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Details matter for policy evaluation: the case of Covid-19 in Belgium

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Abstract

In this paper, we argue that the Covid-19 pandemic highlighted, once again, the necessity for fully utilizing the information on incomes and households gathered by the government, in the evaluation of policy. We demonstrate the importance of capturing heterogeneity in the population and complexity in the tax- and benefit system on the basis of two distributional analyses of the Covid-19 income shock. For both analyses, we make use of the microsimulation model EUROMOD and the underlying EU-SILC data. The two simulations differ in the level of detail and heterogeneity captured in the simulation of the shock on earnings due to the confinement measures and in the modeling of compensation policies. We show that policy-relevant conclusions differ dependent on the level of detail and heterogeneity introduced in the nowcasting techniques. However, even our more detailed nowcasting technique is far from capturing all heterogeneity in income losses and coverage of compensation, which is why we plea for details and heterogeneity in the monitoring of the impact of the Covid-19 crisis, and the evaluation of compensatory policies, and more broadly, for a continued effort to utilize administrative data in microsimulation-based policy-oriented research.

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1. Introduction

Since its conception, arithmetic microsimulation modeling has been a tool for (ex ante) policy evaluation and monitoring of the distributional impact of the tax and benefit system. The attraction of using microdata with heterogeneous households – instead of, or parallel with, an evaluation at the macrolevel – in the analysis of introduced or proposed policies is obvious. In its early days such models were almost exclusively built on survey data. Together with the evolution towards large scale data usage in the broader applied economics field (for a recent example, see Chetty et al. 2020), also policy-oriented microsimulation has turned more and more towards administrative data. The advantages of such datasets in combination with a detailed model are numerous. It allows for modeling specific policies, with interactions between various elements of the tax-benefit system, which all influence the distributional picture and budgetary implication; both are at the center of policy evaluation. Moreover, detailed microsimulation is a tool for the evaluation of policy changes at the margin, often central in public debate.[1] Finally, it captures much of the heterogeneity in several economic and socio-demographic variables in the population, and goes thus far beyond the usual evaluation on the basis of a "representative household" or "typical employee". This is especially relevant in a fast-changing labor market, with increasing diversity in contract types, career paths, and a combination of labor market statuses.

However, several issues explain why the turn towards detailed administrative micro-data has not been taken as quickly as one might have expected within the field of microsimulation. Often, such data are only available with a time-lag of several years. Because of legitimate privacy concerns, the procedures to gain access to the data are time consuming, and the logistic requirements of accessing, storing, and processing such data demands significant investments. So does the development of the accompanying models of detailed tax and benefit rules. Moreover, also administrative data are not "complete", and depending on the research questions at hand, analysis will still need to rely on assumptions or auxiliary survey- or aggregated data.

In this paper we argue that the Covid-19 pandemic highlighted once again the necessity for fully utilizing the information on incomes and households gathered by the government, in the evaluation of policy, both ex ante and ex post. When evidence-based policy is the goal, the evidence should (also) be provided on the detailed micro-level, taking into account the full complexity of the tax-benefit system and the heterogeneity of the population.

Early 2020, far-reaching measures were implemented by governments all over the world to reduce the spread of the Coronavirus. These lockdown measures forced businesses to close doors which caused a reduction or even discontinuation of the professional activity of many employees and self-employed individuals. To cushion the ensuing income shocks and reduce the risk of job loss, governments implemented monetary compensation measures.

From the beginning of the pandemic, researchers turned to microsimulation models to monitor the economic effects of the pandemic, the lockdown and compensation measures. Due to a lack of up-to-date microdata, most papers used nowcasting techniques to update underlying survey-based input-data from before the pandemic to the labor market situation in 2020. Together with tax-and-benefit-models amended with the compensation measures, these analyses were able to provide a first

[1] E.g. in Belgium the debates on the reduced social security contributions paid by professional athletes, the tax reduction for mortgage-payments for a second house, the tax reduction for third pillar pension savings, and the social rate on energy expenses. Traditional survey-based microsimulation models do not capture these specific regulations, and thus could not inform the public debate on the efficacy and efficiency of each of those parts of the tax-benefit system and the effects of reform. Indeed, the budgetary impact of each of these measures is marginal, and they only affect a small part of the population. But that does not mean that we no longer strive for an informed public debate.

picture of the distributional impact of the crisis.[2] The nowcasting techniques, i.e. the imputation of income losses and/or labor market transitions, were mostly based on aggregate information, and thus on assumptions regarding the relationship between the shock and underlying socio-demographic parameters.

Timely administrative data would have safeguarded against several pitfalls in monitoring both the distributional impact of the (ongoing) crisis and the efficacy of compensating measures. First, the relation between the underlying heterogeneous household characteristics and the incidence of the shock is of great importance for distributional analysis. E.g., relying on figures of monetary compensation, job loss or cessation of activity aggregated at the sector-level, does not take into account the income-gradient in the level of vulnerability on the labor market. Second, for the self-employed the heterogeneity in the level of income loss is difficult to gauge without any information on fixed costs after suspension of activities. Third, the coverage of social security and compensation measures is not evenly distributed across all employees and self-employed. Survey-based micro-simulation, both for the modeling of compensation as well as for the imputation of the incidence, can often not fully model such coverage, which is dependent on work history and contract type, and assumes thus often the coverage of a "typical employee".

Our analysis focusses on the impact of the Covid-19 crisis in Belgium during 2020. The first Covid-19 case in Belgium was diagnosed on February 4th, 2020. Six weeks later, on March 18th, public spaces, schools, and all so-called "non-essential" sectors were closed. From the beginning of May, these restrictions were relaxed gradually until they were tightened again in September due to a new wave of Covid-19 infections. The food and accommodation services, the entertainment and recreation sector, and other "non-essential" sectors were again forced to stop their activities for the remainder of the year.[3]

The federal and regional governments implemented economic compensation measures from the outset of the crisis. These policies were intended to absorb the income shock for employees, self-employed, and – more general – for households. To support affected employees and self-employed, the federal government relaxed eligibility for two existing benefit systems and increased the benefit amounts.

The system of temporary unemployment granted income compensation to an employee who was – due to "force majeure" – unable to perform her employment activity. From March 13th, 2020 onwards, all situations of temporary unemployment due to the Covid-19 crisis were regarded as temporary unemployment due to "force majeure", and the benefit replacement rate was increased from 65% to 70% of the daily wage, with a minimum benefit of €55.59 and a maximum of €74.17 per day, and an additional daily supplement of €5.63 per day was granted. Almost 1.4 million employees were granted the temporary unemployed benefit in 2020, which is more than one third of all employees in Belgium (Barrez et al. 2021, National Employment Office 2022).

Also self-employed individuals who had to temporarily stop their activity due to "force majeure" could already rely on a lump-sum benefit before the crisis (i.e. the so-called bridging right). From March 2020 onwards, the eligibility conditions were relaxed. The amount granted depends on the family burden of the self-employed and whether the self-employment is the main or secondary activity. The maximum benefit is €1,614.10 and the minimum is €645.85. From October onwards, self-employed individuals who were forced to put their activity on hold, received a "double" bridging right (which is twice the amount of the "singular" bridging right). Almost 50% of all self-

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[2] See for example, Brewer and Tasseva (2021), Figari and Fiorio (2020), Christl et al. (2021a), Lastunen et al. (2021), Almeide et al. (2021), Christl et al. (2021b), Eurostat (2021).

[3] Our analysis only includes the first two waves of Covid-19, covering the year 2020. The pandemic has continued since then, including new, but less stringent confinement measures.

employed received a bridging right at the peak of the crisis, in April 2020 (Barrez et al. 2021, National Institute for the Social Security of the Self-Employed 2022).

At the regional level, several additional compensation mechanisms were introduced. The most important are those granted to businesses –also to the self-employed – which had to terminate their activities because of the lockdown measures. Both the eligibility and the amount are dependent on the region and changed throughout the year. In Flanders three systems existed throughout the year. The first, the "*hinderpremie*" consisted of a lump sum benefit of €4,000 for all businesses that had to close their business in March, and an additional €160 euros per mandatory closing day after April 6th. The second, the "*compensatiepremie*", was targeted to those businesses that did not have to close but experienced more than 60% decline in their turnover. The benefit was €3,000 for the period March-April. In August a combined scheme was introduced, "*het Vlaams beschermings-mechanisme*", for both the businesses with a decline of more than 60% in turnover and those that had to close due to the lockdown measures. The benefit was calculated as a percentage (7.5% in period August and September, 10% from October onwards) of the turnover in the reference period in 2019, and was limited with a maximum amount, dependent on the status of the activity, and the period in which one applied for the benefit. In Brussels, a lump sum benefit of €4,000 was granted to the businesses that had to close in March. The self-employed that did not have to close but were eligible for the bridging right, received a lump sum benefit of €2,000. In the second wave, from November onwards, the businesses that had to close received an additional benefit of €3,000. In Wallonia, "*l'indimnité compensatoire*", was granted to self-employed in specific sectors and to those receiving a bridging right in March and April. The lump sum benefit ranged from €2,500 to €5,000 depending on sector. From July onwards, it was also targeted to businesses experiencing a decline in turnover of at least 40%, and the benefit was 30% of the turnover in July-September in 2019, with a minimum of €3,000 and with a maximum of €5,000 if the business has no employees, and €10,000 if it has at least one employee. From November onwards, it was again focused on specific sectors that had to close in the second wave, and the benefit was lump sum, dependent on the sectors, and the number of employees working in the business, ranging from €2,250 to €9,000.

The macro-economic impact of the Covid-19 shock, and the lockdown measures is already well documented, at least for 2020. The Belgian national accounts of 2020 (NBB 2021) show a decrease in nominal GDP (B.1g) of more than 21 billion euros or about 4.4%. Wages and salaries of employees (D.1) and gross mixed income (B.3g) declined by respectively 1.7% and 8.7%. However, and not surprisingly, less is known on the distribution of these income losses among households in Belgium.[4]

In this paper we provide two distributional pictures of the impact of the Covid-19 crisis on disposable income in Belgium, based on varying levels of detail, and argue that the level of detail matters for the conclusions. As administrative data on labor and replacement incomes are not available to us, we show this on the basis of survey-based microdata with reported incomes from 2017 (Belgian Survey of Income and Living Conditions), the Belgian module of the microsimulation model EUROMOD, including the compensation measures granted during the pandemic, and nowcasting techniques to project the microdata to 2020, based on external aggregate labor market data. In the less detailed scenario, the imputation of the shock is solely based on the sector of the employees and self-employed. It is also assumed that the self-employed, when affected by the shock, have zero gross self-employment income after regional compensation. Both assumptions were used in Christl et al. (2021b), and the latter assumption underpins the work of Marchal et al. (2021), Cantó et al.

[4] Although, from the outset of the crisis, FPS Social Security, together with other institutions of social security, monitored the impact of Covid-19 on some aggregate figures of the labor market (see WG SIC monitoring reports: https://socialsecurity.belgium.be/nl/sociaal-beleid-mee-vorm-geven/sociale-impact-covid-19 and a summary of the findings in Barrez et al. 2021), and funded the COVIVAT-consortium, which exploited microsimulation and nowcasting techniques. The analysis presented in this paper is funded by the COVIVAT-project.

(2021) and Derboven et al. (2021). In a second, more detailed nowcasting scenario, we include more heterogeneity in the imputation of the shock, i.e., we account for the relation between sector, gender, income and age, and whether one was affected by the pandemic. We also include monthly transitions. Moreover, we allow for heterogeneity in the fixed costs and turnover losses of the self-employed.

The results based on the first, less detailed nowcasting technique seem to confirm the conclusion found in numerous papers on other countries: the household disposable income losses are largest for high-income households; there is a negligible impact on inequality and no (or a small) increase in poverty; the compensation measures were well targeted. However, adding more detail to the nowcasting technique seriously affects those findings. We observe a (small) regressive pattern in household disposable income losses, with slightly higher relative income losses in the first half of the income distribution. This affects the evolution of inequality and poverty. We see an increase in inequality (albeit small) and a large increase in the at-risk-of-poverty-index (AROP).

This paper contributes to the literature on the distributional impact of Covid-19. For Belgium, Marchal et al. (2021) and Cantó et al. (2021) analyzed the distributional impact of the Covid-19 income shock in April 2020. Capéau et al. (2021) described the impact throughout 2020 but focused only on employees. We combine the detailed methodology of Capéau et al. (2021) on employees with a more detailed modeling of the incidence and the magnitude of the shock for the self-employed, to provide a full picture of the distributional impact of the Covid-19 crisis in Belgium in 2020. Our results amend those of Christl et al. (2021b) and Derboven et al. (2021). Both concluded quasi-unchanged levels of poverty and inequality. The different conclusions we draw based on income-dependent modeling of the incidence of temporary unemployment, and the introduction of heterogeneity in fixed costs for the self-employed are relevant for the international literature on the distributional impact of the Corona crisis. See for example, Brewer and Tasseva (2021) for the UK, Figari and Fiorio (2020) for Italy, Christl et al. (2021a) for Germany, Lastunen et al. (2021) for a cross country comparison over five African countries (Ghana, Mozambique, Tanzania, Uganda, and Zambia), and Almeide et al. (2021), Christl et al. (2021b) and Eurostat (2021) for a cross country comparison between almost all EU member states.

However, even the more detailed nowcasting technique is far from capturing all heterogeneity in income losses and coverage of compensation measures. We do not consider any uncompensated labor market transitions for employees, and, as shown in Capéau et al. (2021), the compensation differs greatly over contract type. That is why we plea for details and heterogeneity in the policy evaluation during the Covid-19 crisis, and more broadly, a continued effort to utilize administrative data in the microsimulation-based policy-oriented research.

Therefore, we position our paper primarily within the growing evidence of the importance of detail in microsimulation monitoring of the impact of lockdown measures and in the evaluation of compensation policies introduced during the pandemic. Similar to our analysis, Christl et al. (2021a) make use of richer aggregate information in their nowcasting to update the labor market situation in Germany more precisely. Their results can be compared to the findings for Germany in the cross-country analysis of Christl et al. (2021b). By including the more detailed information in the nowcasting, they found a regressive impact on disposable household incomes and an increase in the Gini of the disposable income distribution and the AROP-index, while simulations of Christl et al. (2021b) resulted in a progressive impact on disposable household income, almost no impact on inequality and a smaller increase in the AROP-index. Also the case of Sweden provides evidence for the importance of detail. Three different methods and data sources can be compared: lagged survey microdata with nowcasting in Christl et al. (2021b), real-time survey data in Clark et al (2021b) and real-time payroll tax register data in Angelov and Waldenström (2021). The three different methods showed different results on the evolution of inequality: the Gini, respectively, remained constant, decreased, and increased. Moreover, as Angelov and Waldenström (2021) could analyze detailed microdata, they could pinpoint where the discrepancy in results comes from. They concluded that one of the key drivers of the increase in inequality was the loss of low-paid, short-term jobs, often not captured in survey data or not taken into account in the imputation of the shock.

In what follows we present our methodology (Section 2), the results – based on the two levels of detail – on the incidence (Section 3.1) and the level of income losses (Section 3.2), on the compensation received (Section 3.3), and finally, on the impact on the distribution of household disposable income (Section 3.4). We conclude by using these results as motivation for the use of administrative data in the monitoring of the Covid-19 crisis and in the broader policy-oriented research.

2. Methodology

Our analysis is based on the Belgian EU Survey on Income and Living Conditions (EU-SILC) of 2018 with reported incomes from 2017, and the EUROMOD arithmetic microsimulation model. To answer the question whether detail matters for an ex ante estimate of the distributional impact of the Covid-19 crisis and policy evaluation of the introduced compensatory measures, we deploy two distinct nowcasting techniques to project the underlying survey-data of 2018 to the situation of 2020. In a first nowcasting technique we use similar assumptions as in Christl et al. (2021b). In a second, we utilize as much as possible the information available to us. We will denote the two techniques by respectively "less detail" and "more detail".

In both nowcasting procedures, monetary values are uprated to 2020 with appropriate indices, and the taxes and benefits are simulated in line with the 2020 regulation, which includes the federal compensation measures: temporary unemployment and bridging right. The difference between the two methods lies mainly in the imputation of the shock (i.e. the labor market transitions), and the level of the income loss for the self-employed. Both methodologies are discussed in detail in Appendix 1.

2.1 Less detailed nowcasting

To transform the EU-SILC 2018 to a dataset that represents the pandemic situation in 2020, we need – next to the uprating of monetary variables – to model labor market transitions. In the less detailed method, we constrict ourselves to the modeling of the transition from being employed in the 2018 dataset towards temporary unemployment in 2020, and from self-employment activity to cessation of activities and receiving bridging rights during the pandemic. Both transitions are modeled for each month during the pandemic, i.e. from March until December 2020.

The transition from employment to temporary unemployment is based on a stratified sampling technique, utilizing figures from the National Employment Office (NEO). This means that for several subpopulations – in this case employees in a specific sector – we assign a transition probability, which is equal to the relative frequency of temporary unemployed individuals for the respective month in the respective sector. For example, if in March 2020 there were 30% temporary unemployed individuals in the manufacturing sector, we draw randomly 30% of the individuals that were employed in that sector in SILC to become temporary unemployed. Additionally, we assume that there is full overlap in temporary unemployment between months. For example, if 30% of employees in the manufacturing sector were temporary unemployed in March 2020, and 40% were in that same sector in April, there will be 30% temporary unemployed in both March and April in that sector, and 10% temporary unemployed in April, but not in March.

In the less detailed nowcasting technique, the transition towards temporary unemployment is always modeled for a full month, so that within a month temporary unemployment cannot be combined with employment.

For the transition of the self-employed individuals toward cessation of activities and receiving a bridging right, we employ figures of the number of persons who received a bridging right per sector furnished by the National Institute for Social Security for the Self-Employed (NISSE). We use the same nowcasting technique as for employees, i.e. stratified sampling at the sectorial level. We thus assign the relative frequency of receiving a bridging right in a specific sector for a specific month as the transition probability to all self-employed active in that sector for that month. We randomly draw as many self-employed from that sector until we reach the relative frequency of bridging right receivers within the sector. We assume – similarly as in the case for employees – full overlap between months.

After assigning whether a self-employed individual has to stop their activities and receives a bridging right, we must make assumptions on the change in the income in those months. In the less detailed method, we assume that gross income becomes zero in months when bridging right was received. Regional compensation measures cannot explicitly be modeled, as they depend on turnover losses, which is not observed or imputed. The assumption of zero gross income including regional compensation implies that the regional compensation covers exactly the remaining costs faced by the self-employed, not covered by the reduced turnover.[5] Since the regional compensation differs over regions, but are not sector-specific, the assumption implies that the fixed costs of the self-employed differ over the regions, but do not differ between sectors.

2.2 More detailed nowcasting

The labor market transitions are similarly imputed by stratified sampling, but differ on the level of detail of the underlying statistics. First, we do not only allow transitions from employment to temporary unemployment (and vice versa) but we also model transitions from and to ordinary unemployment. Secondly, we take up more detail in the transition to (temporary) unemployment by considering several socio-demographic variables in the estimation of the transition probabilities. In the less detailed simulation only the sector determined the transition probability; in the more detailed nowcasting the transition probability is determined by sector, gender, age, wage-category, and labor market status in the previous month. Additionally, we take up more detail in the duration of temporary unemployment, by allowing the combination between temporary unemployment with employment.

Given that we simulate transitions from and to ordinary unemployment, we do not have an intuitive baseline to compare our results. We cannot distinguish transitions to ordinary unemployment due to confinement measures from "baseline" transitions to ordinary employment. Therefore, we take – for employees – the transition to temporary unemployment as the sole consequence of the crisis. We create a baseline dataset based on the 2020 labor market transitions in which periods in temporary unemployment are substituted by periods in employment.

For the self-employed we follow an entirely different approach compared to the less detailed technique, mainly to allow for variation in fixed costs and heterogeneity of turnover losses. First, as we only observe self-employment gross income in SILC, we impute the missing information on underlying turnover and costs in the baseline SILC. We use shares of income over respectively turnover and costs at the sectorial level from external information.[6] We divide the simulated costs further into fixed and variable[7] costs based on estimates of the share of fixed costs in turnover of an enterprise at the sectorial level for Belgium (from Abraham et al. 2020). We assume that in the

[5] In case the self-employed has stopped their acitivity, the remaining costs are equal to the fixed costs.

[6] We use the Structure of Earnings Survey and statistics on national accounts of firms provided by the National Bank to calibrate respectively the share of income over turnover and income over costs.

[7] Variable costs vary with turnover; when activies are completely shut down, variable costs are zero.

baseline turnover, fixed costs, and variable costs are the same for each month that an individual was active as self-employed. In a second step, we allocate the incidence of the shock. We start by allocating whether an individual received a bridging right, based on stratified sampling. We use – similar to the less detailed nowcasting technique – monthly NISSE figures at the sectorial level on the amount of self-employed who received a bridging right. Compared to the less detailed method, we relax the assumption of complete overlap. We utilize figures on the number of bridging right recipients who also received a bridging right in the previous month, aggregate for all sectors (provided by NISSE). We model transitions at the sectorial level so that we approach both the sectorial monthly relative figures of self-employed individuals receiving a bridging right, and the overall monthly share of self-employed receiving a bridging right, that also received a bridging right the previous month. This imputation – contrary to the less detailed simulation – does not fully determine the gross income loss. We explicitly model changes in turnover and variable costs, which is the third step. We impute the turnover loss for each month based on aggregate figures of the real-time ERMG-survey (2020). By modeling separately the turnover loss and receiving a bridging right, we allow for uncompensated earning losses of the self-employed. However, in reality there will be a large overlap between large turnover losses and receiving a bridging right, since the turnover loss is an eligibility condition for the bridging right. We thus seek as much consistency as possible between the allocation of the bridging right and the imputation of the turnover losses. We provide that consistency by first allocating the highest turnover losses to the individuals receiving a bridging right. The remaining turnover losses are then allocated to individuals without a bridging right. Finally, by assuming a proportionate evolution of the variable costs to the turnover loss, and constant fixed costs, we can simulate the individual earnings for each month in the Covid-19 scenario.

Since we explicitly model fixed costs and turnover losses, we can and will explicitly model regional compensation measures. We do not in the less detailed method, as there is no information on turnover loss, an important determinant for the eligibility of the regional compensation. To still be able to compare the results of both methods, we will view the regional compensation as part of gross income. In the less detailed method this income concept will be zero in the months the self-employed was affected by the crisis. In the more detailed method, it will be a result of the turnover loss faced, the proportionate change in variable costs, the unchanged fixed costs, and the regional compensation measures.

Additionally to the more detailed imputation of the shock for employees and self-employed, we allow for more heterogeneity in the random processes of the different stratified sampling procedures. By duplicating each observation 10 times and dividing the sample weights of the baseline dataset by 10, one original observation might experience different shocks in the simulation of the impact of the crisis.

2.3 Main differences

Both nowcasting techniques employ random processes. The stratified sampling method divides the population of interest into homogeneous groups or 'strata' based on socio-economic characteristics. Within these strata, individuals are randomly selected to one of the labor market situations as defined above. The more detailed simulation method takes more socio-economic characteristics into account for the simulation of labor market transitions of employees and eases the assumption of full overlap both for the employees and the self-employed. In addition, the more detailed simulation allows for transition from and to ordinary unemployment. This makes that both simulations result in different baselines. Therefore, we cannot compare individuals across methodologies. However, we can compare aggregate results for specific groups in the population.

The more detailed simulation allows for more heterogeneity in the impact on both employees and self-employed individuals. In the less detailed simulation, temporary unemployment is always modeled for a full month while the more detailed method simulates transitions at the level of days which allows the combination of employment and temporary unemployment within one month.

Regarding the impact of the cessation of the self-employed activity, we assume in the less detailed simulation that gross income is zero in months were bridging right is received and we do not model regional compensation. In other words, we assume that the reduced turnover and the regional compensation covers exactly the remaining costs. In the more detailed simulation, we explicitly model the fixed costs and turnover losses, and model the regional compensation intended to cover both. This allows us to relax some assumptions of the less detailed simulation. First, in the more detailed simulation, the loss of gross earnings does no longer coincide with the receipt of a bridging right. Earning losses are also possible without receiving a bridging right. Secondly, in the more detailed simulation, we no longer assume that regional compensation coincides with remaining costs, and gross income losses will be determined by turnover losses, the proportionate change in variable costs, constant fixed costs, and the explicitly modeled regional compensation.

3. Results

We present the results in four stages. First, we discuss the incidence of the shock for both the more and less detailed nowcasting technique. Second, we examine the distribution of gross earning losses the affected individuals were faced with. Third, the compensation measures introduced by governments to mitigate the gross earning losses are evaluated with both simulations, leading to distinct conclusions. Finally, we show the impact of the nowcasting techniques, simulations of earning losses and compensation measures on the distributional picture of household disposable income and the resulting inequality- and poverty-metrics.

3.1 Incidence of the shock

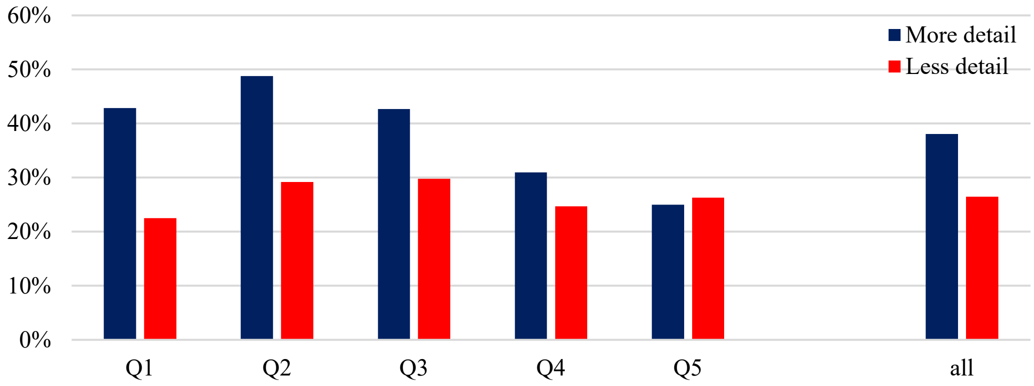
In both simulations there are two possibilities to be affected by the Covid-19 shock: being temporary unemployed for at least one day or being faced with a turnover loss as a self-employed individual for at least one month. When we discuss the incidence of the shock, we mean it purely in this sense, and we do not discuss any of the many other direct and indirect ways individuals were affected by the Covid-19 pandemic in 2020.

Since being affected is only possible for individuals who work in the baseline, we limit our description of the results in this section to the working population, i.e. all employees and self-employed individuals. Figure 1 shows the percentage of affected individuals for each quintile of that working population. The quintiles are constructed on the basis of gross earnings in the baseline.[8] The blue bars give the result for the simulation with more detail, the red bars for the less detailed simulation.

From Figure 1 it becomes immediately clear that taking up more detail in the imputation of the shock results in more individuals being affected on the labor market by the Covid-19 crisis. This is mainly a consequence of the difference in assumption in the overlap of temporary unemployment and cessation of activities between the months. In the more detailed simulation, we use aggregate observed statistics on the overlap of being affected in consecutive months, while in the less detailed simulation, we assume full overlap. In the latter case, there will be fewer employees in temporary unemployment, or self-employed stopping their activities, but those who are, will be so for a longer period.

[8] Note that the baseline is different in both methods.

Figure 1: incidence of the shock

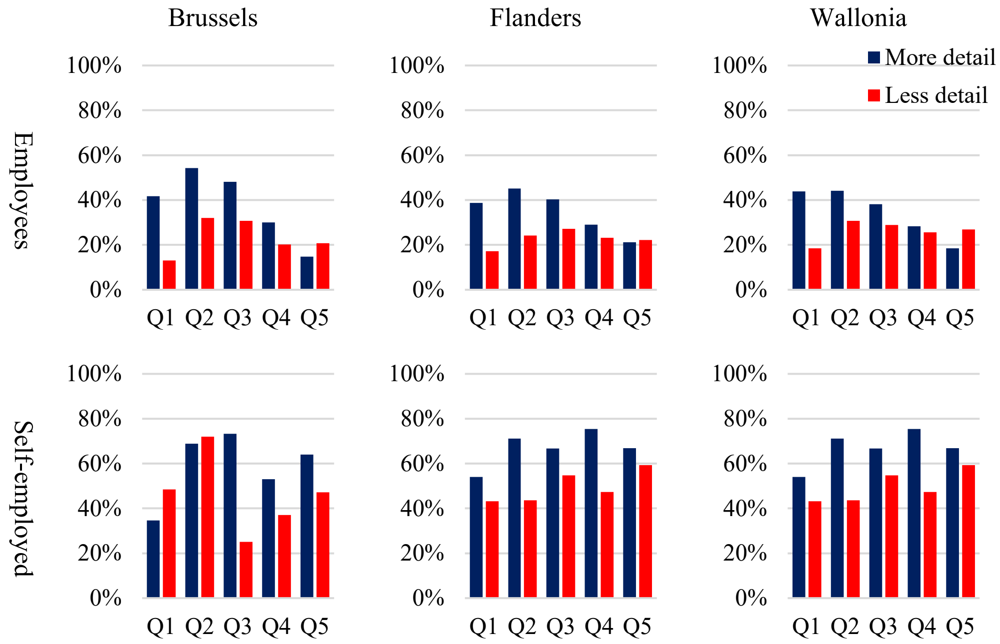


Second, and at least as important for a distributional analysis, the income gradient of the shock is strikingly different between the two methods. Whereas the less detailed imputation method shows no outspoken income gradient, the insertion of additional information in the more detailed method leads to a very different conclusion: there are much more persons hit by an income shock in the bottom three quintiles than in the upper two.

To evaluate the incidence of the shock for specific subgroups, we show in Figure 2 the percentage of affected individuals for each quintile, differentiating between region and employee vs. self-employed. The quintile boundaries remain based on the Belgian working population.

The difference in the income gradient of the shock between the two methods, comes solely from the impact on employees. We do not observe an income gradient for the self-employed in either simulation. This is in line with the external information we used in the nowcasting: for the self-employed there are no figures available (to us) on the relation between income and experiencing turnover losses or receiving bridging rights. We do find, both for employees and self-employed, a larger share of affected individuals in almost all quintiles with the more detailed method, except for employees in the last quintile, and except for the self-employed in Brussels in the first two quintiles.

Figure 2: Incidence of the shock for different subpopulations



Additionally, we find that relatively more self-employed individuals were affected by the confinement measures, compared to employees, in both simulations. Moreover, there is a slightly higher probability of being affected, when living in Brussels and belonging to the bottom three quintiles for employees in the more detailed simulation, which is not obvious from the less detailed simulation. As region is not taken up in the allocation of the shock, this result follows from taking into account the other covariates, such as sector, wage-category and age.

3.2 Level of income losses

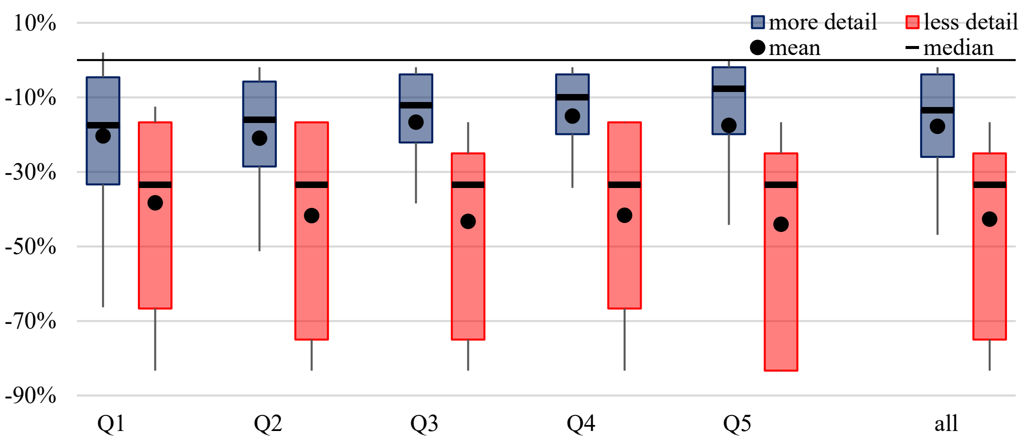
Not all individuals that have been affected, experienced the same drop in earnings. Some employees were only temporary unemployed during the height of the lockdown measures in April 2020, others could not restart their employment in 2020. The same holds for the self-employed. In this section we shed light on the distribution of the earning losses, and compare the conclusions drawn from each of the two nowcasting methods.

For the discussion on the level of the earning losses individuals have been faced with, we limit the scope to the affected individuals. Quintiles shown in the figures below are however based on the total working population, ordered on gross baseline earnings, as in Section 3.1.

We do not explicitly model fixed costs (and thus possibly negative gross earnings), and the regional compensation measures for self-employed individuals in the less detailed method, but assume that the latter coincide with the remaining costs. Therefore, we define the earning loss for the self-employed as the difference between baseline gross income, and gross income during the 2020-situation after they have received the regional compensation, but not including the bridging right. In this way, we can compare the same concept over the two methods.

Figure 3 shows boxplots of the distribution of the relative earnings losses of the affected individuals in each quintile. The blue boxplots correspond to the simulation with more detail, the red ones to the simulation with less detail. The dot represents the smoothed average[9] of the relative change in gross earnings of the affected persons in each quintile. The upper limit of the box shows the 75th percentile of relative change in gross earnings, the middle bar of the box represents the median, and the lower limit shows the 25th percentile of income change. The ends of the whiskers show respectively the 10th and 90th percentile of relative change in earnings.

Figure 3: Percentage change in gross earnings of the affected population



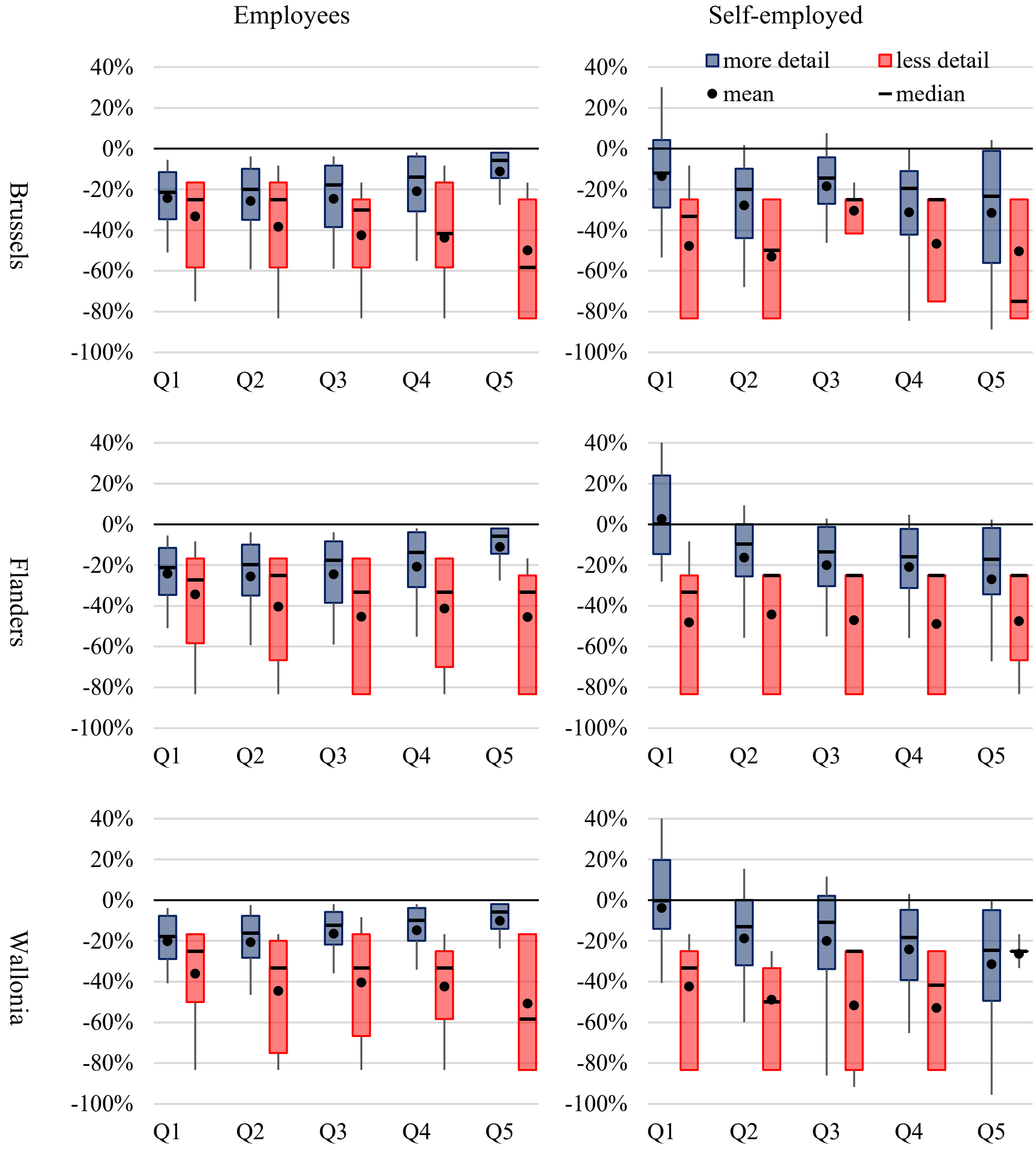
9 The smoothed average is here the sum of gross income losses divided by the sum of baseline income in the respective quintile.

The loss of gross earnings is on average less severe for every quintile in the more detailed simulation. This is explained by taking into account the transitions over the 10 months during the pandemic in 2020, and not assuming full overlap. In addition, we relax the assumption of full-time temporary unemployment and allow a combination of temporary unemployment and employment within one month. The loss is thus smaller in the detailed simulation, since more individuals experience temporary unemployment, or cessation of activities, and for shorter periods than is the case in the less detailed simulation. Moreover, the assumptions on income loss for the self-employed in the detailed method allow for greater heterogeneity, including increases in income after regional compensation.

In the more detailed simulation, we find a regressive impact on incomes; the impact is most severe for the lowest quintiles. The opposite is concluded from the results of the less detailed simulation.

In Figure 4 the population is split into six groups, based on region and whether one is self-employed or an employee. We show similarly constructed boxplots for the five quintiles (based on the working population), for the two simulation techniques.

Figure 4: relative change in gross income for different subpopulations



Both self-employed and employees experience less severe shocks in the simulation with more detail. However, the other general conclusion from Figure 3 is driven solely by the employees: we see a regressive picture in the more detailed simulation for employees. For the self-employed sub-population we even find a progressive impact, i.e. higher losses for the highest income quintiles in the detailed simulation. This can be explained by the explicit modeling of the regional compensation measures in the detailed method. The compensation was mostly a lump sum amount, and did not account for the income losses. Both income gradients in income losses, for employees and the self-employed, are absent in the less detailed simulation.

Another effect of the explicit modeling of fixed costs and the regional compensation measures is the divergence between the three regions. Indeed, regional compensation is much larger in Flanders than in Brussels. Compensation in Wallonia is slightly lower than in Flanders. This results in smaller relative earning losses in Flanders on average over all quintiles compared to Brussels, and to a lesser extent compared to Wallonia. In Flanders and Wallonia more than 50% of the affected self-employed in the first quintile even experienced gains in earnings after the regional compensation, while in Brussels the median income loss in the first quintile is equal to 12%, and 25% had positive change in gross earnings after the regional compensation. This regional heterogeneity is not accounted for in the less detailed simulation.

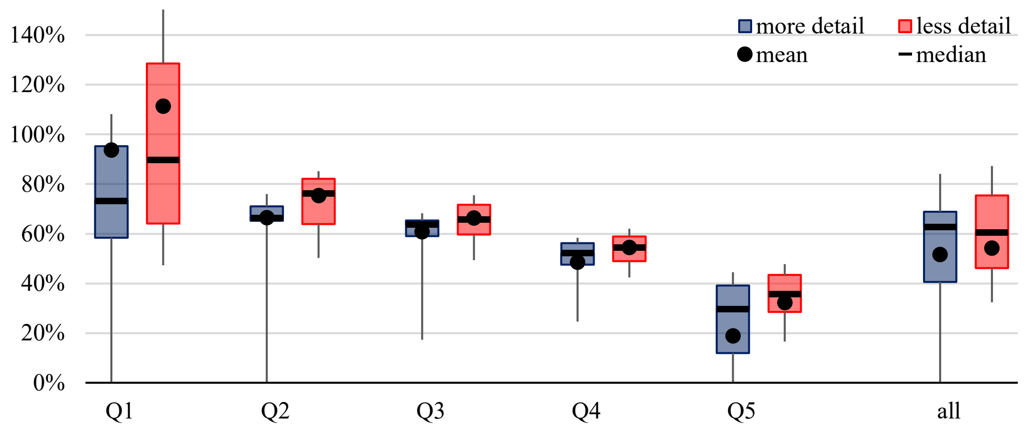
Moreover, Figure 4 illustrates the effect of allowing heterogeneity in the random processes of the nowcasting, in the panel for the self-employed Walloons. In the fifth quintile, there are few observations in the less detailed method. As a consequence, the 10th, 25th, 75th and 90th percentile, the smoothed mean and the median are very close to each other, around -25%. In the more detailed nowcasting, in which we duplicated the observations, we do not see such bunching. By allowing the random processes to play in different directions in the more detailed simulation, we capture richer heterogeneity within that specific group. Of course, administrative data (with in general larger sample sizes, and with heterogeneity being driven by observables instead of by random processes) would facilitate a more sound analysis of the heterogeneous impacts of the crisis. However, the synthetic heterogeneity allows us already to capture different possible scenarios in certain subgroups – while still based on the available aggregate information – so that we can assess how the income losses and, in the next section, the compensation rate depends on these scenarios, even if we don’t know how likely it is they occurred in reality.

3.3 Compensation

Belgian governments introduced from the outset of the pandemic monetary compensation measures to absorb the earning losses. In what follows, we show how much of the gross earning loss has been covered by these compensation benefits, so that we can assess whether the compensation did indeed mitigate the economic impact of the confinement policy on households. In this evaluation, we assume that the main objectives of government during the crisis was to avoid large drops in household incomes, and to avoid families falling into poverty. To assess whether the compensatory measures were well targeted, we show the distribution of the compensation rate for different subgroups. We define the compensation rate as the gross monetary compensation received relative to the loss in gross earnings. Earnings losses are defined as above, namely the self-employed earning losses are calculated after the regional compensation is received, since it is not specifically modeled in the less detailed method. The compensation includes the temporary unemployment benefit for employees (including the premium for long-term temporary unemployment) and the (single and double) bridging right for self-employed individuals. Later in this section we focus on the regional compensation, only for the detailed method.

In Figure 5, we show the distribution of compensation rates for all affected individuals in each earning quintile by use of boxplots, similar to the ones shown in Section 3.2. The quintile boundaries are still based on the gross earnings of the working population.

Figure 5: The distribution of compensation rates



Although the pattern and level of relative earning losses differed remarkably between the two simulation methods, the distribution of compensation rates are closer to each other. Figure 5 shows for both simulations a comparable progressive pattern, but with lower smoothed average compensation rates in all quintiles in the more detailed simulation.[10] In the first quintile, the average compensation rate in the less detailed method is even higher than 100%, while in the more detailed method, less than 25% of individuals in the first quintile receive full compensation of the experienced losses.

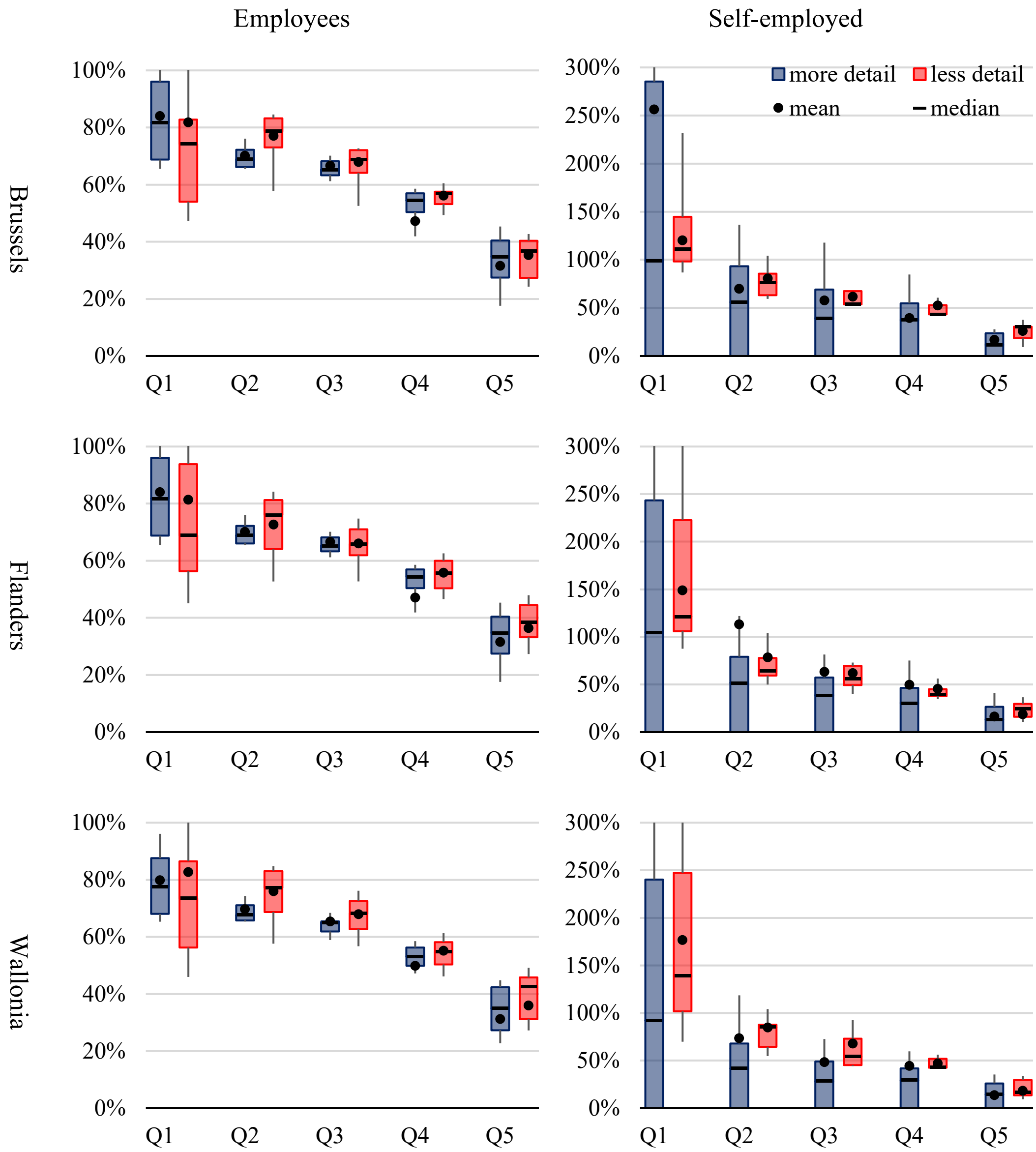
Figure 6 shows compensation rates for six different groups based on region and whether one is self-employed or an employee. The pattern of decreasing compensation rates from Figure 5 holds for each of the six groups. Regarding the employees, this pattern can be explained by the calculation of the temporary unemployment benefit. The benefit is in proportion to the gross income loss but bounded by a minimum and maximum amount, dependent on work intensity.

Although, the compensation is calculated similarly in both simulation methods, we see higher compensation rates in almost all quintiles in the less detailed simulation. The explanation again relates to the difference in assumptions on overlap of impact between consecutive months between the two simulation methods. In the less detailed simulation, we see fewer temporary unemployed individuals, but they face longer periods of temporary unemployment and thus receive higher compensation due to the premium for long-term temporary unemployment.

Regarding the self-employed, we also observe a notable difference between the two simulations. The more detailed simulation allows for uncompensated losses in earnings (not compensated by the federal bridging right) while the less detailed simulation only allows income loss for those receiving a bridging right. This is clearly visible in the right-hand panel of Figure 6, where the 25th percentile of the compensation rate in the more detailed method (the lower limit of the blue bars) is equal to zero for each quintile in each region, while even the 10th percentile of the compensation rate in the less detailed method is everywhere higher than zero. The pattern of extremely decreasing compensation rates, which we find in both simulations, can be explained by the calculation of the bridging right. It is a lump sum benefit, which makes the compensation rate very high for self-employed with low baseline earnings, and thus generally low absolute loss in earnings. The compensation rate decreases for larger earning losses, which are more likely to occur for those with higher earnings in the baseline.

[10] The smoothed average is here calculated as the sum of gross compensation received divided by the sum of gross income losses in the respective quintile.

Figure 6: The distribution of compensation rates for different subgroups



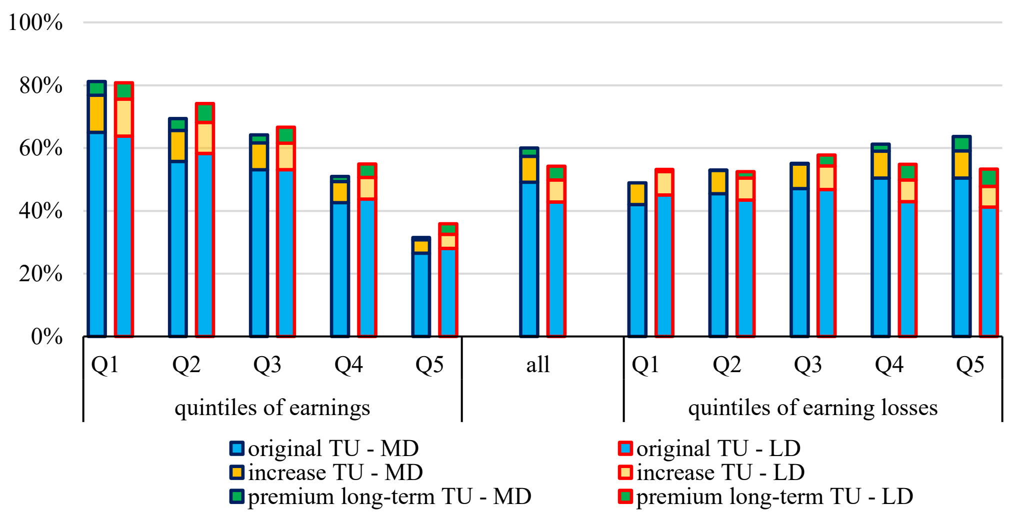
The compensation rates shown in Figure 6 give an idea of the overall efficacy of the entire set of compensatory measures. We find that for most employees earning losses were compensated by at least 50%, except in the highest income quintiles. The compensation for employees has been targeted towards the lower quintiles, indeed mitigating the impact on poverty. These conclusion holds for both simulation techniques. For self-employed individuals we see those conclusions only hold in the less detailed simulation. Moreover, the targeting towards the bottom quintile is more extreme than for employees, resulting in overcompensation (with compensation rates higher than 100%) in the bottom quintile and compensation rates below 50% for the top two quintiles. Simulating the earning losses for the self-employed while allowing for more heterogeneity, shows that compensation for all quintiles for the self-employed was not covering all individuals with earning losses.

The assessment of the entire set of compensatory measures – although useful – does not correspond to the decision of policymakers at the time. Both the temporary unemployment benefit and the bridging right already existed before the pandemic hit. The governmental decision on compensation was thus limited to expanding eligibility, increasing the amounts of those original benefits, and introducing additional compensation measures. To evaluate these decisions, we decompose the overall compensation rate in the different components: those that existed before (including expanded eligibility), and those that were additionally introduced during the crisis.

Figure 7 shows the decomposition of the compensation rates for employees. The compensation is split in the original temporary unemployment benefit (original TU), the increase of the benefit amount (increase TU), and the premium for the long-term unemployed (premium long-term TU).[11] We show the average compensation rate for each of those compensation components, for all affected employees ranked on earnings quintiles as above (left panel) and ranked on relative earning losses (right panel, with lowest losses in Q1 and highest losses in Q5). This allows us to separately evaluate how the different components contributed to the two objectives of compensation measures we put forward in the beginning of this section: mitigating the earning losses of households and avoiding additional poverty. If compensation is targeted towards the lower earning quintiles it, it was targeted to lower poverty risks; if compensation is targeted towards higher earning loss quintiles, it better mitigated the large earning losses.

We compare the decomposition of the more detailed simulation (MD - blue frames) with the less detailed simulation (LD – red frames) and assess whether our conclusions differ dependent on the details in the nowcasting technique.

Figure 7: Decomposition of compensation for employees



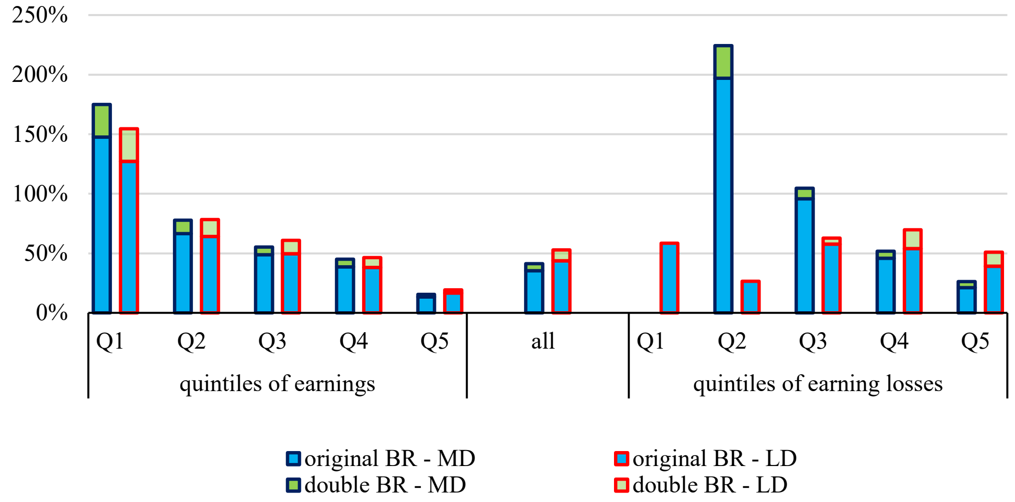
In the left panel we observe a decrease in the share of extra Covid-19 support, on top of the original temporary unemployment benefit, along with the decrease of the overall compensation rates over the earnings distribution, for both methods. This means that compensation for employees was targeting the most vulnerable individuals with low baseline earnings. We find that the different components of compensation follow the targeting of the original temporary unemployment benefits in the less detailed method. In the more detailed method, the premium for the long-term unemployed is targeting, more so than the original benefits, vulnerable individuals with low baseline earnings. The right panel, where individuals are ordered on the earning losses, show a more significant difference between both simulation methods. In the less detailed method, there is less of a relation between earning losses and compensation rates. In the more detailed method, we find that large shocks on earnings were slightly more compensated. Again, the premium for the long-term

[11] The benefit increased from 65% to 70% of the daily wage, with a minimum benefit of €55.59 and a maximum of €74.17 per day, and an additional daily supplement of €5.63 per day was granted. The premium for the long-term unemployed was a benefit of minimum €150 for those that were temporary unemployed for at least 53 days in 2020. The benefit increased with €10 for each day of temporary unemployment above 67 days.

unemployed is targeting, more than the original benefits, the high earning losses when taking up more details in the simulation.

Figure 8 shows the decomposition of compensation received by the self-employed. We limit our view to the self-employed that experienced a negative change in gross earnings after regional compensation.[12] The quintile boundaries of the right panel are based on all affected self-employed.[13] We decompose the bridging right into the single bridging right and the increase with the introduction of the double bridging right from October onwards.

Figure 8: Decomposition of compensation for self-employed



The pattern in the left panel is – as explained above – in line with what we can expect from a lump sum benefit compensation: those with low earnings faced generally low absolute earning losses which are (over)compensated by a lump-sum benefit. In both methods the double bridging right followed the targeting of the original benefit. In the right panel, the conclusion depends much more on the method followed. For the less detailed method, we find more or less constant compensation rates over the distribution of the losses in gross earnings for the original bridging right. The double bridging right has clearly been targeted towards those with higher losses in earnings. The average compensation rates for all income loss quintiles are considerably lower for the self-employed compared to those of the employees. Adding heterogeneity in the analysis changes the picture considerably. The original bridging right, as well as the double bridging right overcompensates lower earning losses, while it only compensates 25% of earning losses on average for the self-employed who were faced with the largest shocks. From both methods, we can deduct that the compensation for self-employed was well targeted towards the most vulnerable, with lowest pre-shock earnings, but the more detailed method leads us to believe that it was not well targeted for mitigating the large shocks on income. This is a conclusion we can draw by adding more heterogeneity and simulating the income loss of self-employed individuals with more detail but that we could not draw from the results of the less detailed nowcasting.

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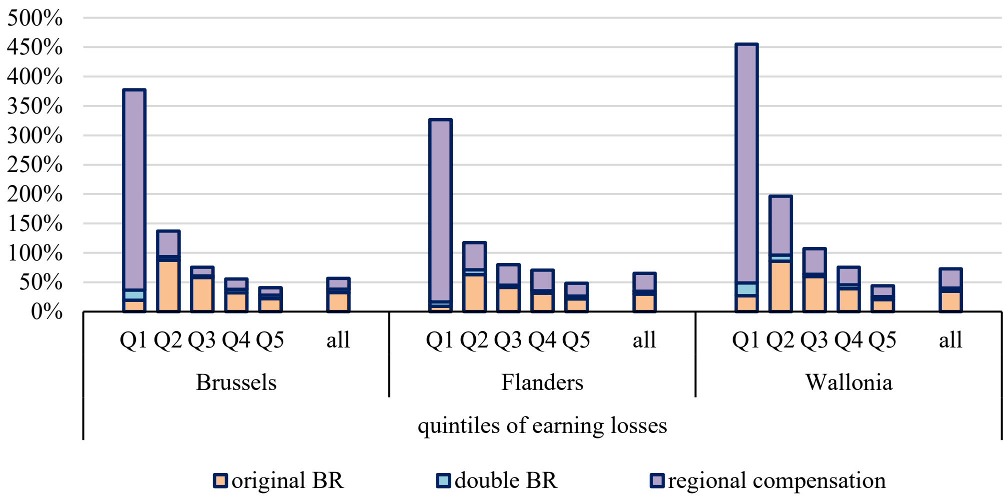
12 In previous graphs, the "affected self-employed" was defined as experiencing a change in turnover. In the more detailed method, this did not always imply a negative change in gross earnings after regional compensation, since such regional compensation could overcompensate the decrease in gross earnings. Moreover, we allow turnover to increase during 2020, in line with the results of the ERMG-survey.

13 Since in the more detailed method we have more than 20% affected self-employed individuals who experience a positive change in gross earnings after regional compensation, and we only show those with earning losses, after regional compensation, the first quintile is empty in Figure 8 for the more detailed simulation.

An important part of the compensation for the self-employed were the regional compensation measures. They are not explicitly modeled in the less detailed method, but they are included in the more detailed method. We can thus assess the targeting of these measures under the assumptions of the more detailed method. We redefine the compensation rate as the ratio between received gross compensation (including now both the bridging right and regional compensation) over the gross income loss, now before receiving the regional compensation.

In Figure 9, we show the decomposition of the adjusted compensation rates for the three regions, for the quintiles of earning losses. We observe a similar pattern as shown in the right panel of Figure 8 with lower average compensation rates for individuals that faced higher earning losses. We see that those with small relative losses were – on average – highly overcompensated, while those with the highest losses in gross earnings faced a compensation rate of less than 50%. This can – as with the bridging right – be explained by the fact that regional benefits were often lump sum benefits too, which are not well targeted to the highest income shocks.

Figure 9: Decomposition of compensation for self-employed per region



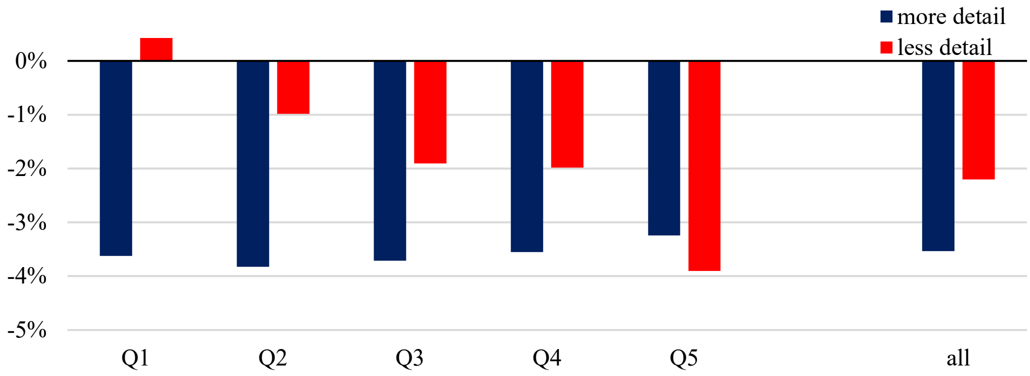
Another contributory factor for the high compensation rate in the first quintile is the shock effect in the beginning of the crisis. Due to the very strict lockdown, many self-employed activities were forced to stop, but only for a short period of time. After a few weeks many could restart activities. However, these self-employed individuals did receive the full lump sum benefits (both regional and federal) and were – under our assumptions on fixed costs – overcompensated for the losses they experienced. Those who were forced to close for a longer period faced larger earning losses and were relatively speaking less compensated.

Since the regional compensation was different for the three regions, we find varying levels of compensation rates. The highest compensation rate is found in Flanders and Wallonia, where more than 30% of the earnings losses was on average compensated by regional compensation, while in Brussels this was only 18%.

3.4 The impact on household disposable income

The incidence of the shock, the magnitude of the income losses experienced, and the compensation received by individuals and households culminated in an impact on the distribution of household disposable income, which we show in Figure 10. We divide the total population in five quintiles based on equivalized disposable household income, and we show in each quintile the average relative change in equivalized disposable household income. The blue bars represent the disposable income changes from the more detailed simulation, while the red bars represent the results from the less detailed simulation.

Figure 10: Change in household disposable income



On average, for the entire population, there is a considerably larger shock in household disposable income in the more detailed simulation, albeit still limited compared to the shock on the market incomes. It seems the social security system and compensation measures are slightly less successful in mitigating the economic shock according to the detailed simulation, which is in line with our findings on the compensation rate, presented in Section 3.3.

With regards to the distribution of the shock on disposable income, we would ex ante expect a progressive effect, i.e. more impact on the higher quintiles, since the working population – the population that could be confronted with income losses – is more densely populated in the right hand tail of the disposable income distribution. This is indeed what we see in the less detailed simulation, with even a small positive change in household income in the first quintile, and the largest average loss of almost 4% in the highest income quintile. However, in the more detailed simulation we find a different story. There is a very small opposite income gradient in the relative change in household disposable income, with a slightly higher relative impact on household disposable income in the first three quintiles, than the impact on the last two quintiles. This is surprising, since there are still only few affected households in the lowest quintiles. This is explained by relatively high disposable income losses of those few affected households in the lowest quintiles, resulting in an average income loss, which is slightly higher, than the average income loss in the highest income quintiles, generated by smaller losses among many more affected households.

These different effects on disposable income depending on the two methodologies, affect also the evolution of inequality and poverty due to the confinement measures. We show this in Table 1. Both in the less and more detailed scenario we see a small but negligible impact on the Gini-coefficient. Contrary to the less detailed scenario – which is in line with much of the literature – we see a significant increase of 2.21 percentage points in the at-risk-of-poverty rate[14] in the more detailed simulation, corresponding to an additional 255,000 individuals living in poverty. In the less detailed simulation, the rise in poverty is present, but limited to 0.14 percentage points or 16,000 individuals.[15]

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[14] Decoster et al. (2014) found that "poverty and inequality measures tend to show important differences when calculated either with disposable income reported in SILC data, or with the same income concept calculated on the basis of the microsimulation model EUROMOD, which start from the gross income in SILC". This explains why the Gini-coefficient and AROP-index are 3 to 4 percentage points lower as when calculated based on the reported disposable income in SILC.

[15] See Appendix 2 on how to compare these figures with the AROP figures calculated on the SILC 2021, as communicated by Statbel (https://statbel.fgov.be/en/themes/households/poverty-and-living-conditions/risk-poverty-or-social-exclusion).

Table 1: Impact on Gini-coefficient and At-risk-of-poverty rate

	Gini-coefficient			At-risk-of-poverty rate[16]		
	Baseline	Covid-19	Δ	Baseline	Covid-19	Δ
More detail	0.222	0.232	0.009	11.70%	13.91%	2.21pp.
Less detail	0.222	0.216	-0.006	11.56%	11.70%	0.14pp.

4. Conclusion

We presented in this paper two analyses of the distributional economic impact of the pandemic in 2020, and the accompanying lockdown and compensation measures. The two analyses differ in the level of detail and heterogeneity they take into account in the nowcasting technique. The conclusions drawn differ significantly.

The income gradient of the incidence of the shock is remarkably different between the two methods due to the use of more covariates in the allocation of temporary unemployment. Secondly, the difference in assumption in the overlap of temporary unemployment and cessation of activities between consecutive months results in more affected individuals in the more detailed simulation. The assumption of full overlap in the less detailed simulation results in less affected individuals, who then face higher relative earnings losses.

The additional heterogeneity in the simulation of the earnings shock resulted in different income gradients in the shock on earnings. With the more detailed imputation we find that income losses are decreasing in income, with less detail we find a slightly progressive pattern of the income losses.

The heterogeneity in the level of income loss is especially relevant for the self-employed where it is difficult to simulate earning losses without any information on fixed costs after suspension of activities. Allowing for heterogeneity in the fixed costs and turnover losses of the self-employed, earning losses (after regional compensation) show a progressive pattern, i.e., earning losses were higher for the highest incomes, which is not visible in the less detailed simulation.

We also find that the efficacy of the compensatory measures is differently evaluated, dependent on the level of detailed used. The compensation rate is on average lower when less detail is used, for all earning quintiles, and for both employees and self-employed. When including more detail and heterogeneity in the analysis, we find a much broader distribution of the compensation rate for the self-employed, many of which received no compensation of their loss in gross earnings.

Relying on the less detailed method, we might have concluded that both the increase in temporary unemployment, as well as the premium for long-term temporary unemployed are simply exacerbating the targeting of the original temporary unemployment benefits. By adding in more detail, we conclude that the premium for the long-term unemployed was well targeted towards those with highest income shocks and those who were most vulnerable. For the self-employed we would conclude on the basis of the less detailed method that both the bridging right is targeted towards the most vulnerable (by overcompensating the gross earning income losses for the lowest earning quintiles) and provide constant compensation rates over the distribution of earning losses. But adding more detail in the methodology, changes the second part of that conclusion considerably, providing evidence of a targeting of both the original and double bridging right towards those with

[16] The at-risk-of-poverty rates in the baseline and the covid-19 crisis scenario are calculated with a constant poverty line, which is 60% of the median equivalized household income in the baseline. As the baseline is different for each methodology, the fixed poverty line is different in both methodologies.

small earning losses. This goes against the objective of mitigating the large economic shock of the pandemic.

The more detailed analysis also allows us to analyze the differences in the regional compensation measures. Since these were often lump-sum benefits as well, we find a similar overcompensation of small earning losses, and low compensation of high earning losses. Since the benefit was larger in Flanders and Wallonia compared to the one in Brussels, Flanders and Wallonia did overcompensate more and for a larger share of the self-employed, but also knew a larger compensation rate for those with the highest earning losses.

The incidence of the shock, the simulation of earning losses, and the simulation of compensatory measures, taxes and benefits, lead to different conclusions regarding the overall impact on the distribution of household disposable income, dependent on which method is used. Based on the less detailed simulation, we might conclude that the impact is larger for the highest household disposable income quintiles, leading to quasi-unchanged inequality and poverty figures. But once we insert more detail, we find a slightly higher average impact for the lowest income quintiles, leading to a considerable increase in the at-risk-of-poverty rate with more than two percentage points.

Our paper provides clear evidence that policy-relevant conclusions differ greatly when more detail and heterogeneity is used in the microsimulation of the impact of the Covid-19 crisis. Therefore, the results in this paper should not be read as an endpoint, since much more heterogeneity could still be added based on other existing, but not publicly available, data sources. For example, in the imputation of the shock for self-employed the relation with underlying observable characteristics is under-utilized, since the information is not publicly available. But even then, a lot of heterogeneity in the population can simply not be captured with lagged survey-based microsimulation. For example, there is reason to believe that hard-hit sectors (accommodation and food, entertainment sector, …) employ more employees with atypical contracts, such as interim-workers, short-term contracts, self-employed status, flexi-jobs, … the information on the contract type is not available in surveys. It is however available in the administrative data for the crossroad bank of Social Security and has – to the best of our knowledge – not yet been used to analyze the poverty impact of the Covid-19 crisis, or to evaluate the introduced compensatory measures. A second example is the case of the self-employed. Much of the resilience of self-employed individuals during such a shock as the pandemic, depends on the underlying structure of the baseline earnings. If fixed costs cover a large part of turnover, the decrease in turnover will be translated in a sharper decrease in earnings. The necessary information for 2020 on the evolution of costs for the self-employed is available to government administrations, as the VAT tax returns have already been filed. Yet again, this rich information, necessary for a decent monitoring of the Covid-19 crisis, and the evaluation of the introduced compensatory measures, was – to the best of our knowledge – not yet exploited.

5. References

Abraham, F., Bormans, Y., Konings, J. & Roeger, W. (2020). Price-cost margins and fixed costs. VIVES Discussion paper N85.

Almeida, V., Barrios, S., Christl, M., De Poli, S., Tumino, A. & Van Der Wielen, W. (2021). The impact of COVID-19 on households´ income in the EU. *The Journal of Economic Inequality* **19**, 413-431.

Angelov, N. & Waldenström, D. (2021). COVID-19 and income inequality: evidence from monthly population registers. CESifo Working Paper No. 9178.

Barrez, J., Bevers, T., Coenen, A., Gilbert, V., Mattheussens, G., Van Dam, R. & Vleminckx, K. (2021). De werkgelegenheids- en sociale impact van de Covid-19 crisis. In Coete, J. et al. (eds.) *Jaarboek Armoede en Sociale Uitsluiting 2021*, 204-224.

Basselier, R. & Minne, G. (2021) Household savings during and after the COVID-19 crisis: lessons from surveys. *NBB Economic Review.*

Bormans, Y. & Konings, J. (2020). Ondernemingen met hoge vaste kosten en kleine wisntmarges meest gehlopen met subsidies. VIVES Briefing Note.

Brewer, M. & Tasseva, I. (2021). Did the UK policy response to Covid-19 protect household incomes?. *The Journal of Economic Inequality* **19**, 433-458.

Cantó, O., Figari, F., Fiorio, C. V., Kuypers, S., Marchal, S., Romaguera-de-la-Cruz, M. & Verbist, G. (2021). Welfare Resilience at the Onset of the COVID-19 Pandemic in a Selection of European Countries: Impact on Public Finance and Household Incomes. *Review of Income and Wealth.*

Capéau, B., Decoster, A., Vanderkelen, J. & Van Houtven, S. (2021), De impact van de COVID-19 schok voor loon- en weddetrekkenden in 2020, COVIVAT Beleidsnota 9, KU Leuven Department of Economics.

Chetty, R., Friedman, J.N., Hendren, N., Stepner, M. & the Opportunity Insights Team (2020). How did Covid-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data. NBER Working Paper Series, WP 27431.

Christl, M., De Poli, S., Hufkens, T., Peichl, A. & Ricci, M. (2021a). The role of short-time work and discretionary policy measures in mitigating the effects of the Covid-19 crisis in Germany. CESifo Working Paper No. 9072.

Christl, M., De Poli, S., Figari, F., Hufkens, T., Papini, A. & Tumino, A. (2021b). The cushioning effect of fiscal policy in the EU during the covid-19 pandemic. JRC Working Papers on Taxation and Structural Reforms No 02/2021.

Clark, A., Ambrosio, C. & Lepinteur, A. (2021a). The fall in income inequality during COVID-19 in four European countries. *The Journal of Economic Inequality* **19**, 489-507.

Clark, A., Ambrosio, C. & Lepinteur, A. (2021b). The fall in income inequality during COVID-19 in five European countries. HAL Working Paper 2021-21.

Crossley, T. F., Fisher, P. & Low, H. (2021). The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data. *Journal of Public Economics* **193**, 104334.

Decoster, A., Vandelannoote, D. Vanheukelom, T. & Verbist, G. (2014). Gross incomes in the Belgian SILC dataset: An analysis by means of EUROMOD. EUROMOD working paper series EM16/14.

Christl, M., De Poli, S., Hufkens, T., Leventi, C. & Papini, A. (2022) EUROMOD Labour Market Adjustment (LMA) Add-on – Technical Note. European Commission, Seville, JRC128274.

Derboven, J., Neelen, W., Vanderkelen, J., Verbist, G. & Marchal, S. (2021). Maandinkomens in Covid-19-jaar 2020. In Coene, J. et al. (eds.) *Jaarboek Armoede en Sociale Uitsluiting 2021*, 225-244.

Economic Risk Management Group. (2020), ERMG survey [Dataset]. https://www.nbb.be/nl/ermg-enquetes.

Eurostat. (2021), Early estimates of income inequalities during the 2020 pandemic. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Early_estimates_of_income_inequalities_during_the_2020_pandemic.

Figari, F. & Fiorio, C. V. (2020). Welfare resilience in the immediate aftermath of the COVID-19 outbreak in Italy. EUROMOD Working Paper No. 06/20.

Institute for Social and Economic Research, University of Essex; Joint Research Centre, European Commission, EUROMOD: Version I3.40+ (software), 2021.

Lastunen, J., Rattenhuber, P., Adu-Ababio, K., Gasior, K., Jara, H. X., Jouste, M. & Wright, G. (2021). The mitigating role of tax and benefit rescue packages for poverty and inequality in Africa amid the COVID-19 pandemic (No. wp-2021-148). World Institute for Development Economic Research (UNU-WIDER).

National Bank of Belgium. (2021). Detailed national accounts – Composition and identity of GDP [Dataset]. https://www.nbb.be/en/statistics/nationalregional-accounts/publications-and-figures.

National Employment Office. (2022), Tijdelijke Werkloosheid wegens CORONAVIRUS COVID-19: https://www.rva.be/nl/documentatie/statistieken/tijdelijke-werkloosheid-wegens-coronavirus-covid-19/cijfers.

National Institute for the Social Security of the Self-Employed. (2022). Statistieken. https://websta.rsvz-inasti.fgov.be/nl.

Sutherland, H. & Figari, F., (2013). Euromod: the European Union tax-benefit microsimulation model. *International journal of microsimulation* 6, 4-26.

1. Appendix 1: Labor market transitions

In this appendix, we go deeper into the two nowcasting methodologies used in this paper. The input dataset of the EUROMOD model is the Survey of Income and Living Conditions (SILC) which is usually available with a time lag of 2-3 years. The default nowcasting method in the EUROMOD model consists solely of uprating all monetary variables. Given that the Covid-19 shock has brought about major changes in the labor market, monetary uprating is not sufficient to project the Belgian 2018 SILC to a 2020 dataset. We therefore extend the default EUROMOD nowcasting method by simulating labor market transitions, followed by an adjustment of their earnings and/or benefits.[17]

The labor market transitions are simulated using a stratified sampling technique. The active population is divided into subpopulations, or so-called "strata", based on socio-demographic characteristics. Within each stratum, we estimate transition probabilities, based on external labor market statistics. We sample individuals from each of those strata that make labor market transitions, accounting for those transition probabilities. The transitions are simulated on a monthly basis, from March 2020, the start of the Covid-19 pandemic, until December 2020. The simulation differs between employees and self-employed individuals, and differs between the two methodologies. We first explain the estimation of transition probabilities for employees in both methods, thereafter we turn to the self-employed.

1.1 Employees

1.1.1 Less detailed method

In the less detailed scenario, we divide the employees in subpopulations based on labor market status and the sector of employment, s (NACE level 1). We simulate individual labor market transitions starting from the reported labor market status in the SILC 2018 (status in each month of 2017), to the labor market status in 2020 for March until December. The reported labor market status in SILC will serve as the baseline labor market states over the year.

The transition probabilities on which the simulations are based, are determined at the sectorial level and are calculated from monthly temporary unemployment figures of the National Employment Office (NEO)[18] and employment figures of the National Social Security Office (NSSO)[19]. The probability an individual's labor market status is equal to temporary unemployed (noted as tu), given the sector of employment, s, and given that the labor market status of an individual i's labor market status in the baseline in month t is employed (noted as $l_i^{Bt} = em$), is equal to the ratio of the number of temporary unemployed individuals in month t of 2020 in sector s, $N_{tu}^{s,t}$, over the number of employed individuals in that sector at the end of the first quarter in 2020, N^s. Formally, we have:

$$\Pr\left(l_i^{Rt} = tu \mid s_i = s, l_i^{Bt} = em\right) = \frac{N_{tu}^{s,t}}{N^s} \tag{1}$$

To simulate the transitions themselves, we sample a random term $e \sim U(0,1)$ with a uniform distribution between zero and one, for each individual that reported to be employed at least one month in 2017.

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17 The "less detailed method" is inspired on the Labour Market Adjustment (LMA) add on in EUROMOD. It is a tool that is developed to simulate individual labor market transitions (Christl, et al. 2022).

18 See https://www.rva.be/nl/documentatie/statistieken/tijdelijke-werkloosheid-wegens-coronavirus-covid-19/cijfers

19 See https://www.rsz.be/statistieken

For each month the transition from employment to temporary unemployment is simulated if the individual random term e_i is lower than or equal to the estimated probability for that month:

$$e_i \leq \Pr\left(l_i^{Rt} = tu \mid s_i, l_i^{Bt} = em\right). \tag{2}$$

The fact that we keep this random term e_i constant for all months, means that we assume full overlap of temporary unemployment. An individual i who transitioned to temporary unemployment in t and was employed in the baseline in month $t+1$, will also be temporary unemployed in $t+1$, if the total number of temporary unemployed in their sector s grew from t to $t+1$:

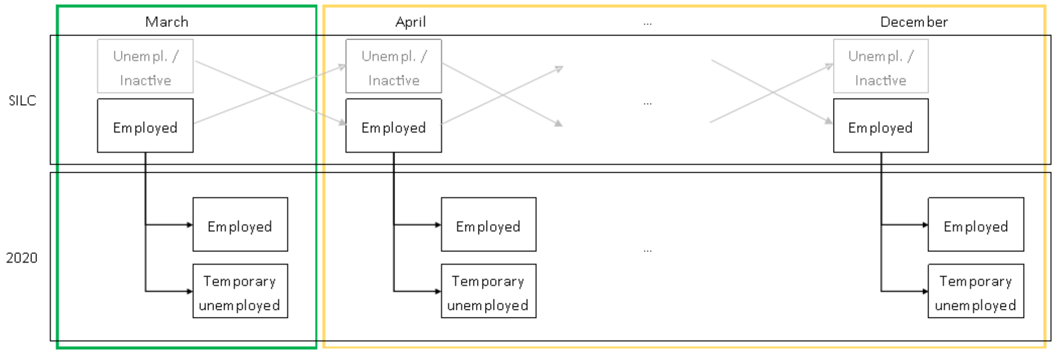
$$\begin{aligned} &\Pr\left(l_i^{Rt+1} = tu \mid s_i = s, l_i^{Bt+1} = em, l_i^{Rt} = tu\right) = 1 \\ &\Leftrightarrow N_{tu}^{s,t+1} \geq N_{tu}^{s,t} \end{aligned} \tag{3}$$

On the other hand, an individual who did not transition to temporary unemployment in t, and was employed in the baseline in $t+1$, will still be employed in $t+1$ if the total number of temporary unemployed in their respective sector declined between t and $t+1$.

$$\begin{aligned} &\Pr\left(l_i^{Rt+1} = em \mid s_i = s, l_i^{Bt+1} = em, l_i^{Rt} = em\right) = 1 \\ &\Leftrightarrow N_{tu}^{s,t+1} \leq N_{tu}^{s,t} \end{aligned} \tag{4}$$

The transitions are modeled for each month, starting from the set of employed individuals in the baseline in each month (see Figure 11). We thus follow the transitions to and from unemployment and in and out of the labor market (e.g., pensioners, students, inactive) from the reported labor market states in SILC. Note that this implies that individuals unemployed or inactive in March 2017 will still be taken up in the transitions to temporary unemployment if they are employed in one of the following months in 2017.

Figure 11: labor market transition in the less-detailed method for employees



Starting from these simulated labor market transitions, we can recalculate the market income from employment in the Covid-19 scenario. The change in gross income from employment, is proportional to the change in months employed, and thus to the relative duration of the simulated temporary unemployment. The employment income in the baseline, y_i^B is rescaled with the ratio of months in employment in the simulation, $m_i^{R,em}$ over the months in employment in the baseline, $m_i^{B,em}$. The result is the gross employee income of individual i in the Covid-19-scenario:

$$y_i^R = y_i^B \cdot \frac{m_i^{R,em}}{m_i^{B,em}} = y_i^B \cdot \left(\frac{m_i^{R,em}}{m_i^{R,em} + m_i^{R,tu}}\right) \tag{5}$$

1.1.2 More detailed method

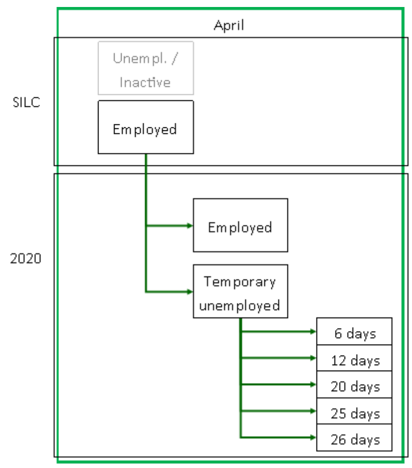
The strata and transition probabilities are determined differently in the simulation method with more detail. The simulation of individual transitions starts from the reported labor market situation in April 2017, since it is the first full month of confinement measures. The simulation is based on a more detailed division of employees into different subgroups or "strata". They are not only based on the sectorial level of employment (NACE level 1) but also on gender (male, female), age (<30, 30-39, 49-49, >50 years old) and three categories of a daily wage concept[20] (<79.52, 79.52-105.95, >105.95 euros). In addition, the simulation to (and from) different labor market states is extended from two (employment and temporary unemployment) to seven categories, by accounting for the duration of temporary unemployment within one month, and including the transition to ordinary unemployment. Moreover, we model the transitions for each month, starting from the simulated labor market status in the month before, and not from the labor market status in the baseline. In doing so, we fully take into account the observed transitions between and from (temporary) unemployment as observed in aggregate figures of NEO.[21]

First, we simulate the transition from the baseline to the height of the temporary unemployment wave, from reported labor market status in SILC in April, $l_i^{B,4}$, to the labor market status in April 2020, l_i^4. We simulate transitions from employment to temporary unemployment (Figure 12). The transition probability equals the relative frequency of temporary unemployment in April 2020:

$$\Pr\left(l_i^4 = tu \mid x_i = x, l_i^{B,4} = em\right) = \frac{N_{tu}^{x,4}}{N^{x,4}}, \tag{6}$$

with x a vector of socio-demographic characteristics (sector of employment, age, gender and the daily wage), $N_{tu}^{x,4}$ the number of individuals temporary unemployed in April 2020 within the subpopulation for which $x_i = x$, and $N^{x,4}$ the number of employees in April with characteristics x in SILC 2018.

Figure 12: Labor market transitions in the more detailed method for employees in April



We again sample an individual random term e_i^4, uniformly distributed between one and zero. The transition is simulated if the random term is smaller than the calculated transition probability.

After sampling the individuals that make the transition to temporary unemployment in April 2020, we assign the number of days that these individuals were temporary unemployed. We use the breakdown of temporary unemployment figures of the NEO. We first sample from the set of individuals that work (on average) 26 days or more in the months in which they were employed in

20 The categories are based on the "reference wage" which was used to calculate the temporary unemployment or unemployment benefits.

21 In the context of the COVIVAT project and the WG SIC (Working Group Social Impact Corona) we received detailed tables on the number of recipients of temporary unemployment from the NEO. The tables showed for each month the absolute frequency of temporary unemployment for each cross-category in the socio-demographic variables and the labor market status in the previous month. The tables for September, October and November were non-final. The table for December was unavailable. We assumed the same transitions as in November.

the baseline and were assigned the transition to temporary unemployment, the number of individuals that were temporary unemployed for 26 days, and assign 26 days of temporary unemployment. Then we sample the number of temporary unemployed for 20-25 days from the individuals that work on average more than 25 days and were assigned the transition to temporary unemployment, but were not yet assigned a number of days, and assign 25 days of temporary unemployment. We continue this process until we have assigned a number of days of temporary unemployment to all those that transitioned to temporary unemployment in April 2020.

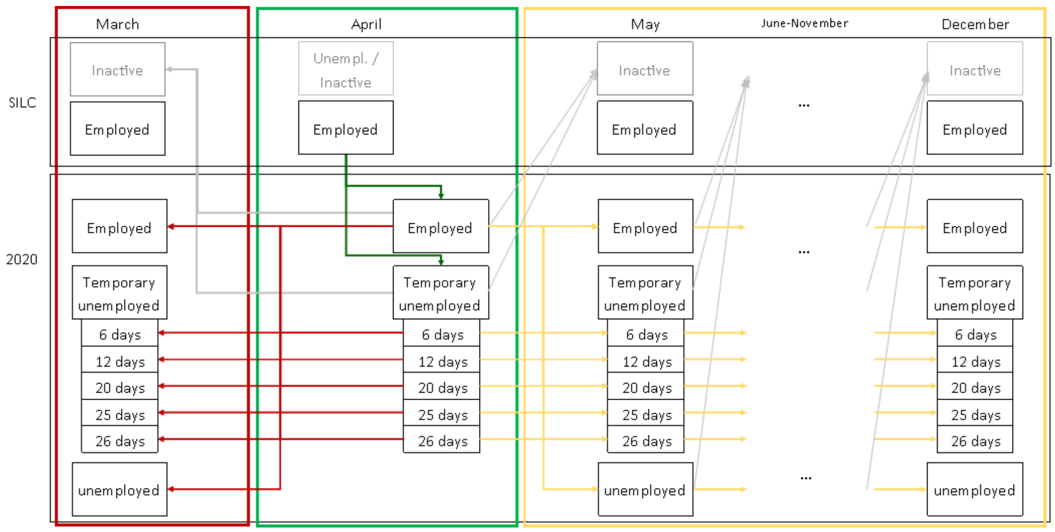
In a second step (yellow box in Figure 13), we rely on transition figures of the National Employment Office (NEO) to compute individual transitions probabilities from the simulated labor market status in April 2020 to May 2020. These figures are absolute numbers of monthly transitions from (and to) employment, temporary unemployment and unemployment. We construct transition probabilities by relating the NEO figures to employment figures retrieved from the SILC data and the simulated transitions in April.

$$\Pr\left(l_i^{t+1} = d \mid x_i = x, l_i^t = e\right) = \frac{N_{e,d}^{x,t+1}}{N_e^{x,t}}, \tag{7}$$

with x a vector of socio-demographic characteristics (sector of employment, age, gender and the daily wage), l_i^t the state variable identifying the labor market in period t. Possible labor market states d and e are either temporary unemployed for 6 days, 12 days, 20 days, 25 days or 26 days, employed or unemployed. And finally, $N_{e,d}^{x,t+1}$ is the absolute number of individuals within the subpopulation with characteristics x, facing a specific monthly labor market transition, from $l^t = e$ to $l^{t+1} = d$, and $N_e^{x,t}$ is the simulated number of employees in month t with labor market status e and characteristics x in SILC.

Contrary to the less detailed method, the random term with which the transitions are modeled is not constant over the months. The outcome of the sampling, i.e. the simulated labor market status in May 2020, determine the transition probability for June 2020. We thus first calculate transition probabilities for one month, simulate the transitions for that month, and then calculate transition probabilities for the next month, as shown in the yellow box in Figure 13.

Figure 13: Labor market transitions in the more detailed method for employees



Since we started the modeling of labor market transitions from the situation in April – to account as much as possible for the structure of temporary unemployment at the height of the lockdown measures, and to fully take advantage of the breakdown for number of days in the first possible full month of temporary unemployment – we also need to simulate the transitions between March and April. To do so, we start from the situation as simulated in April, and go back to the previous month (shown in the red box in Figure 13), using the same statistics on labor market status in March and April 2020 from the NEO transition tables.

Note that, contrary to the less detailed method, we don't follow all transitions in and out of employment as reported in SILC 2018. Transitions to and from inactivity, including pensioners and students, are taken from the reported transitions in SILC 2018. But we take up the transition from employment to ordinary unemployment in our model. This means that an individual that was employed for several months before being unemployed in 2017, can be employed the entire year in our 2020 simulation. This poses some questions for our baseline. Since the differences in labor market trajectories in SILC 2018 and in the simulation on the individual level cannot always be attributed to the impact of the pandemic, we construct a new baseline. In this baseline we follow all transitions to and from unemployment except those that are most likely explained by the pandemic, i.e. those to and from temporary unemployment. In practice, we replicate the simulated labor market transitions substituting employment for temporary employment to construct our baseline.

Both in the Covid-19 scenario, and in the baseline, we adjust the gross labor market incomes in line with the change in days in employment. The simulated gross labor market income in both scenarios is equal to the (uprated) income reported in SILC, y_i^S, scaled with the ratio of days in employment in respectively the Covid-19 scenario, $d_i^{R,em}$, or the baseline, $d_i^{B,em}$, over the days in employment as reported in SILC, $d_i^{S,em}$:

$$y_i^B = y_i^S \cdot \left(\frac{d_i^{B,em}}{d_i^{S,em}} \right) \quad \text{and} \quad y_i^R = y_i^S \cdot \frac{d_i^{R,em}}{d_i^{S,em}} \tag{8}$$

1.2 Self-employed

1.2.1 Less detailed method

The simulation to (and from) "being affected" by the lockdown measures for self-employed is similar to the simulation method for employees in the less detailed methodology. The transitions probabilities are based on monthly figures on the "bridging right" – the monetary compensation for affected self-employed – of the National Institute for the Social Security of the Self-employed (NISSE) at the sectorial level. Similar as for employees, we assume a 100% overlap in monetary compensation between two consecutive months, by sampling one random term for each individual that stays constant for all transitions to ´being affected`. A transition to "being affected" and receiving the bridging right is simulated, if

$$e_i \leq \Pr\left(l_i^{Rt} = br \mid s_i, l_i^{Bt} = se\right) = \frac{N_{br}^{s,t}}{N^s}, \tag{9}$$

with e_i a uniformly distributed random term, l_i^{Rt} the simulated labor market status, and l_i^{Bt} the labor market status in the baseline. If the labor market status is br, the self-employed is affected and receives the bridging right, and se means one is self-employed. The sector at NACE level 1 detail is denoted as s. Finally, $N_{br}^{s,t}$ is the number of individuals receiving a bridging right in sector s in month t, and $N^{s,t}$ is the total number of self-employed in sector s at the end of the first quarter of 2020 (as reported by NISSE). The transitions in and out of self-employment, towards or from inactivity, or employee activity, follows the transitions in the reported labor market states in SILC.

In the less detailed scenario, we assume that gross self-employment income is zero in the months a self-employed was affected by the crisis. All affected self-employed individuals will be eligible for bridging right, since we use statistics on receiving the bridging right to model the transitions to "being affected".

We do not model regional compensation in the less detailed method, since eligibility is based on turnover losses, which is not taken into account. This, together with the assumption of zero gross self-employment income when affected, can also be interpreted as perfectly targeted regional compensation: it covers exactly the remaining costs the self-employed face, i.e. the difference between turnover and costs in the months where the self-employed was affected by the crisis. As a result, the gross income, including the regional compensation, is equal to zero. This assumption is relaxed in the more detailed methodology.

1.2.2 More detailed method

In the less detailed method being affected by the crisis coincided fully with receiving compensation through the bridging right. To allow for income losses that were not fully compensated, we utilize a two-pronged approach, where we first allocate transition from self-employed to receiving bridging right, and thereafter allocate being affected by the crisis with income losses.

The simulation of individual transitions towards receiving the bridging right only slightly differs from the method used in the "less detailed" scenario. We could not take into account other socio-demographic variables than sector, nor could we fully account for transitions over the months, due to the absence of detailed transition tables. However, we did receive figures of the monthly share of self-employed remaining in monetary compensation over all sectors, which we utilize in the more detailed modeling. We assume the share to be constant over all sectors. The transition to receiving bridging right is thus no longer only dependent on the sector and labor market status in the baseline, but also dependent on the simulated transition in the previous month. The transition to receiving bridging right in March is the same as modeled in the less detailed method, based on (9). We calculate the probability to transition to receiving a bridging right from April onwards as:

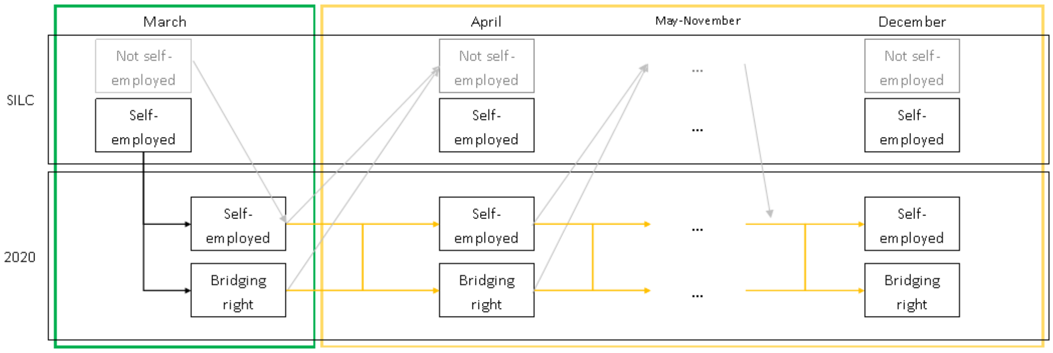
$$\Pr\left(l_i^{Rt+1} = br \mid s_i = s, l_i^{Bt+1} = se, l_i^{Rt} = br\right) = \alpha^{t,t+1} \cdot \frac{N_{br}^{s,t+1}}{N^s}, \qquad (10)$$

for those self-employed that received a bridging right in the previous month. $\alpha^{t,t+1}$ is the share of self-employed that received a bridging right in month t from those receiving a bridging right in month $t+1$. The probability for those not receiving a bridging right in the previous month is:

$$\Pr\left(l_i^{Rt+1} = br \mid s_i = s, l_i^{Bt+1} = se, l_i^{Rt} = se\right) = \left(1-\alpha^{t,t+1}\right) \cdot \frac{N_{br}^{s,t}}{N^s} \qquad (11)$$

For each month, the transitions themselves are simulated by sampling an individual random term, uniformly distributed between 0 and 1. If the random term is lower (higher) than the assigned transition probability, the individual (does not) transition(s) to the new labor market status. The procedure is schematically presented in Figure 14. Transitions out of the self-employment follow those reported in SILC.

Figure 14: labor market transitions in the more detailed method for the self-employed



The second step in the modeling of transitions of the self-employed is simulating change in gross income. Contrary to the less-detailed method, we no longer assume that every self-employed that faced an income loss is compensated with the bridging right. We model the income loss through changes in turnover, variable costs and fixed costs. This element adds another layer of heterogeneity to our model, as the income loss will depend on the structure of turnover, costs and income in the baseline, which varies over sectors.

We don't observe turnover, variable and fixed costs of self-employed individuals in SILC. We only observe gross self-employment income. Therefore, we add extra information to our baseline SILC dataset, based on aggregate statistics on income-turnover ratios and costs-income ratios at the sectorial level, retrieved from the Structure of Earnings Survey[22], and from statistics on national accounts of firms provided by the National bank of Belgium[23]. The ratios are shown in Table 2.

Table 2: Structure of income, turnover and costs

	$\frac{Turnover}{Income}=\beta^s$	$\frac{Costs}{Income}=\delta^s$
B-E Mining, manufacturing, utilities*	5.20	4.20
F Construction*	5.83	4.83
G Wholesale and retail trade**	17.20	16.20
I Accommodation and food service activities**	4.84	3.84
H-J Transportation and communication**	4.52	3.52
L-N Real estate, liberal professions and scientific services**	3.80	2.80
Total***	**6.89**	**5.89**

*Based on statistics of all enterprises; **Based on statistics of enterprises with 0 or 1 employees; ***Average over all enterprises

We divide the simulated costs further into fixed and variable costs based on estimates of the share of fixed costs in turnover of an enterprise at the sectorial level as calculated by Abraham et al. (2020), which we can denote by σ^s for each sector s. This allows to disentangle the gross self-employment income, y_i, into three components:

$$\begin{aligned} y_i &= \beta^s y_i - \sigma^s \beta^s y_i - \left(\delta^s - \sigma^s \beta^s\right) y_i \\ &= g_i - f_i - v_i \end{aligned} \tag{12}$$

for a self-employed individual i, active in sector s; namely, in turnover, g_i, fixed costs, f_i, and variable costs, v_i. We assume these three components to be constant over different months in the baseline. In addition, we assume that fixed costs remained constant on the short term during 2020, and that variable costs changed in proportion to the change in turnover in each month.

To model the shock on turnover, we use information from the survey of the Economic Risk and Management Group (ERMG).[24] This survey collected information on the impact of turnover of on average 3,500 self-employed and businesses each month from the start of the Covid-19 crisis onwards. The responses on the impact of turnover are distributed in seven categories for each sector: a decline of 100%, 75-99%, 50-75%, 20-50%, 0-20%, no impact on turnover, or a positive impact on turnover. Based on these monthly distributions, we simulate changes in turnover at the sectorial level.

However, we find that allocating these turnover losses would result in a significant overestimation of the overall turnover loss if compared to the turnover loss as reported on the basis of VAT registrations[25]. Our simulation would lead to a turnover loss of around 30% for the self-employed, while based on VAT statistics, it was only 8.7% in 2020. The discrepancy can be explained by

[22] See https://statbel.fgov.be/nl/themas/ondernemingen/structurele-ondernemingsstatistieken#figures.

[23] See https://stat.nbb.be/ "Statistics from annual accounts", "Financial ratios of companies".

[24] See https://www.nbb.be/en/covid-19/ermg/ermg-surveys.

[25] See https://statbel.fgov.be/nl/themas/ondernemingen/omzet-en-investeringen.

oversampling of affected self-employed individuals and affected enterprises in the ERMG survey. To align the simulation of the turnover losses based on the ERMG-survey results with the VAT-statistics, we assume that the share of respondents without any impact was underestimated. To account for the underrepresentation, we downscale all shares with impact and upscale the shares without impact with one factor γ, between zero and one.

We define the factor γ so that

$$\frac{\Delta G^{q,s}}{G^{s}} = \sum_{t} \frac{1}{3} \cdot \left(\sum_{\Delta g/g} \gamma^{s,q} \cdot p^{t,s}_{\Delta g/g} \cdot \frac{\Delta g}{g} + \frac{p^{t,s}_{no}}{\gamma^{s,q}} \cdot 1 \right), \tag{13}$$

i.e. so that the relative change in overall turnover, $G^{q,s}$ in quarter q in sector s based on the VAT-statistics, is reached by taking the average, over the three months in that quarter q, of a “pseudo-mean” percentage loss in that sector in that month. The pseudo-mean percentage loss is calculated based on the share of respondents that faced a loss $\Delta g / g$ (which ranges from -100% to +5%), denoted by $p^{t,s}_{\Delta g/g}$, and on the share of respondents that faced no loss, $p^{t,s}_{no}$, where the first are multiplied by factor $\gamma^{s,q}$, and the latter is divided by that same factor.[26] As we do not weigh for the initial level of turnover in each of the loss-categories (because we don’t have that information), this is not a “real mean”, but a “pseudo-mean”. We calculate such factor for each quarter and each sector (for which we have enough information). The resulting turnover loss in our simulation after such correction becomes 11.6% which is closer to the VAT-based statistic of 8.7%.

To guarantee consistency between the two prongs of our method – on the one hand receiving bridging right, on the other hand, facing a turnover loss – we first randomly allocate the largest turnover losses to self-employed individuals receiving a bridging right that month. We thus assume that the largest losses are faced by those receiving a bridging right, by first sampling from those receiving a bridging right. At the end of the procedure, each month t the share of self-employed in sector s that face a turnover loss $\Delta g / g$, is equal to $\gamma^{s,q} \cdot p^{t,s}_{\Delta g/g}$, with $p^{t,s}_{\Delta g/g}$ the share of respondents from the ERMG-survey.

This does not yet guarantee consistency between the allocation of turnover losses and receiving bridging right. In some cases there are still small (large) turnover losses allocated to individuals with (without) bridging right, which is not very realistic given the eligibility criteria for the bridging right. We solve this by adjusting the allocated turnover loss, dependent on whether one receives a bridging right. We prioritize receiving a bridging right over the allocated turnover loss in guaranteeing consistency, as the former is based on administrative statistics, whereas the latter is based on survey-data and a correction for underrepresentation of certain levels of turnover loss. In the consistency correction, we follow the eligibility criteria of the bridging right over the year. In March, April and May, the turnover loss is at least 25% if a bridging right is received and is not more than 25% if there is no bridging right. This corresponds to the condition to be closed at least one week in a month. In November and December, the turnover loss is more (less) than 60% if (not) receiving a bridging right, corresponding to the eligibility criteria for self-employed active in a sector that did not face an obliged closure. We assume that in sectors with obligatory closure, the relative turnover loss will automatically be at least 60%. For the months June until October, the eligibility criteria are less easily translated in such rules on turnover loss, so we do not correct the turnover loss in those months.

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26 We take the midpoint of the categories as the relative loss. Categories 0-20%, 20-50%, 50-75%, 75-99% and 100% are thus translated into numerical values 10%, 35%, 62.5%, 87.5% and 100%. We use – in line with the calculations of ERMG – a 5% turnover gain for the category “positive impact”.

The allocated monthly turnover changes determine the gross self-employment income.

$$y_i^R = \sum_{t=1}^{12} \left(1 - \frac{\Delta g_i^t}{g_i^B}\right) \cdot \left(g_i^B - v_i^B\right) - f_i \tag{14}$$

with g_i^B the baseline monthly turnover, $\Delta g_i^t / g_i^B$ the allocated percentage change in turnover (and, by definition, in the variable costs) in month t. The baseline monthly variable costs are denoted by v_i^B, and the fixed costs by f_i. The latter stay, by definition, constant between baseline and 2020-scenario. Note that if the percentage change in turnover is equal to zero, the monthly gross income stays constant.

Since we explicitly model fixed costs and turnover losses, we simulate – contrary to the less detailed method – regional compensation measures. These depend on the region, and the simulated turnover losses. Therefore, we also calculate a second market income concept, which allows us to compare between the two methods, namely the market income after regional compensation:

$$y_i^{R'} = r_i + \sum_{t=1}^{12} \left(1 - \frac{\Delta g_i^t}{g_i^B}\right) \cdot \left(g_i^B - v_i^B\right) - f_i \tag{15}$$

with r_i the received regional compensation in 2020. It depends on the turnover losses each month, but is not granted every month, and is modeled for the entire year. In all tables and figures in the paper where the results of the two methods are compared, we use this gross income concept for the self-employed that includes the regional compensation.

2. Appendix 2: Comparing poverty figures

The simulation of earning losses and monetary compensation for both employees and self-employed allows to present a distributional picture of the disposable income losses. The impact on disposable incomes affects the evolution of the at-risk-of-poverty (AROP) index. The AROP-index increases in both simulation scenarios, with a much larger increase in the more detailed scenario (+2.21pp) compared to the less detailed scenario (+0.14pp).

On March 28th, 2022, the Belgian Statistical office (Statbel) published poverty figures for 2020 based on the EU-SILC survey of 2021.[27] The survey showed that in 2020 about 13.1% of the Belgian population had a disposable household income below the poverty line, i.e. 60% of the median equivalent household disposable income. In 2018 and 2019, that share was respectively 14.8% and 14.1%. The number of Belgians at risk of monetary poverty has thus fallen in 2020 with 1 percentage point. In this Appendix 2, we will discuss how the evolution of the AROP-index resulting from our simulations relates to the AROP-index based on the EU-SILC.[28]

First, it is worth noticing that nowcasting and microsimulation do not intend to exactly predict reality and, consequently, predict the "real" (evolution of) the AROP-index. Its strength is to isolate (policy) changes and to estimate the impact of these isolated changes. We aim at simulating these isolated changes as close as possible to how these changes occurred in reality. In the nowcasting methods presented in this paper, we only simulated the impact of labor market transitions and income losses which are linked to the Covid-19 crisis. The changes in the income distribution in our simulation, and, accordingly, in the AROP-index are solely driven by these simulated changes. This is of course

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[27] Incomes from 2020 were surveyed in 2021.

[28] Notice that we discuss how to compare the evolution of the AROP-index and not the comparison of the level of the AROP-index itself. We know that there is a discrepancy between the AROP-index resulting from microsimulations and the EU-SILC (see for example Decoster et al. 2014).

not the case in AROP-index based on the EU-SILC survey. In reality, there were changes which were not covered by our simulations, such as demographic changes, work intensity, etc. These changes were not necessarily linked to the Covid-19 crisis. This makes that the AROP-index as deducted from EU-SILC responses gives a more complete picture of reality. Furthermore, there are three – more technical - important differences between the evolution of the poverty index based on (micro)simulations and based on EU-SILC 2021.

A first difference is the reference period. To show an evolution of the index, one needs to compare with a baseline. The poverty figures in this paper compare the evolution of the AROP-index with a counterfactual scenario, a "2020 scenario without Covid-19". The evolution of the AROP-index based on the EU-SILC shows the difference between 2019 and 2020.

Secondly, the construction of the poverty line differs. The poverty figures in this paper are based on the poverty line, which is calculated on the baseline, the counterfactual "2020 scenario without Covid-19". This line remains fixed, and the evolution of the AROP-index equals the extra share of individuals falling below this fixed poverty line. The poverty figure as reported by Statbel are calculated with a floating poverty line, which is calculated on the 2020 data itself.

Finally, the disposable income concept is different. The disposable income used in our paper is calculated with the use of the EUROMOD microsimulation model. In this model, all incomes and taxes paid on those incomes are brought together to one year. The EU-SILC poverty figures are based on a different disposable income concept, which can be interpreted as "spendable" income of the household during a year. It is equal to income received minus taxes and contributions paid in 2020. These taxes and contributions can relate to income received in the years before 2020.

The difference in income concept is a key element when evaluating policy measures. The policy measures that were implemented to absorb the income losses, can be divided into two categories: monetary compensation measures[29] and "deferral of payment" measures[30]. The latter had obviously a direct impact on the short term "spendable" income of households, and thus on the AROP-index as reported by Statbel. But, since those deferred contributions and taxes will have to be paid at some point, they have no impact on the disposable income concept used in our simulations.

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[29] This category consists of all kind of benefits: the federal temporary unemployment benefits for about 1.4 million of temporary unemployed employees and the lump sum "bridging right" benefit for self-employed accompanied with regional compensation benefits in Brussels, Flanders and Wallonia.

[30] This group of measures is related to the deferral of all kind of payments: the withholding tax on temporary unemployment benefits was lowered from 26.75% to 15% from May 2020 onwards and self-employed individuals could request a postponement of payment of their social security contributions.