pre-COVID wage quintile onwards, with an especially large drop in the 5th quintile.

At the household level, this pattern looks rather different. First of all, the substantial decreases in higher earnings quintiles are balanced when we group losses over equivalized disposable household income quintiles. The decreases in disposable incomes in the highest quintiles become far less outspoken. Alternatively, decreases are, especially in absolute terms, somewhat higher in the lower household income quintile. Third, grouped by individual earnings quintiles, we saw absolute and relative decreases in the disposable income increase steadily from the 1st to the 2nd and 3th quintile. Organizing households by equivalized disposable household income quintiles, the pattern disappears, with decreasing relative losses until the 4th quintile, and only in the 5th quintile there is again a larger relative decrease. (This is of course not the case when looking at absolute losses (panel A), where we do observe a relatively steady deterioration in the decrease in average disposable income.)

6.3.2.2 Households with self-employed individual(s)

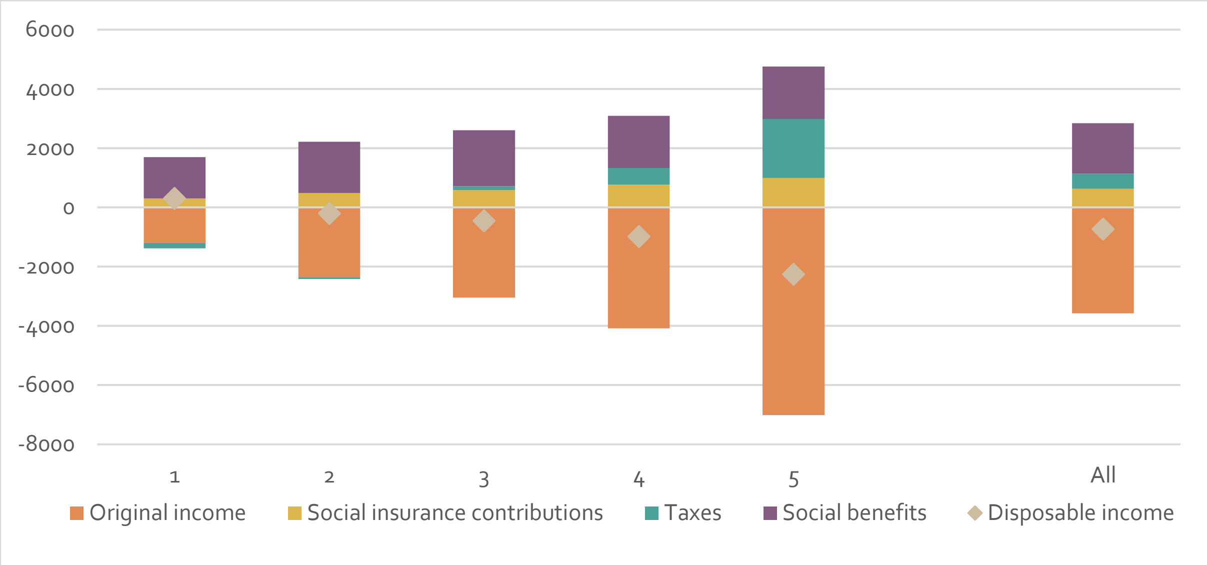
Error! Reference source not found. shows the changes in disposable income by pre-COVID equivalised disposable household income quintiles for households with affected self-employed. As mentioned before, interpretation of the results for self-employed are fraught with difficulties. In addition, in some pre-COVID equivalised disposable household income quintiles, only a limited number of observations of affected self-employed households are present.

We therefore only focus on the broad trends. A first observation is that, compared to the individual approach (section 6.3.1), in- and decreases at the extremes are far less pronounced, both in absolute as in relative terms, as self-employed in different earnings quintiles find themselves in different equivalised disposable housing income quintiles. Still, affected self-employed who find themselves in the first equivalised disposable household income quintile see their incomes increase after the bridging right, due to the low reported self-employment incomes in the EU-SILC.

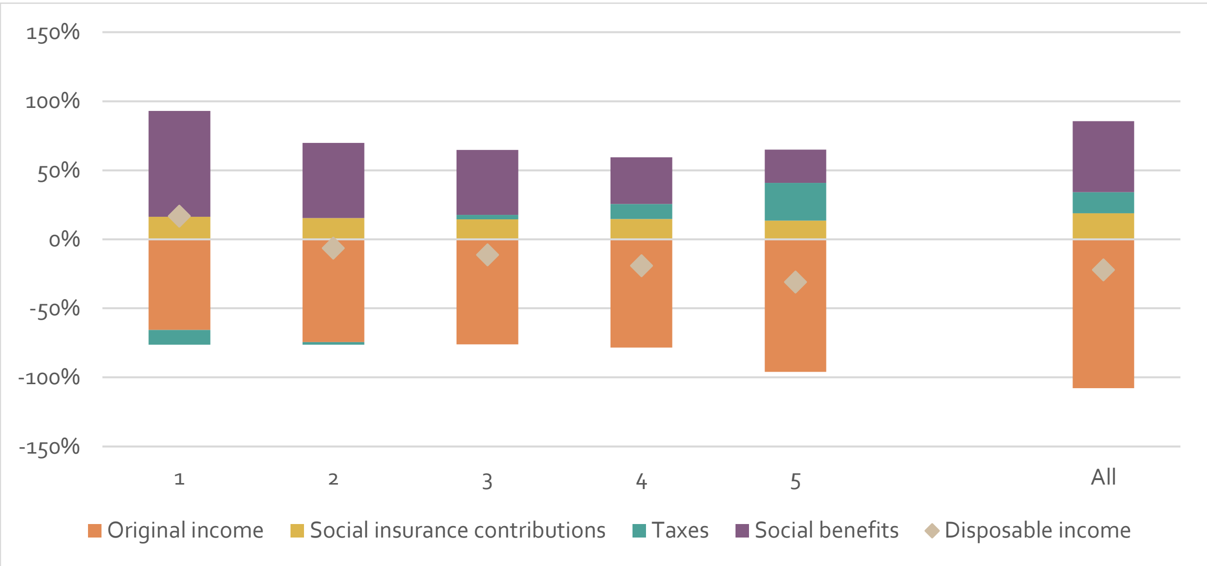
Second, the importance of the (lump-sum) social benefit decreases for higher income quintiles. This is however to large extent mitigated by the decrease in social insurance contributions and withholding tax. Regarding the latter, we should note that our modelling of the withholding tax of the self-employed is an abstraction of the real-life situation, and will likely underestimate the actual funds self-employed have to set aside.

Figure 7. Estimated change in disposable income and income components of households with affected self-employed, over pre-COVID equivalized disposable household quintiles

Panel A. Absolute changes



Panel B. Relative changes



Note: Quintiles are calculated based on the distribution of equivalised household disposable income for the total population. Changes are calculated on non-equivalised household incomes. Source: Authors' calculations

6.3.2.3 Characteristics of the (most) affected at the household level

In Table 23 and Table 24 we describe the characteristics of individuals living in affected households. We distinguish between the individuals that experienced no or only a moderate loss in household incomes, individuals that experienced a medium loss, and those that were substantially affected in terms of disposable household income. Table 23 groups individuals by relative household income losses, whereas Table 24 looks at individuals by absolute household income losses.

We compare the characteristics of these individuals affected to different degree with the overall characteristics of those affected.

As we have done before, when considering the characteristics of those experiencing large losses in their individual disposable income (section 6.3.1.4), we observe that those experiencing large relative losses at the household level are more often higher educated. Also households with affected self-employed generally experience larger losses.

In contrast to our findings the individual level, we see that individuals living in households that experience a large (relative) decrease in income are far more often single. Couples are no longer overrepresented when considering relative household income losses. Those most severely affected in relative terms are also more often tenants.

In absolute terms, the observation that the more well-off experienced the largest losses remains true, also when considering household incomes.

Table 23. Characteristics of affected self-employed and employees, by extent of their relative loss

	No loss - 10% loss	10%-25% loss	>25% loss	All affected individuals	All active individuals
Share of all affected	**54%**	**31%**	**16%**	**100%**	**-**
Share of all actives	16%	9%	5%	**31%**	**100%**
Age group					
16-29	19%	16%	12%	17%	**15%**
30-39	28%	31%	27%	29%	**27%**
40-49	22%	27%	28%	25%	**26%**
50-59	26%	22%	27%	25%	**27%**
60+	6%	3%	6%	5%	**5%**
Gender					
Women	41%	40%	36%	40%	**47%**
Men	59%	60%	64%	60%	**53%**
Education					
No or primary	8%	8%	6%	8%	**7%**
Secondary	65%	63%	51%	63%	**44%**
Tertiary	27%	29%	43%	30%	**49%**
Labour status					
Employee	83%	83%	65%	80%	**88%**
Self-employed	17%	17%	35%	20%	**12%**
Household type					
Single	9%	10%	34%	13%	**14%**
Single parent	2%	3%	2%	2%	**2%**
Couple	36%	34%	29%	34%	**34%**
Couple with children	34%	45%	26%	36%	**37%**
Other	19%	9%	8%	14%	**13%**
Tenure status					
Owner	52%	53%	45%	51%	**56%**
Tennant	48%	47%	55%	49%	**44%**
Quintile employees (pre-COVID employment wages)					
1	30%	29%	21%	29%	**20%**
2	24%	19%	12%	21%	**20%**
3	21%	22%	17%	21%	**20%**
4	16%	16%	22%	17%	**20%**
5	9%	13%	28%	12%	**20%**
Quintile self-employed (pre-COVID self-employment incomes)					
1	47%	2%	2%	24%	**23%**
2	31%	14%	4%	20%	**21%**
3	17%	39%	13%	21%	**20%**
4	3%	30%	22%	15%	**17%**
5	2%	14%	59%	21%	**20%**

Note: groups identified based on individual relative losses in household disposable income. Source: Authors' calculations

Table 24. Characteristics of affected self-employed and employees, by extent of their absolute loss (in euros)

	No loss - 500	500 – 1000	> 1000	All affected individuals	Not active individuals
Share of all affected	**64%**	**22%**	**14%**	**100%**	**-**
Share of all actives	19%	7%	4%	**31%**	**100%**
Age group					
16-29	18%	18%	10%	17%	**15%**
30-39	29%	30%	26%	29%	**27%**
40-49	22%	26%	33%	25%	**26%**
50-59	26%	22%	25%	25%	**27%**
60+	6%	3%	5%	5%	**5%**
Gender					
Women	42%	37%	35%	40%	**47%**
Men	58%	63%	65%	60%	**53%**
Education					
No or primary	9%	7%	6%	8%	**7%**
Secondary	67%	63%	42%	63%	**44%**
Tertiary	24%	30%	52%	30%	**49%**
Labour status					
Employee	83%	82%	63%	80%	**88%**
Self-employed	17%	18%	37%	20%	**12%**
Household type					
Single	15%	12%	8%	13%	**14%**
Single parent	3%	2%	1%	2%	**2%**
Couple	36%	29%	36%	34%	**34%**
Couple with children	31%	42%	46%	36%	**37%**
Other	16%	15%	9%	14%	**13%**
Tenure status					
Owner	47%	59%	56%	51%	**56%**
Tennant	53%	41%	44%	49%	**44%**
Quintile employees (pre-COVID employment wages)					
1	36%	15%	13%	29%	**20%**
2	25%	16%	7%	21%	**20%**
3	21%	31%	6%	21%	**20%**
4	13%	27%	20%	17%	**20%**
5	6%	11%	54%	12%	**20%**
Quintile self-employed (pre-COVID self-employment incomes)					
1	43%	2%	3%	24%	**23%**
2	32%	8%	4%	20%	**21%**
3	23%	38%	4%	21%	**20%**
4	0%	49%	19%	15%	**17%**
5	2%	3%	71%	21%	**20%**

Note: groups identified based on individual absolute losses in household disposable income. Source: Authors' calculations

6.4 Overall impact on the income distribution

How does this average impact on the affected population ripple through to the overall population?

In se, this depends on the distribution of the affected individuals (and households) over the income distribution of the entire population. We discussed this extensively in section 6.2. Mainly, we found that even though it are mainly the lower earners (at least for employees) that faced temporary unemployment, in the household income distribution those affected are mainly found in higher regions of the equivalised household disposable income distribution, precisely because there are (often multiple) incomes from work present in the household.

Therefore, when we observe the largest average relative decreases in household disposable income among the affected employee households in the first equivalised disposable household income quintile (section 6.3.2.1), we should consider that this is calculated on a relatively small group. Averaged out over all the households present in the first equivalised disposable household income quintile, this decrease disappears (see Table 25 below). However, this is not to say that those affected did not experience a very real hardship.

Table 25. Estimated relative change in disposable income by quintiles of pre-COVID equivalized disposable household income

	1	2	3	4	5	All
Absolute change						
All individuals	-1	-31	-44	-65	-123	-53
All households	-2	-64	-108	-176	-319	-122
Relative change						
All individuals	0%	-3%	-3%	-4%	-5%	-4%
All households	0%	-3%	-3%	-4%	-5%	-4%

Note: Quintile groups based on pre-COVID equivalized disposable household incomes of the total population. Source: Authors' calculations

The loss in disposable income increases over the quintiles, both in relative and absolute terms, and both when considering individual as well as household disposable incomes. While on average the fall in individual disposable income is hardly visible in the lowest quintile, there is a decrease of about 5% of pre-COVID disposable income in the highest quintile. Looking at the total population instead of solely considering the affected population, we clearly see a different pattern. Whereas affected employees saw the largest decreases in the lowest pre-COVID equivalised disposable household income quintile, averaged out over all individuals or households in this first quintile, this average decrease very nearly disappears. Indeed, most individuals and households in the first quintile are inactive, already unemployed or retired, hence they did not feel the direct effect of the labour market shock as we modelled it. In higher household income quintiles, larger shares of the population are in-work (and hence also have a higher likelihood of being affected), leading to larger (but still limited) decreases in average disposable income. Indeed, what Table 25 mainly shows is the effect of averaging out the shock, of which the brunt was carried by around 30% of the population, over the total population.

In Table 26 and Table 27, we zoom in on the characteristics of the individuals unaffected, slightly affected and most affected by the shock. We now expand the scope to the total population and move from individual disposable income to disposable income at the household level. Table 26 shows the characteristics over four different subgroups: individuals with (i) no loss in disposable household income, (ii) a loss of less than 10% of their pre-COVID disposable household income, (iii) a loss between 10% and 25% of their pre-COVID disposable household income and (iv) a loss of more than 25% of the pre-COVID disposable household income. Only 3.5% of all individuals lives in a household experiencing a loss of more than 25% of disposable household income. And, these individuals are mainly present in the 4^{th} (22%) and 5^{th} quintile (34%). The same characteristics are presented in Table 27 but over four subgroups divided by the absolute loss in disposable household income: (i) no loss, (ii) a loss of less than 500 euros, (iii) a loss between 500 and 1,000 euros or (iv) a loss of more than 1,000 euros. Only 4.3% of all individuals are situated in a household with a loss of more than 1,000 euros, of which more than 80% is living in a household in one of the top two quintiles.

Table 26. Characteristics of individuals among the total population, by extent of their relative loss

	No loss	0–10% loss	10-25% loss	>25% loss	All individuals
Share all actives	**72%**	**15%**	**9%**	**3%**	**100%**
Age group					
0-15	16%	20%	25%	21%	**18%**
16-29	15%	24%	19%	16%	**17%**
30-39	11%	17%	20%	19%	**13%**
40-49	12%	14%	17%	19%	**13%**
50-59	14%	19%	14%	18%	**15%**
60+	32%	6%	5%	7%	**25%**
Gender					
Women	52%	47%	50%	51%	**51%**
Men	48%	53%	50%	49%	**49%**
Education					
No or primary	27%	27%	32%	23%	**27%**
Secondary	43%	49%	46%	43%	**44%**
Tertiary	30%	23%	23%	34%	**28%**
Labour status					
Employee	30%	54%	49%	42%	**35%**
Self-employed	3%	5%	8%	21%	**5%**
Unemployed	4%	2%	1%	1%	**3%**
Retired	27%	3%	3%	2%	**20%**
Inactive (including <18y)	36%	36%	38%	33%	**36%**
Household type					
Single	18%	2%	4%	19%	**15%**
Single parent	5%	1%	2%	3%	**4%**
Couple	32%	28%	24%	25%	**30%**
Couple with children	29%	43%	50%	40%	**33%**
Other	16%	25%	19%	13%	**18%**
Tenure status					
Owner	38%	58%	58%	49%	**43%**
Tennant	62%	42%	42%	51%	**57%**
Quintile (pre-COVID) equivalized household disposable income					
1	25%	5%	8%	9%	**20%**
2	21%	16%	23%	17%	**20%**
3	19%	20%	26%	19%	**20%**
4	17%	32%	25%	22%	**20%**
5	18%	26%	19%	34%	**20%**

Note: groups identified based on relative losses in disposable household income. Source: Authors' calculations

Table 27. Characteristics of individuals among the total population, by extent of their absolute loss (in euros)

	No loss	0-500	500-1000	>1000	All individuals
Share all actives	**72%**	**17%**	**7%**	**4%**	**100%**
Age group					
0-15	16%	20%	24%	27%	**18%**
16-29	15%	22%	23%	15%	**17%**
30-39	11%	18%	19%	16%	**13%**
40-49	12%	15%	15%	19%	**13%**
50-59	14%	19%	14%	16%	**15%**
60+	32%	6%	4%	6%	**25%**
Gender					
Women	52%	48%	48%	52%	**51%**
Men	48%	52%	52%	48%	**49%**
Education					
No or primary	27%	27%	30%	31%	**27%**
Secondary	43%	51%	47%	32%	**44%**
Tertiary	30%	22%	23%	37%	**28%**
Labour status					
Employee	30%	54%	48%	41%	**35%**
Self-employed	3%	6%	8%	16%	**5%**
Unemployed	4%	2%	1%	0%	**3%**
Retired	27%	4%	2%	3%	**20%**
Inactive (including <18y)	36%	34%	41%	39%	**36%**
Household type					
Single	19%	6%	5%	3%	**15%**
Single parent	5%	2%	2%	1%	**4%**
Couple	32%	30%	21%	25%	**30%**
Couple with children	28%	42%	47%	56%	**33%**
Other	16%	21%	26%	15%	**18%**
Tenure status					
Owner	38%	54%	63%	60%	**43%**
Tennant	62%	46%	37%	40%	**57%**
Quintile (pre-COVID) equivalized household disposable income					
1	25%	8%	6%	2%	**20%**
2	21%	21%	19%	5%	**20%**
3	19%	24%	24%	13%	**20%**
4	17%	26%	30%	32%	**20%**
5	18%	20%	21%	48%	**20%**

Note: groups identified based on absolute losses in disposable household income. Source: Authors' calculations

We further zoom in on the impact of the COVID-induced economic shock and the policy response on the equivalised disposable household income distribution. We compare shares of the population below (different percentages of) the pre-COVID median calculated on monthly equivalised disposable incomes and inequality indicators prevailing in the pre-COVID period with those after the shock and policy response are accounted for.

As already evident from the previous sections, when considering the impact of the COVID 19 shock over the entire population, the effect remains relatively limited. In Table 28, we consider the share of the population that falls back in the overall (equivalised disposable household) income distribution. We show the share of the population with a monthly disposable income lower than respectively 60, 80 and 100% of the median equivalised disposable household monthly income. For the overall population, the shift remains relatively limited: only 4.7% of the population falls from the upper half of the pre-COVID distribution to the lower half after the shock and the policy response. The share of the population with a monthly income below 80% of the median only increases with 3.2 percentage points, and only 1.2% of the population ends up below 60% of the median due to the lockdown.

Table 28. Estimated shares of individuals below 60%, 80% or 100% of the median equivalized disposable household income

	<60%		**<80%**		**<100%**	
	Pre	Post	Pre	Post	Pre	Post
Total population	12.5%	13.7%	30.5%	33.7%	50.0%	54.7%
Affected population	4.8%	8.6%	17.6%	27.8%	37.7%	52.6%
Affected employees	2.6%	6.8%	14.7%	24.4%	34.1%	49.4%
Affected self-employed	13.1%	14.3%	26.6%	39.6%	50.0%	67.9%

Note: All shares are calculated based on the pre-COVID median equivalized disposable household income of the total population. Affected population refers to individuals living in a household with an affected worker. Affected employees refers to the group of individuals living in a household with only affected employees, whereas the group of affected self-employed refers to the group of individuals living in a household with affected self-employed. Source: Authors' calculations

Even so, and in line with other observations made in this paper, the shifts among the affected population were substantial. When we consider the groups of individuals living in a household with an affected employee, far larger shares fell below different percentages of the pre-COVID median. Before the lockdown, only 34.1% of this group find themselves below the median, in line with their relatively favourable position thanks to their income(s) from work. However, the share of individuals living in a household with an affected employee below the median increases to nearly 50% after taking account of the shock and policy response. The share below the 80% line increases with 10 percentage points, whereas the share with post-COVID monthly income below 60% nearly triples.

The cushioning effect of policies is evident when we look at inequality (Table 29). Inequality of disposable income is hardly affected when taking account of the shock and policies, while the impact on original income is substantial, both for the entire as for the affected population.

Table 29. Estimated inequality indices on the monthly income distribution pre- and post-COVID, for total and affected population

	Pre-Covid	Post-Covid
Gini index original income		
Total population	0.50	0.55
Affected population	0.30	0.45
Gini index disposable income		
Total population	0.22	0.22
Affected population	0.18	0.18

Source: Authors' calculations

7 Conclusion

The COVID-19 pandemic and the subsequent Spring lockdown affected economic life in Belgium in ways not witnessed in many a generation. The scale as well as the speed of the shock was wholly unprecedented, dwarfing the impact of the financial crisis of 2008 and earlier recessions. Whole sectors of economic life were effectively brought to a (near) halt causing major revenue losses for firms.

This shock would probably have had considerable consequences for households as well were it not for the compensating measures taken by Belgium's governments. These were in part extensions or relaxations of existing provisions, such as Belgium's extensive temporary unemployment scheme. For another part the response consisted of new measures. Some of these targeted firms or creditors, thus supporting workers and business owners indirectly. Other measures targeted workers or self-employed persons directly. The primary focus in this present paper is on two measures that were of particular importance in stabilizing household incomes during the early stages of the COVID19 crisis: temporary unemployment and the bridging right for the self-employed. That means that we offer only a partial assessment of a much broader government response.

The aim of this paper is to report on our efforts to set up a methodology that can be used to monitor the impact of compensating measures targeting workers and self-employed people as the COVID19 crisis unfolds. The primary focus is on the distribution of individual earnings and household disposable incomes. We examine so-called first-order effects only. This means that we make no attempt to estimate the consequences or behavioural reactions on the part of firms or workers themselves. For that purpose we build on the Belgian version of the microsimulation tax-benefit model EUROMOD, which runs on a representative sample of Belgian households, the EU-SILC. We have recalibrated the EU-SILC to reflect the labour market impact of the COVID-19 shock. This first paper focuses on the impact on monthly household incomes in April of the partial lockdown that started in the mid of March.

One of the challenges of this exercise is that the most recent data of EU-SILC refer to pre-COVID times, i.e., 2018. We remedy this through techniques of nowcasting, which we document extensively in this paper. A particularly challenging task was to predict changes in labour market status due to the COVID-19 shock. We describe in detail how the outcomes of predictive models were used to simulate changes in labour market status for employees and self-employed in the EU-SILC 2018 database. These nowcasted data were then used in combination with EUROMOD in order to estimate the impact of both the change in earnings as well as of policy measures taken.

The main results are as follows:

First, the potential impact of the COVID19 shock and the subsequent partial lockdown on individual incomes would have been quite significant in absence of a policy response. We find that total earnings of the active population likely decreased by 19%. If we look at those who probably enjoyed temporary unemployed or bridging right benefits, the estimated drop in total earnings was far larger, even amounting to 71%.

Second, the brunt of the lockdown was not borne equally. Those affected are mainly male, 30-39 years old, lower educated and tenants. The largest decreases in earnings (both in absolute as in relative terms) are found among the highest earnings quintiles, whereas the largest shares of affected persons are found in lower earnings quintiles.

Third, the potential decreases in household incomes would have been far less severe than the potential decreases at the individual level even in the absence of compensating measures. This is due to the cushioning effect of other incomes in the household. The majority of those affected lived in households were other income sources were present.

This is also evident if we compare the position of the affected workers in terms of their individual earnings as opposed to their position in the household income distribution. While most of the affected workers had earnings in the lower ranges they were usually to be found in the higher ranges of the pre-COVID household income distribution. This explains a recurring theme in this paper: the effects of the policy measures look *very different* depending on whether one considers the effects at the individual or the household level.

At the individual level for instance, we find that those experiencing the largest losses in (individual) disposable income of those affected are more likely to be highly educated, living in couples without children, and owners. Among affected employees, the decreases in disposable income are lowest in the second pre-COVID wage quintile, and increase steadily onwards. Those around the second pre-COVID wage quintile benefit from the relatively high replacement rate guaranteed by the temporary unemployment benefit, and, to the extent they only became part-time temporary unemployed, from a disproportionate drop in withholding tax. Even though this effect will likely be negated through the final personal income tax, it did protect monthly disposable incomes in the month of April. The opposite is true for very low income earners, who could not benefit from a decrease in withholding tax, and may even have missed some tax credits. Again, those will be applied in the final personal income tax, but nonetheless, their absence likely felt very hard in April.

At the household level, those among the affected population experiencing the highest relative disposable income losses, are more often single, and tenants. The relative losses of households with affected employees are smallest in the third pre-COVID equivalized disposable household income quintile, and largest in the 1st and 5th quintile (although in the first household income quintile, the affected share of the population is relatively small).

Fourth, the welfare state clearly acted as a social stabiliser. Taking account of the effect of temporary unemployment and bridging rights, household disposable income declined with 4% among the total population (and by 22% among households with affected self-employed, and by 13% among households with affected employees). The loss in labour income due to the economic shock was for the most part offset by the compensatory measures put in place. Yet, among the affected population, a substantial share fell below 60% of the pre-COVID median of monthly equivalised disposable household income, with even larger shares falling below 80% and 100% of the pre-COVID median. This means that temporary employment and bridging right schemes effectively absorbed the massive economic impact of COVID-19. At the same time, it also indicates that even among workers being entitled to compensatory measures, a non-negligible share experienced a substantial fall in household incomes and in their living standard. Moreover, these are conservative estimates since we only focus on those persons who were working before the COVID-19 pandemic struck. Changes in the incomes of the inactive and unemployed population were not taken into account, nor do we measure effects not captured well by survey data, such as the observed increases in the use of food support at the local level.

This exercise has four main limitations.

First, we estimate the shock on only a very specific part of the population. We focus on the impact of the large influx into temporary unemployment and the bridging right for the self-employed. Our model does not allow to identify those who were impacted by the lockdown in a manner different from (temporary) unemployment or the bridging right. We do not observe nor simulate the overall impact of those under the radar of our survey or the macro statistics: those who could not rely on the bridging right or (temporary) unemployment, but who nevertheless (or even more so) faced severe challenges due to the lockdown. Obvious examples are persons who saw their weekly working hours heavily reduced, without becoming (temporary) unemployed, such as flexijobbers or persons on temporary contracts.

Second, and relatedly, we hence only simulate the impact of the measures directly applicable to this target group: the (extension of the) temporary unemployment scheme and the bridging right for the self-employed, in addition to the “mechanic” reaction of the tax benefit system to this decrease in earnings, through the withholding tax system, the social insurance contributions and potential increases in social assistance benefits. We do not include additional, more specific or in-kind support measures, such as the effect of the large subsidies to local welfare agencies, or the measures to postpone mortgage payments.

Third, the counterfactual scenario is necessarily a rudimentary one. We effectively assume that workers would have had no income in absence of temporary unemployment or bridging right benefits. That is obviously not realistic but we have at this time no practical way of constructing a more sophisticated counterfactual. It is extremely hard to know what would have happened without the measures we assess the first round impact of here. Estimating how long firms or businesses would have been able to stay afloat and service payrolls is obviously hard. It is unclear how fast they would have started to lay off people, how many and who would have had to go first. It is even unclear how banks and other creditors would have acted in absence of government measures. Any counterfactual thus requires strong assumptions on what might have happened if existing stabilizers had not kicked into action and if governments had stayed passive. Also, it is important to reiterate that we look here at the impact of the *estimated* take-up of benefits, not the actually observed take up.

Fourth, there are a number of standard limitations to micro-simulation modelling. It assumes full and instantaneous take up of right, in this case temporary unemployment benefits and bridging right.

In next working papers, we aim to follow up and improve upon this exercise, by tracing the impact of the shock and policies also in additional months. Whereas we do think our focus on monthly disposable income has brought to light some fluctuations that were felt hard, but may have gotten lost in an annual approach, we plan to also add an annual assessment in the future. Finally, we aim to further improve upon our nowcasting model as more and better reference data become available.

Even though our current method has clearly advantages in term of speed and distributional focus, some of the abovementioned limitations cannot be addressed with the current method. Therefore, we will release additional exercises based on data with other and complementary strengths to the EU-SILC.

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9 Appendix

9.1 Comparison with random allocation

Our nowcasting method is based on both available macroeconomic statistics and the Corona Study. First, we use the Corona Study to estimate two binomial logit models to predict probabilities at the individual level in EU-SILC, similar to the method use by Brewer and Tasseva (2020). And in a second stage, we use the available statistics to align these probabilities with the macroeconomic situation. However, without the Corona Study, the available macroeconomic statistics would have been our only source of information. In that case, we would have relied on a similar method as used by Figari and Fiorio (2020) and Beirne et al. (2020). This method consists of randomly allocating individuals to an outcome status only based on aggregate statistics. In our case, we could have used target occurrences z_G, presented in the contingency tables Table 9 and Table ***10***, and randomly select individuals in each group G of which we change the labour market status. We compare our method with this random allocation method based on target occurrences z_G to see if the Corona Study adds value to our method.

Table 30 presents the relative share of changed labour market status for different subgroups and compares both methods with the aggregate statistics of temporary unemployment and the receipt of bridging rights. It can be concluded that both nowcasting methods approaches the macroeconomic situation reasonably well. Disparities can be found for certain sectors, which are likely caused by the limited number of observations within each subgroup. However, it is not surprisingly that both methods perform similarly when looking to gender, age and sector subgroups since we use these target occurrences z_G in our current method to align with the macroeconomic situation.

Table 30: Relative share of changed labour status per subgroup

		Employees			Self-employed		
		Random allocation	Binomial logit model	External Statistics	Random allocation	Binomial logit model	External Statistics
Gender	Male	31.64%	31.61%	33.95%	52.57%	52.53%	52.35%
	Female	22.60%	22.53%	25.10%	51.07%	51.35%	51.00%
Age	36 and older	25.42%	25.44%	27.46%	48.49%	48.61%	49.95%
	35 and younger	31.06%	30.85%	34.12%	66.48%	66.33%	60.51%
Sector	Agriculture and forestry	27.79%	22.39%	10.20%	22.52%	22.53%	61.29%
	Mining and quarrying; manufacturing; electricity, gas and water supply; community facilities	40.50%	40.57%	41.46%	53.72%	52.97%	53.90%
	Construction	61.88%	61.59%	63.96%	60.12%	60.17%	50.48%
	Wholesale and retail	46.89%	46.75%	47.29%	53.65%	53.39%	73.17%
	Transport and storage; information and communication	24.57%	24.63%	24.40%	50.73%	51.32%	43.16%
	Accommodation and restaurants	74.24%	74.15%	79.28%	74.25%	74.06%	73.17%
	Financial and insurance activities	11.73%	11.82%	11.25%	30.70%	31.83%	22.69%
	Real estate; services to businesses	43.86%	43.85%	44.03%	44.48%	44.70%	28.27%
	Public administration and defense	0.80%	0.56%	0.12%	33.81%	33.81%	0.00%
	Education	5.29%	5.24%	3.24%	63.07%	63.41%	55.93%
	Human health and social work activities	13.27%	13.28%	12.59%	59.52%	59.87%	59.90%
	Arts, entertainment and recreation; personal service activities	38.00%	38.05%	38.86%	64.24%	63.51%	65.03%
Total		27.28%	27.23%	29.57%	52.07%	52.13%	51.88%

Source: Authors' calculations based on *EU-SILC* and *RVA, RSZ, RSVZ* data (note: shares are average share over 500 simulations)

In Figure 8, the shares of affected employees over pre-COVID wage quintiles are shown. We find that among the employees, the shares of affected employees decreases as income increases. Comparing the two nowcasting methods, it is clear that this pattern is less visible when using random allocation where the shares of affected employees are more evenly distributed over the quintiles. The difference is caused by using the Corona Study allowing us to take account of the distribution according to education, occupation and working time. However, Figure 9 shows that this does not hold for the self-employed individuals. Looking at the shares of affected self-employed individuals over pre-COVID wage quintiles, both nowcasting methods result in a similar pattern.

Figure 8: Estimated share of employees experiencing a change in employment status to temporary unemployment among the employees, by quintiles of pre-COVID individual wages, based on two different nowcasting methods

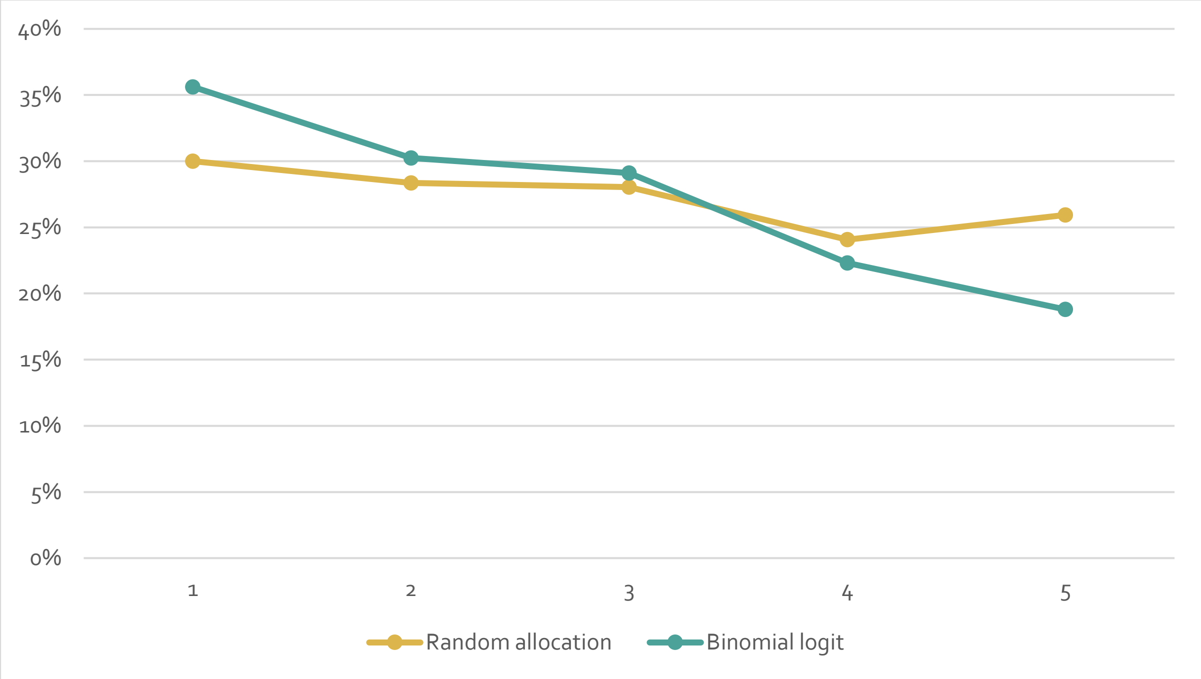
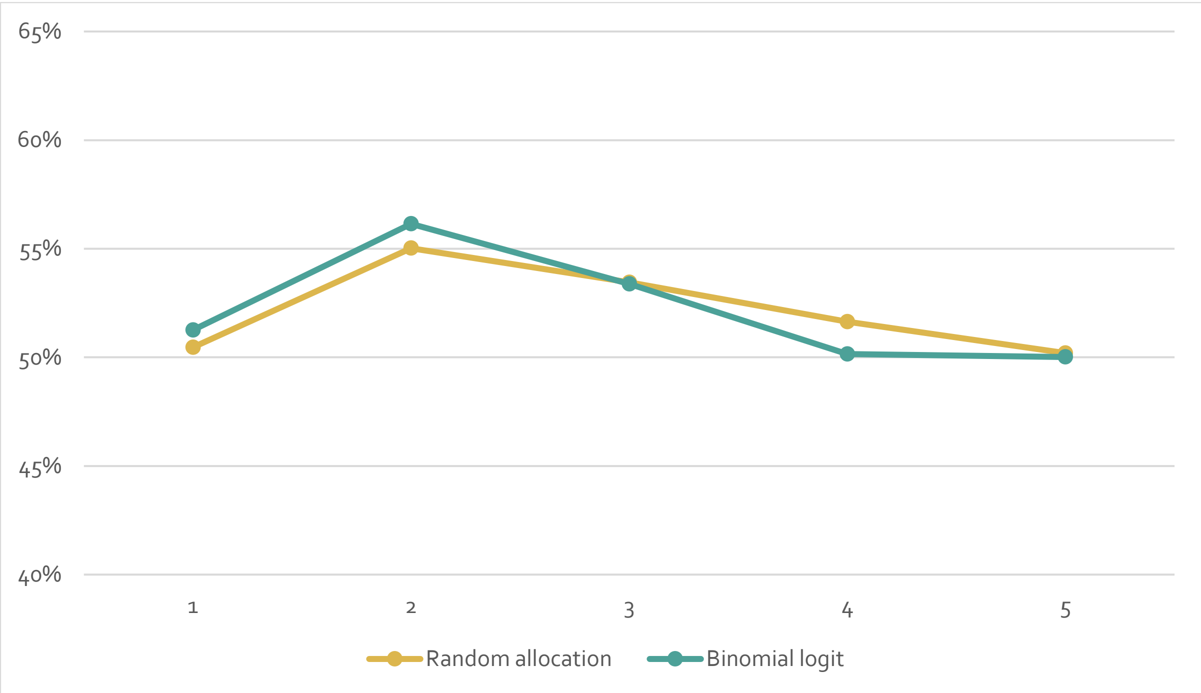


Figure 9: Estimated share of self-employed experiencing a change in employment status to bridging right among the self-employed, by quintiles of pre-COVID self-employment incomes, based on two different nowcasting methods



9.2 Calculation of the identification condition after rescaling of probabilities

Section 5.3.2 explains the determination of the predicted labour status when probabilities are unweighted. Recall that respondent i will be assigned $\hat{Y} = 1$, hence identified as having become temporary unemployed, if

$$u_i \geq -\beta_1 X_i. \tag{A.1}$$

From Equation (7), we know that this happens with probability π_i, equal to

$$\pi_i = \frac{\exp(\beta_1 X_i)}{1 + \exp(\beta_1 Xi)} \tag{A.2}$$

The aim of the rescaling process is to simulate such that respondent i will be assigned $\hat{Y} = 1$ with probability $s_G \pi_i$. In order to achieve this, one can determine a value a such that

$$s_G \pi_i = \frac{\exp(\beta_1 Xi + a)}{1 + \exp(\beta_1 X_i + a)}. \tag{A.3}$$

and we then respondent i is assigned $\hat{Y}_i = 1$ 1 if

$$u_i \geq -\beta_1 X_i - a. \tag{A.4}$$

One can see that Equation (A.3) holds if and only if

$$a = \ln(s_G \pi_{i1}) - \ln(1 - s_G \pi_{i1}) - \beta_1 X_i. \tag{A.5}$$

We plug this value for a into the Equation (A.4) and retrieve the new identification condition; respondent i will be assigned $\hat{Y} = 1$ if

$$u_i < \ln(s_G \pi_i) - \ln(1 - s_G \pi_i). \tag{A.6}$$

9.3 Conversion table annual to monthly incomes

Table 31. Changes to annual incomes depending on labour market status in March

Labour market status in March[a]	Annual employment income	Annual self-employment income	Annual unemployment benefit	Annual pensions	Annual disability pension	Annual sickness benefits	Other incomes
Pre school	none	none	none	none	none	none	none
Employer/ self-employed	If employed in other months: 0 Else: none	*12/number of months mainly in this labour market status	0	If pensioner in other months: 0 Else: none	If sick or disabled in other months: 0 Else: none	If sick or disabled in other months: 0 Else: none	None
Employee	*12/ number of months mainly in this labour market status	If self-employed in other months: 0 Else: none	0	If pensioner in other months: 0 Else: none	If sick or disabled in other months: 0 Else: none	If sick or disabled in other months: 0 Else: none	None
Pensioner	If employed in other months: 0 Else: none	If self-employed in other months: 0 Else: none	0	*12/ number of months mainly in this labour market status	If sick or disabled in other months: 0 Else: none	If sick or disabled in other months: 0 Else: none	None
Unemployed	0	0	*12/ number of months mainly in this labour market status	0	0	0	None
Student	none	none	none	none	none	None	none
Inactive	none	none	none	none	none	None	none
Sick or disabled	If employed in other months: 0 Else: none	If self-employed in other months: 0 Else: none	0	If pensioner in other months: 0 Else: none	*12 / number of months mainly in this labour market status	*12/ number of months mainly in this labour market status	None
other	none	none	none	none	none	none	none

Note: [a] The labour market status is taken to be the one reported in the EU-SILC in March (2017). A perhaps more intuitive option would be to base the monthly incomes on the situation in April. However, in following notes, we would like to show the unfolding of the social impact of the crisis. A fixed baseline will then aid in interpreting results. Because of the timing of the COVID-19 lockdown, we take March as baseline already in this paper.

9.4 Change in withholding tax scales over quintiles

Figure 10: Share of affected employees in each of the four withholding tax scales in pre-COVID scenario, by quintiles of pre-COVID individual wages

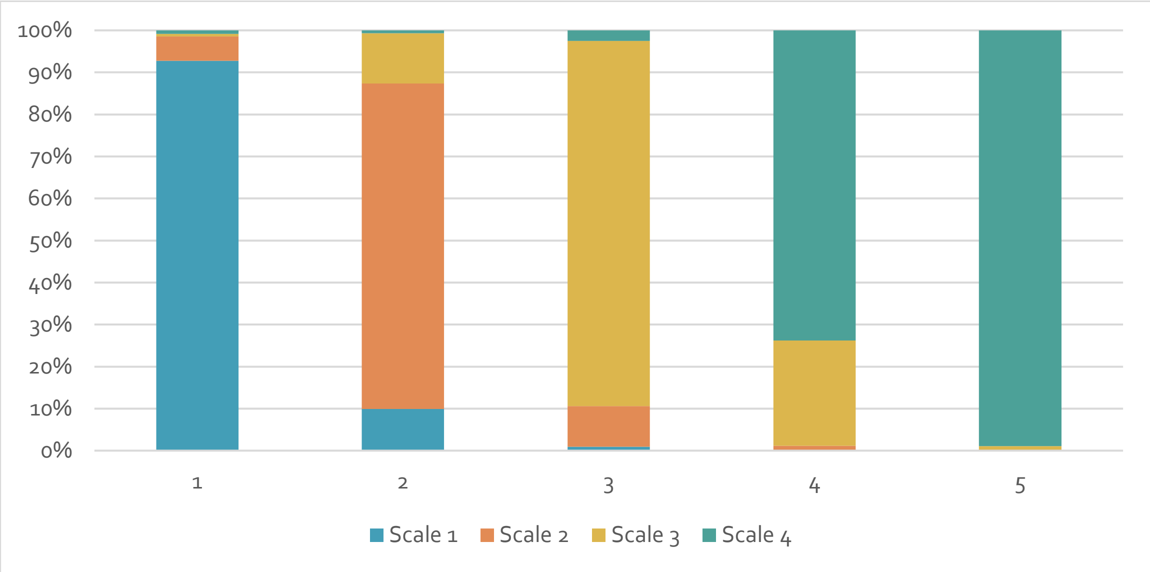
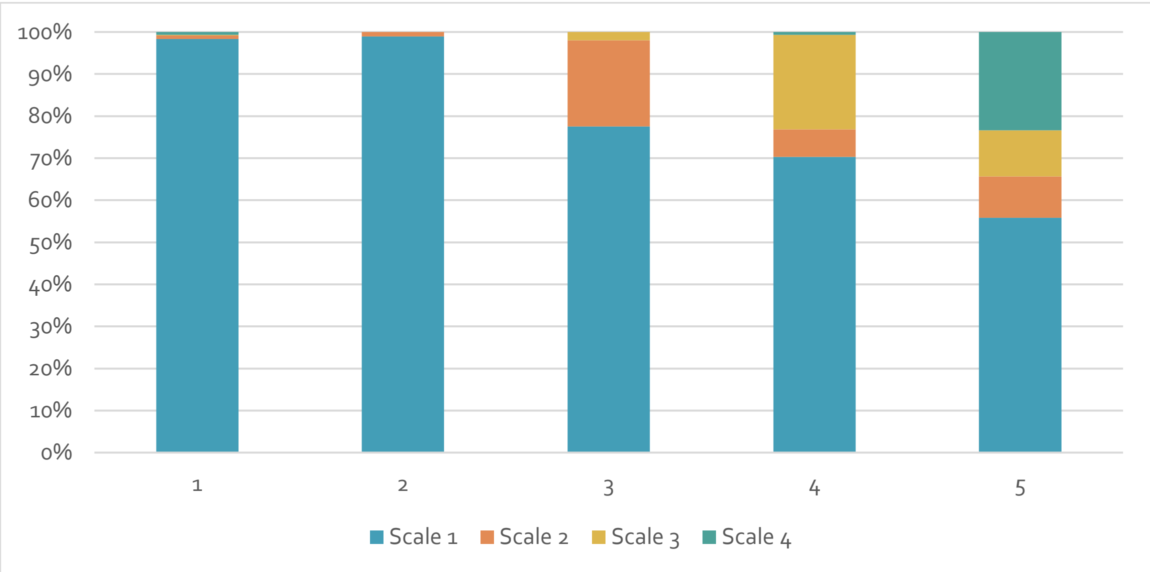


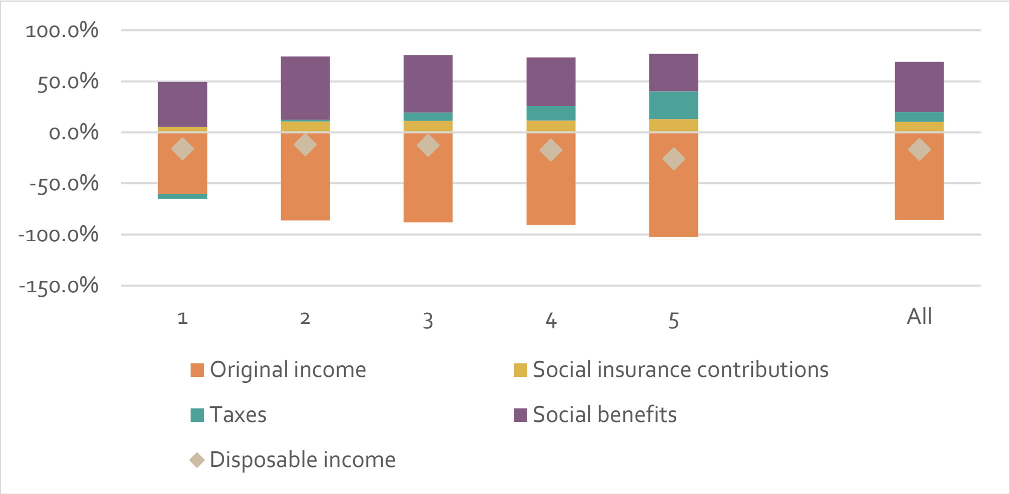
Figure 11: Share of affected employees in each of the four withholding tax scales in post-COVID scenario, by quintiles of pre-COVID individual wages



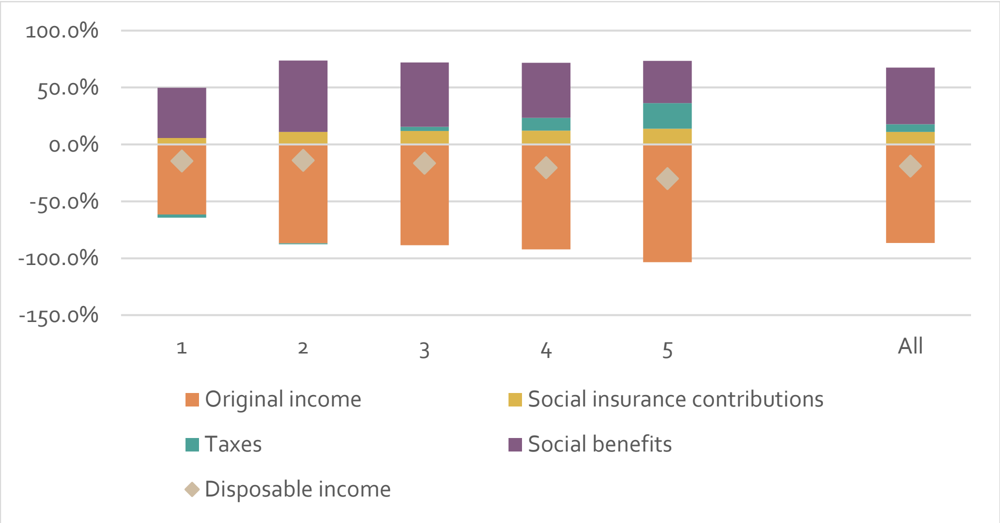
9.5 Comparison impact withholding tax – personal income tax

Figure 12. Estimated change in disposable income and income components of affected employees, over pre-COVID wage quintiles, relative changes

Panel A. Impact on monthly incomes in April, through blind application of withholding tax



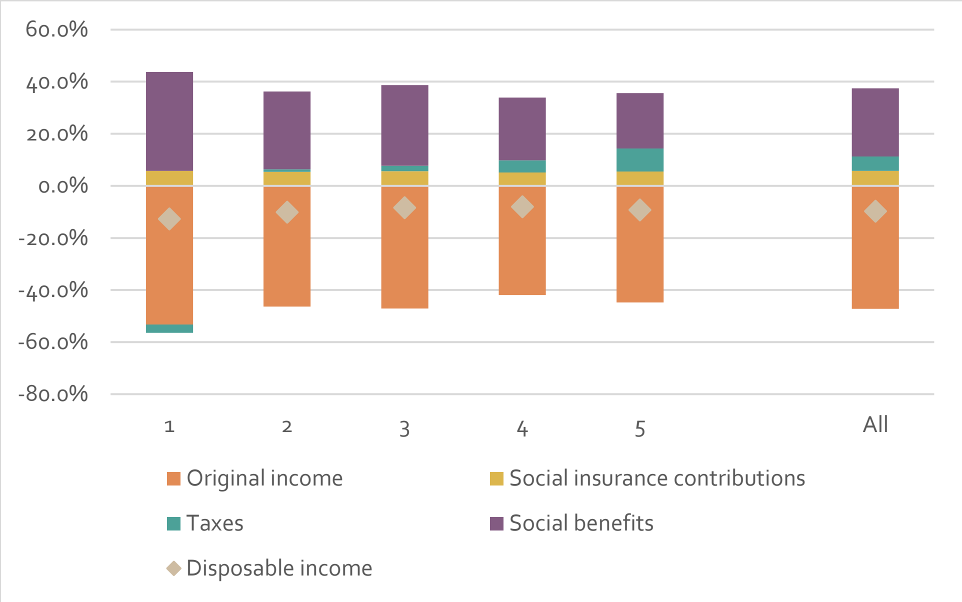
Panel B. Impact on monthly incomes after personal income tax, in a fictional scenario where the April situation lasts a full fiscal year



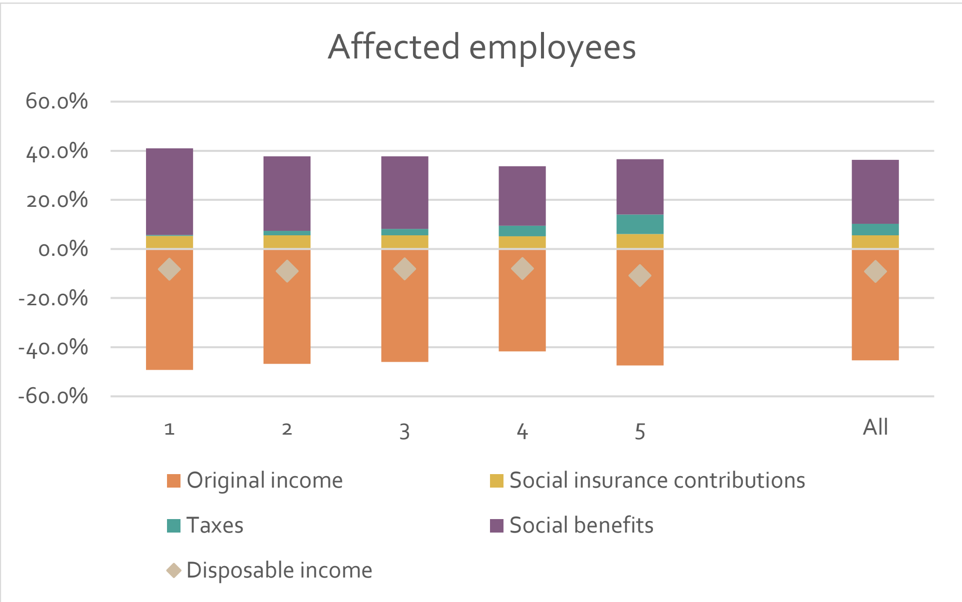
Note: The share of winners under the fictional scenario shown in Panel B decreases from 9.2% to 2.3% of the affected employees.

Figure 13. Estimated change in disposable income and income components of households with affected employees, over pre-COVID equivalized disposable household quintiles

Panel A. Impact on monthly incomes in April, through blind application of withholding tax



Panel B. Impact on monthly incomes after personal income tax, in a fictional scenario where the april situation lasts a full fiscal year



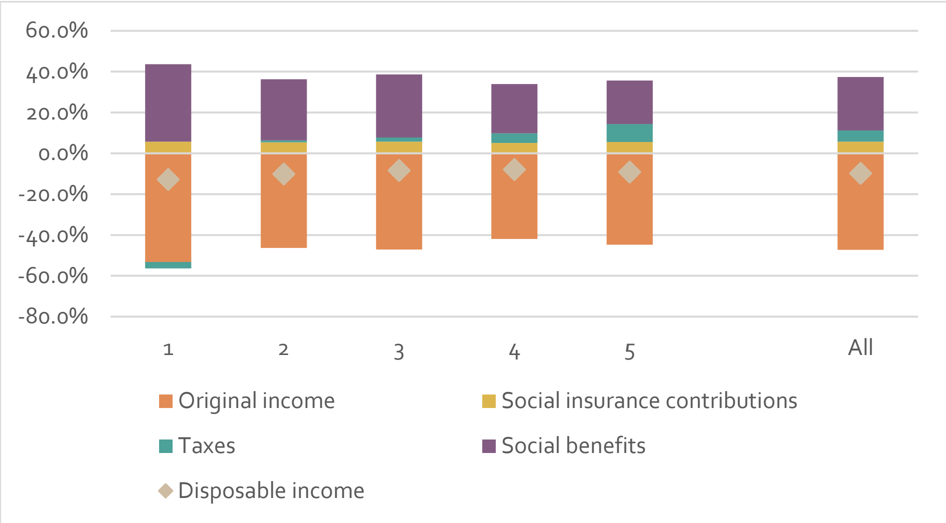
Note: The share of winners under the fictional scenario shown in Panel B decreases from 7.3 % to 0.8% of the households with affected employees.

9.6 Comparison impact conversion bun to monthly incomes

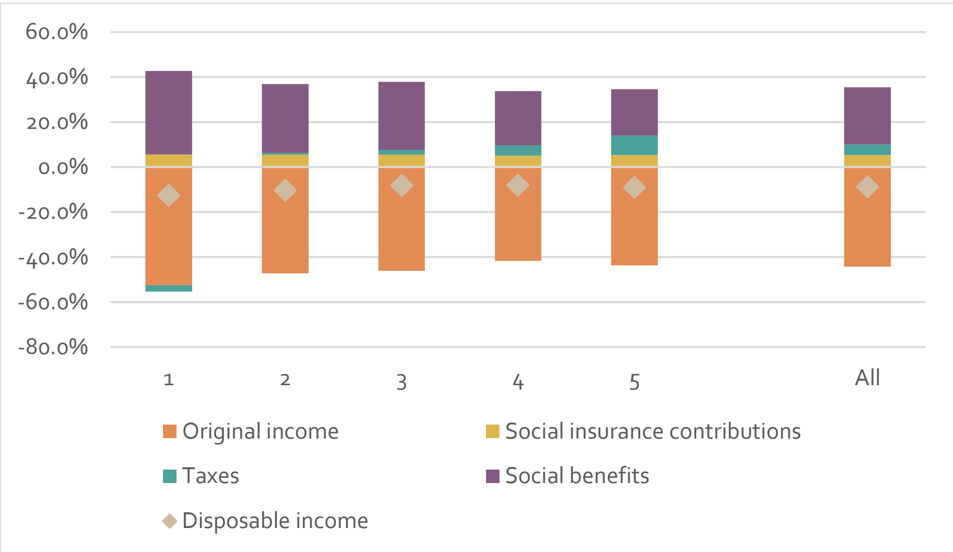
We assess here the impact of our conversion rule for the annual to the monthly unemployment benefit. This rule does not allow observations who do not report a main labour market status "unemployed" to have a monthly unemployment benefit in March. Alternatively, we can treat the unemployment benefit as we treat other benefits, by converting the benefit only to zero if it is likely received in a different month (per labour market status unemployed was indicated for a month other than March). Below we show the change in disposable income at the household level under both assumptions.

Figure 14. Estimated relative change in disposable income and income components of households with affected employees, over pre-COVID equivalized disposable household quintiles

Panel A. Conversion unemployment benefit as per section 5.4.1



Panel B. Conversion unemployment benefit in line with other income components



Ultimately, our treatment of bun has not a large impact on our results. (Especially as we focus on changes between scenarios.)