BE-FAST: Data Infrastructure and Indicators for Fast Monitoring of Social and Labor Market Developments in Belgium

BRAIN 2.0 Belgian Research Action through Interdisciplinary Networks (Pillar 3)

Deliverable 2.2.

A comparison of nowcasted social outcomes for the COVID-19 pandemic with the post-hoc observed outcomes for Belgium: lessons for the next pandemic?

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Abstract

During the COVID-19 crisis, researchers interested in gauging the socio-economic impact of the pandemic on household and individual incomes heavily turned to nowcasting methodologies to overcome the lack of timely observational data on incomes. Leveraging the most recent macroeconomic statistics, nowcasting techniques enabled updating available pre-pandemic income distributions to proxy as well as possible the situation in the pandemic years of 2020, 2021 and 2022. For Belgium, nowcasting techniques with different degrees of detail were applied throughout 2020 - 2022, in line with the increasing availability of external, aggregate data.

This deliverable follows up on the work reported in D2.1, that presented an inventory of the various nowcasting approaches employed for conducting distributional analyses in Belgium from both national and international papers, and proposed a strategy for a post-hoc validation of the nowcasted pandemic prognoses. The current deliverable D2.2 compares the previously nowcasted results with the ex-post observed distributional impact of the crisis according to both administrative data and the EU-SILC. We end with an overview of the lessons learned from this post-hoc comparison.

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1 Introduction

During the COVID-19 crisis, researchers interested in gauging the socio-economic impact of the pandemic on household and individual incomes turned to nowcasting methodologies to overcome the lack of timely observational data on incomes. Leveraging the most recent macroeconomic statistics, nowcasting techniques facilitated the updating of information on the income distribution before the pandemic to the situation in 2020. To monitor the situation in Belgium, different nowcasting techniques have been employed, with varying degrees of detail in line with the (then) available external, aggregate data. In FAST deliverable 2.1, we presented an inventory of the various nowcasting approaches employed for conducting distributional analyses in Belgium in both national and international papers. We described and compared the different techniques on the basis of the following aspects: the policy measures incorporated in the simulation model; the publication date and period of analysis; the input data and data used for nowcasting (including a discussion on the level of detail and timeliness of the data); the nowcasting method and level of detail included in the modelling; and the way monetary variables are uprated. Additionally, we compared the main findings of the different papers regarding the impact of the pandemic on employment, incomes, poverty and inequality. Overall, we found that despite the variations in nowcasting method and data used, the conclusions drawn from different studies showed a considerable degree of similarity.

In this follow-up deliverable, we report the results of an ex-post validation of the different nowcasting approaches employed during the pandemic to monitor the impact of the pandemic as well as the effectiveness of the amalgam of social policies used.

In the first section, we compare the results reported in the various nowcasting exercises executed during the pandemic years, with trends in social outcomes as observed based on the SILC data that have since become available.

Next, we zoom in on a number of nowcasting approaches performed in the context of the COVIVAT project. As we have access to the underlying microdata for those exercises, we are able to i) re-assess the impact of specific methodological choices, and ii), to assess the accuracy of the projected distributive outcomes more in-depth, in a comparison with the post-hoc observed SILC data. Also, as over the past years analyses based on administrative data have become possible, we can assess how well the nowcasted outcomes reflect the administratively recorded recipiency characteristics and trends. Importantly, such a comparison also allows to illustrate more clearly what we did not cover with the nowcasted data.

In the final section, we distil the lessons learned and relate the insights obtained from the post-hoc validation and robustness checks, to other valuable findings obtained in the FAST project.

2 Comparison of main findings to the trends observed in the EU-SILC

2.1 Nowcasting approaches applied to Belgium, 2020 – 2022

In FAST deliverable 2.1 we presented an inventory of the various nowcasting approaches that were employed for conducting distributional analyses in Belgium for the period 2020-2022. Below, we briefly recap the main points. Table 1 provides a detailed summary[1].

Only one contribution, Almeida et al. (2021), used a static ageing technique in which the latest available micro data was 'reweighted' on the basis of macroeconomic information. This study was one of the first (among those exercises including Belgium) to publish its findings.

The majority of studies adopted a dynamic ageing approach and adjusted the observed labor market statutes in the underlying pre-pandemic microdata, to reflect the impact of the labor market shock on the active population during the pandemic. The transitions were initially limited to transitions from employment to temporary employment, and from self-employment to bridging right, but, as the crisis progressed, and more external data became available, also included transitions to unemployment, and consecutive transitions into and out of the different statuses. Most of the dynamic ageing approaches used a non-parametric allocation. This technique implied that different labor market statuses were randomly allocated to individual observations in the latest microdata available (most often the EU-SILC2018, with 2017 incomes) in line with recent external, administrative data on the incidence of these statuses in different strata of the population. The precise strata used differed between studies, and included characteristics such as age group, previous wage level and sector, and gender. In contrast, Eurostat's 2020 and 2022 flash estimates and the first COVIVAT working paper (Marchal et al., 2021) estimated the individual probabilities of making a certain transition, modeled on respectively the quarterly LFS microdata and the April 2020 online Corona study. Aggregate statistics were still relevant to calibrate the overall labor market status changes in line with external recipiency statistics.

Earnings loss was in most cases directly derived from the estimated changes in labor market status[2]. Next, the microsimulation model, most often EUROMOD, assessed the reaction of the tax benefit system on the presumed earnings losses. Those microsimulation models were updated and extended to include new, COVID-specific social protection benefits. Eligibility and entitlement of the affected population to social support benefits were calculated, and resulted in nowcasted net disposable incomes after policy intervention. Those were used for distributional analyses of the impact of the crisis, often in comparison with a fictional 2020 baseline in which no pandemic occurred.

In general, the different approaches found that the policy measures taken by the governments were likely effective at reducing both the size and the regressivity of the COVID-19 pandemic, although there are some minor differences in the precise point estimates and the distribution of the severity of the impact over different (baseline) earnings and (baseline) income quintiles. We turn back to this in section 2.3 below, where we assess to what extent the nowcasted findings are in line with post-hoc observed outcomes.

[1] Section 3.1 zooms in on the approaches applied in the framework of the COVIVAT research project.

[2] Observations that underwent a labour market status transition were generally assumed to experience a proportional reduction in earnings. Later contributions, specifically Capéau et al. (2021; 2022) adopted more nuanced changes to earnings, as reduction could also occur through drops in overtime or side jobs. Also drops in self-employed earnings were likely more varied than simple proportionate reductions (Capéau et al., 2022).

Table 1. Nowcasting approaches

Paper	Period	Microsimulation model and input data	Method	External statistics	Level of detail and transitions included
Thuy et al. (2020) - Federal Planning Bureau	2020 [a]	EXPEDITION Admin	Dynamic ageing, non-parametric (administrative recipiency statistics)	E: linked RVA-RSZ data, detailing TU by occupational status (2), gender (2), daily wage level (cont.) and parity committee SE: BR, general recipient numbers	Stratified sampling at gender (2), statute (2), daily wage (5) and committee level E -> TU; SE -> BR
Almeida et al. (2021) - JRC	2020 [a]	EUROMOD EU-SILC 2017	Reweighting (external economic forecasts)	Forecasts European Commission	
Marchal et al. (2021) - COVIVAT	April 2020	EUROMOD EU-SILC 2018	Dynamic ageing, parametric (Corona-study, administrative recipiency statistics)	E: TU, by sector (21), age group (5 years), gender, province, region, occupational status (2) SE: BR, by occupation code (>60), age group (5 years), region, type of SE and gender	Logit model using gender (2), age (2), educational attainment (2), occupation (4), work regime (2) and sector (NACE1) E -> TU; SE -> BR (April SILC to 'April 2020')
Christl et al. (2021) – JRC	2020	EUROMOD EU-SILC 2018	Dynamic ageing, non-parametric (LFS and administrative data)	E: TU by sector (up to August) SE: BR by sector (Q1-Q2)	Stratified sampling at sectorial level; gender and occupation (only UN) E -> TU; SE -> BR; E/SE -> U
Capéau et al., (2021) - COVIVAT	2020	EUROMOD EU-SILC 2018	Dynamic ageing, non-parametric (administrative recipiency statistics)	E: TU by gender, age group (4), sector (22), daily wage (5) and numbers of days in TU (5) + monthly info on transitions	Stratified sampling at the sectorial level, gender (2), age (4), wage-category (3), labor market status previous month E -> TU*; TU* -> E; E -> U; U -> E; TU* -> U ; U -> TU* (Month to month)
Derboven et al. (2021) - COVIVAT	Mar-Dec	EUROMOD EU-SILC 2018	Dynamic ageing, non-parametric (administrative recipiency statistics)	E: TU by gender, age group (4), sector (22), daily wage (5) and numbers of days in TU (5) + monthly info on transitions SE: BR by occupation code (>60), age group (5 years), region, type of SE and gender (M/F)	Stratified sampling at the sectorial level (22), gender (2), age (4), wage-category (3), labor market status previous month (E); Stratified sampling at sectorial level (SE) E -> TU*; TU* -> E; E -> U; U -> E; TU* -> U ; U -> TU* ; SE -> BR (Month to month)
Eurostat (2021) – 2020 FE	2020	EUROMOD EU-SILC 2018	Dynamic ageing, parametric LFS and administrative recipiency statistics	E: number of TU (admin.) [tbc] SE: number of BR (admin.) [tbc]	Logit model using gender (2), age group, sector (10), occupation (4) and type of contract (2) U -> E; E/SE - > STU; STU -> LTU; E/SE -> TU/BR Quarterly, net transitions
Capéau et al., 2022 (less detail) - COVIVAT	2020	EUROMOD EU-SILC 2018	Dynamic ageing, non-parametric (administrative recipiency statistics)	E: TU by sector SE: BR by sector	Stratified sampling at the sectorial level E -> TU; SE -> BR
Capéau et al., 2022 (more detail) - COVIVAT	2020	EUROMOD EU-SILC 2018	Dynamic ageing, non-parametric (administrative recipiency statistics)	E: TU by gender, age group (4), sector (22), daily wage (5), number of days in TU (5), LM status previous month SE: BR by sector (and aggregate transitions)	Stratified sampling at the sectorial level (22), gender (2), age (4), wage-category (3), labor market status in previous month (E); Stratified sampling at sectorial level (SE) E -> TU*; TU* -> E ; E -> U; U -> E; TU* -> U ; U -> TU*; SE -> BR ; BR -> SE

Neelen et al., (2022) - COVIVAT	Mar-Dec	EUROMOD EU-SILC 2018	Dynamic ageing, non-parametric (administrative recipiency statistics)	E: TU by gender, age group (4), sector (22), daily wage (5), number of days in TU (5), LM status (7) + monthly transitions SE: BR by gender, age, sector, income (2019), LM status (2) + monthly transitions	Stratified sampling at the sectorial level, gender (2), age group (4), wage-category (3), labor market status previous month (E) stratified sampling at sectorial level, gender (2), yearly income category (SE), peak-to-peak transition) E -> TU*; TU* -> E; E -> U; U -> E; TU* -> U; U -> TU*; TU* -> TU*; SE -> BR; BR -> SE Month to month
Eurostat (2022) – 2021 FE[b]					
Eurostat (2023) – 2022 FE	2021	EUROMOD EU-SILC 2020	Dynamic ageing, parametric (LFS and administrative recipiency statistics)	E: number of TU (admin.) SE: number of BR (admin.)	Logit model using gender, age group, sector, occupation and type of contract + calibration based on aggregate data (gender(2), age (2), occupation (2), sector(7), contract type (2)) U -> E; E/SE - > STU; E/SE - > LTU; STU -> LTU Quarterly, net transitions

Note: [a] Assumptions regarding continuation crisis in the remainder of 2020; [b] Belgium not included in final estimates.

(E = Employed, SE = Self=employed, TU = Temporary Unemployed, BR = Bridging Right, U = Unemployed, STU: short-term unemployed; LTU: long-term unemployed).

2.2 Post-hoc validation: a comparison with the trends observed in the Statistics on Income and Living Conditions survey

2.2.1 Challenges

We set out to compare the findings reported in the various contributions listed in Table 1 to the post-hoc observed changes in the distribution of incomes measured in the EU-SILC microdata that have since become available. Those nowcasting exercises either use administrative data (Thuy et al. 2020) or the EUROMOD input file based on EU-SILC 2018 (with incomes for 2017) or EU-SILC 2020 (with incomes for 2019, in the more recent Eurostat flash estimates) to estimate the situation in 2020, 2021 or 2022. By now, it has become possible to compare the findings for 2020, 2021 and 2022, with those observed in EU-SILC 2021 (incomes 2020), EU-SILC 2022 (incomes 2021) and EU-SILC 2023 (incomes 2022)[3].

There are a number of challenges when comparing the levels and trends observed in the nowcasted data with the post hoc available EU-SILC data. We list these challenges below, along with our preferred approach to address those challenges. A more elaborate discussion of the various options can be found in deliverable 2.1.

First, as is clear from Table 1, some of the papers included in our inventory, focused on ***the monthly, rather than annual impact*** of the pandemic on the income and earnings distribution. This focus on monthly incomes does hinder a straightforward comparison of the reported findings with the information in the EU-SILC, that is designed to capture as well as possible an annual income concept. We decided to respect the annual focus of the post-hoc observed EU-SILC data. In section 2.3, we therefore focus on the comparison of the previous nowcasting exercises that projected annual income changes. In section 3, we use the previously converted monthly to annual projections, and use these in an in-depth post-hoc validation with SILC and administrative data.

Second, most of the results reported in the papers listed in Table 1, did not include ***indications of the uncertainty surrounding the reported estimates***. Throughout this assessment, we provide additional context as to the precision of the various estimates.

Finally, the nowcasted results were often[4] reported as changes in earnings and net disposable incomes ***relative to a baseline scenario***. This baseline scenario was generally a hypothetical 2020 in which no COVID-19 pandemic took place. Practically, this was simulated by uprating the underlying microdata (generally 2017 incomes, as present in the SILC2018 files) to 2020, assuming that no labor market transitions occurred, and no new COVID-19 inspired social policy measures were implemented. Monetary amounts were uprated in line with appropriate inflation indices. This uprated data was then updated to reflect regular policy changes, by running the 2020 pre-pandemic tax benefit policies. By comparing the shock scenario to this baseline, researchers could show how the COVID-pandemic, and the crisis measures taken, impacted the income distribution.

In a post-hoc validation, the question arises how we should compare social outcomes in the post-hoc available microdata with the simulated changes reported relative to such a hypothetical baseline. It is indeed not straightforward to directly compare simulated outcome statistics to summary measures derived from observational microdata. Capéau et al. (2022) already refer to these problems in the annex to their paper, when they compare the obtained (simulated) change in poverty rate between

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[3] https://ec.europa.eu/eurostat/documents/203647/771732/Datasets-availability-table.pdf

[4] In contrast, Eurostat opted to report its flash estimates as changes relative to the previous years.

their baseline and nowcasted scenario, to the figures that were at the time just published by Statbel, prior to the release of the microdata to the research community. The various simulation scenarios generally assessed the impact of (socio-demographic and social policy) changes relative to a "2020 without COVID-19", although it was constructed in different ways[5]. Evidently, a 2020 without COVID-19 is a hypothetical scenario that cannot actually be observed. An obvious challenge when assessing the robustness of the findings reported in the various nowcasting exercises therefore relates to the identification of a useful "reference baseline" to assess the simulated and observed changes against.

In addition, there is yet another caveat related to comparing simulated and observed empirical data. Capéau et al. (2022) highlight that the disposable income concept from microsimulations is different to the concept available in SILC. For pragmatic reasons, the annual version of EUROMOD calculates the impact of the applicable tax benefit rules, concentrated in one year. That means that tax returns that in reality will only be paid out in the following year, are included in the currently simulated year. The same goes for other income components that are in reality only relevant to citizens with a certain lag. The EU-SILC income concept includes the tax rebates that stem from the previous year, whereas EUROMOD includes the tax rebates that will be paid out based on the current year's incomes. Capéau et al. (2022) hypothesize that the nature of specific COVID-19 measures, such as deferral of payments, may further contribute to a discrepancy between simulated and observed outcomes.

The issue regarding the disposable income concept reaches even wider. EUROMOD applies the tax-benefit system as it is intended to work. That means that all benefits and taxes are taken up, in a timely way. Even though there are some modifications to proxy the non-take-up of means-tested benefits, it is unlikely that the Belgian tax-benefit system functions as well in reality as is simulated in EUROMOD. This is often seen as a reason why simulated poverty rates are lower than actually observed outcomes (e.g. Vinck & Verbist, 2022).

The Eurostat flash estimates explicitly recognize this discrepancy between simulated and observed social outcomes, and account for it in the publication of their nowcasted social outcome statistics. The nowcasted estimates are based on the most recently available EU-SILC income years, usually referring to t-3 or t-2, where t is the year the flash estimate refers to. The nowcasted outcome statistics are derived by first calculating the year-on-year change between the model-based flash estimates from t-1 to t. Next, this year-on-year change on the aggregate outcome statistic is applied to the most recently available SILC-based outcome statistic, to get a nowcasted estimate. Importantly, this nowcasted point estimate is not published as such. Instead, only the rounded uncertainty interval around the point estimate is shown, to stress the uncertainty of the nowcasted results.

To accommodate these challenges, we combine different approaches. In section 2.2.2, we focus on a comparison of a simulated COVID (including extended COVID-policies) 2020 with a simulated hypothetical 2020 without COVID. The latter is obtained by uprating EU-SILC 2020 (incomes 2019) to a no-COVID 2020 using EUROMOD (i.e. we only include uprated pre-existing policies and do not include discretionary emergency support measures). The former is derived from EU-SILC 2021 (incomes 2020), after running it through EUROMOD to account for the discrepancy between simulated and observed data (cf. our above discussion). (Specifically, we use the EUROMOD input data for this analysis.)

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[5] The fact that people could be temporary unemployed even when they were in the original EU-SILC 2018 data fully unemployed in a specific month, led to readjusted baselines in later working papers and policy notes (e.g. Capéau, Decoster, Vanderkelen, & Van Houtven, 2022; Wizan, Neelen, & Marchal, 2023).

It is clear that this approach hinges on changes observed between the EU-SILC 2020 and the EU-SILC 2021. The COVID-19 pandemic evidently also impacted the EU-SILC 2020 rollout (Statbel, 2020). We therefore also include a comparison with the results from analyses based on administrative micro data that have by now become available (see section 3.3.2 below).

2.2.2 Results

In the next step, we compare the results of the different papers in D2.1's inventory with the post-hoc observed results to assess the accuracy of the various nowcasting exercises. We focus on the projected changes to average incomes (for the different target groups identified in each paper), poverty rates and inequality.

The changes to average incomes as reported in the different nowcasting exercises are shown in Table 2. The second column shows the percentage change in individual or household income as a result of the COVID-19 outbreak taking into account the compensation measures implemented by the government, relative to the baseline used in each paper, often a "2020 without COVID-19" scenario. All papers showed that the COVID-19 impact without compensating measures would have been severe, in terms of average earnings, poverty and inequality (see deliverable 2.1). Importantly, due to the unequally distributed opportunities to work from home over the income distribution, with more options to continue working higher up the distribution, the impact of COVID-19 on earnings would also have been highly regressive. All nowcasting approaches however found that the compensation measures introduced by the government were to a large extent effective in compensating large parts of the income losses for the affected population (see deliverable 2.1, and Table A in appendix). The initial regressive impact of the COVID-19 pandemic was overturned in terms of disposable income, leading to a projected progressive or only mildly regressive pattern of reduction in average incomes by income deciles or quintiles.

For comparability of the nowcasted results of the different papers with the post-hoc observed data about the COVID period, a first step was to construct an appropriate baseline. Evidently, a hypothetical 2020 without COVID-19 taking place cannot actually be observed. We therefore constructed a counterfactual 2020 without COVID-19, using the EU-SILC 2020 data (income 2019) in the EUROMOD baseline system of 2020. In this EUROMOD baseline system, the monetary values are uprated to 2020 prices, changes in policies are implemented (but without discretionary COVID-19 policies) and no changes are applied to labour market statuses. Next, we aimed at replicating the published results of the different papers by looking at the same income source and group of interest as studied in the papers. For the sake of completeness, we add (in columns 4 and 5) also the observed change in incomes from 2019 – 2020 (as reported in the EU-SILC, in column 4 as apparent from the data, and in column 5 after applying the EUROMOD tax benefit models for 2019 and 2020 on the underlying data).

From Table 2, we can make the following observations. First and foremost, overall, there are no large differences - nor between the nowcasted results relative to one another, nor with post-hoc observed income changes. Overall, the main results obtained from the nowcasting exercises are confirmed: the policy measures taken did succeed in mitigating the overall impact of the COVID-19 pandemic. Second, the nowcasted results slightly overestimated the loss in income in comparison with the observed EU-SILC results.

Table 2. Comparison of changes in income after compensation measures, nowcasted results vs observed SILC results

Paper	Nowcasted 2020, relative to no-COVID baseline[a]	Observed 2020, relative to hypothetical no-COVID baseline[b]	Observed 2019 – 2020 (EU-SILC 2020-2021)	Simulated 2019 - 2020 (EU-SILC 2020-2021, EUROMOD)
Thuy et al. (2020)	-0,7% in average, disposable income (pop.) (average annual impact, based on a 3-month crisis period)	-0,57% [-0,51%:-0,63%] in average, disposable income (pop.)	-0.36% [-0.31;-0.41]	-1,98% [-2,04%;-1,92%] in average, disposable income (pop.)
Almeida et al. (2021)	-2% in average equivalised disposable hh income (pop.)	-1,10% [-1,02%;-1,18%] average equivalised disposable hh income (pop.)	-0,64% [-0,49%;-0,79%] average equivalised disposable hh income (pop.)	-1,37% [-1,45%;-1,30%] average equivalised disposable hh income (pop.)
Capéau et al., (2021)	-1,0% in annual, disposable income (all E)	-1,13% [-1,11%; -1,15%] in annual, disposable income (all E)	-0.36% [-0.31;-0.41]	-1,54% [-1,57%;-1,52%] in annual, disposable income (all E)
Christl et al. (2021)	-1.3% in average, equivalised disposable hh income (pop.)	-1,1% [-1,02%;-1,18%] average equivalised disposable hh income (pop.)	-0,64% [-0,49%;-0,79%] average equivalised disposable hh income (pop.)	-1,37% [-1,45%;-1,30%] average equivalised disposable hh income (pop.)
Eurostat (2021) – 2020 FE	-3,5% in average, gross income (working pop.)	-2,0% in average, gross income (working pop.)	-0.59% in average earnings (whole sample)	-2,15% [-2,15%;-2,14%] in average, gross income (working pop.)
Capéau et al., 2022 (- detail)	-2,2% in annual equivalised disposable hh income (pop.)	-1,10% [-1,02%;-1,18%] average equivalised disposable hh income (pop.)	-0,64% [-0,49%;-0,79%] average equivalised disposable hh income (pop.)	-1,37% [-1,45%;-1,30%] average equivalised disposable hh income (pop.)
Capéau et al., 2022 (+ detail)	-3,6% in annual equivalised disposable hh income (pop.)	-1,10% [-1,02%;-1,18%] average equivalised disposable hh income (pop.)	-0,64% [-0,49%;-0,79%] average equivalised disposable hh income (pop.)	-1,37% [-1,45%;-1,30%] average equivalised disposable hh income (pop.)

Note: Values between brackets refer to confidence intervals. No direct comparison is possible for the monthly results reported in Marchal et al. (2021), Derboven et al. (2022) and Neelen et al. (2023). See section 3 for an alternative comparison. [a] As constructed and reported in the different nowcasting exercises. [b] EU-SILC 2021 (incomes 2020), used as input data in EUROMOD to eliminate differences due to simulated versus observed data, as compared to EU-SILC 2020 (2019 incomes), uprated to a no-COVID 2020 using EUROMOD. (hh = household, pop. = population, E = employees).

Source: Own calculations (columns 3 – 5) on EUROMOD (2021) and EU-SILC, Eurostat (2021)

The nowcasting exercises also projected expected changes on poverty rates and inequality levels (see Table 3). Policy measures were able to counteract the inequality increasing effect of the COVID-19 pandemic, as inequality in the scenario including policy measures decreased (Almeida et al., 2021; Christl et al., 2021; Capéau et al., 2021) or stayed more or less the same (Marchal et al., 2021). With regard to poverty, the JRC (Almeida et al. 2021), Eurostat and some of the COVIVAT papers reported on the change in the At-Risk-of-Poverty (AROP) rate as a result of the COVID-19 crisis. Not surprisingly, most papers found that the AROP rate would increase significantly due to the COVID-19 pandemic compared to their baseline scenarios. When accounting for policy measures, however, this increase was less pronounced (Almeida et al., 2021; Christl et al., 2021). Finally, Eurostat published yearly flash estimates (FE) of the AROP using a rounded uncertainty interval. For both the 2020 FE and 2022 FE, this interval ranged between a projected -1,2 and 1,2 percentage point change compared to the AROP rate in the previous income year.

Table 3. Comparison of projected and effective change in GINI and AROP-rate

	Nowcasted 2020, relative to no-COVID baseline[a]	**Observed 2020, relative to hypothetical no-COVID baseline[b]**	**Observed 2019 – 2020**
Thuy et al. (2020)	-		
Almeida et al. (2021)	-0.001 Gini +0.9 pp in AROP (compared to no-covid baseline)		
Marchal et al., (2021)	Stable Gini		
Capéau et al., (2021)	-3,1% Gini		
Christl et al. (2021)	-0.004 Gini +0.2 pp in AROP fixed line (-0.2 pp floating line)	-1.55 ppt AROP Gini -0.006	Gini -0.013 -1.4 ppt AROP
Eurostat (2021) – 2020 FE*	[-1,2;1,2] AROP*		
Capéau et al., 2022 (less detail)	-0.006 Gini +0.14 pp. AROP		
Capéau et al., 2022 (more detail)	+0.009 Gini +2.21 pp. AROP		
Eurostat (2023) – 2022 FE*	[-1,2;1,2] AROP*	Not relevant	AROP: -0.9 ppt

Note: * Eurostat flash estimates project the year-on-year change. Hence, comparison with column 4 is more appropriate. [a] As constructed and reported in the different nowcasting exercises. [b] SILC 2021 (incomes 2020), used as input data in EUROMOD to eliminate differences due to simulated versus observed data, as compared to SILC 2020 (2019 incomes), uprated to a no-COVID 2020 using EUROMOD.

Source: Own calculations, columns 3 – 4, EUROMOD and EU-SILC, Eurostat

Table 3 then lists the projected changes in AROP and Gini, and compares those to the post-hoc observed changes. In general, the post-hoc observed results confirm the small decrease in inequality in the net disposable (equivalized) income distribution. In contrast, the change in the AROP among the general population does not confirm the most common nowcasted projections. The projections generally predicted small to moderate increases in the AROP rate, when taking compensatory measures into account. In contrast, post-hoc observed trends in the AROP rate for Belgium, point towards a decrease of the poverty risk among the general population. For 2020, this decrease even goes beyond the uncertainty interval projected in the Eurostat Flash estimates.

3 A closer look

3.1 COVIVAT[6]

Several of the nowcasting approaches applied for Belgium were developed in the context of the COVIVAT consortium, a joint effort of the KULeuven and the UAntwerpen. Between 2020 and 2022, the COVIVAT team undertook various initiatives to assess the ongoing impact of the pandemic. These included inter alia hypothetical household calculations to assess the impact of the policy proposals on typical cases (Cantillon, Marchal, Peeters, Penne, & Storms, 2020; Marchal, Penne, & Storms, 2020), explorative descriptions of the profiles working in the most affected sectors (Decoster, Van Lancker, Vanderkelen, & Vanheukelom, 2020; Horemans, Kuypers, Marchal, & Marx, 2020), ad-hoc surveys among local welfare agencies and food banks, in order to monitor early warnings (De Wilde, Hermans, & Cantillon, 2020), assessments on administrative data (Vinck, Audenaert, & Van Lancker, 2022), as well as various nowcasting exercises (Capéau, Decoster, Vanderkelen, & Van Houtven, 2021; Capéau et al., 2022). In this section, we discuss more in-depth the changes between the different nowcasting approaches adopted throughout the COVIVAT project. A summary is available in Table 1 in section 2.

Specifically, the COVIVAT consortium joined forces for the **first COVIVAT nowcasting working paper (Marchal et al., 2021)**. This paper assessed the impact of the lockdown in April 2020 in Belgium on individual and household incomes in that month. Their nowcasting built on a parametric model, derived from an ad-hoc, non-representative (though widely filled out) online survey, the Corona Study (Universiteit Antwerpen & Universiteit Hasselt, 2020). This timely data allowed to estimate the odds of becoming temporary unemployed or receiving a bridging right in April 2020, based on *gender, age, educational attainment, occupation, work regime and sector*. This model was then applied to the (representative) EU-SILC 2018 data in order to identify the likelihood of individual observations becoming temporary unemployed or receiving the bridging right. The results of the parametric model applied on the EU-SILC were calibrated based on external aggregated administrative data available from the *RVA (Rijksdienst voor Arbeidsvoorziening – National Employment Service)*, *RSZ (Rijksdienst voor sociale zekerheid – National Social Security Office)* and *RSVZ (Rijksinstituut voor de Sociale Verzekeringen der Zelfstandigen - National Institute for the Social Security of the Self-Employed)* that allowed to calculate the share of temporary unemployed and those receiving bridging right by sector, age group and gender (Marchal et al., 2021).

For those identified as temporary unemployed in the EU-SILC 2018, in a second step the number of days of temporary unemployment in April 2020 was determined. At the time, publicly available RVA data showed the share of temporary unemployed individuals in each sector that was less than 6 days, 6 to 12 days, 13 to 19 days, 20 to 25 days and 26 days or more temporary unemployed. Note that these categories are based on a 6-day workweek, which is the (theoretical) basis used for the calculation of (temporary) unemployment by the RVA, rather than the actual work week of respondents. Therefore,

[6] This section is largely based on a discussion in Neelen, Derboven, and Marchal (2022).

first, for each respondent the maximum number of days that a respondent was eligible for temporary unemployment was calculated. Based on the reported hours worked per week, the maximum number of days each EU-SILC respondent could become temporary unemployed was calculated, assuming a standard 8-hour workday and 4.33 weeks per month. This information was used to assign in which category each temporary unemployed observation would fall. Ultimately, each temporary unemployed observation was assigned the upper category border (i.e. 6, 12, 19, 25 or 26 days), or his or her own number of work days, whichever was lowest. Finally, all 2017 monetary variables included in the EU-SILC 2018 were uprated to 2020 in line with appropriate indexation indices. Labour market earnings for those affected were reduced in line with the number of days of temporary unemployed or put to zero in case of bridging right receipt. Relevant policy measures were simulated using EUROMOD, in order to obtain the best approximation of net disposable incomes, taking account of both pre-existing and newly introduced social protection measures.

In a later stage, the KULeuven team developed a non-parametric nowcasting approach for employees. This approach was pursued given concerns regarding the continued validity of a parametric model that would be estimated on the Corona Study for consecutive months, with increasing attrition over time. **COVIVAT Policy Note 9, by Capéau et al. (2021),** projected the impact of the COVID-19 shock on the incomes of employees, for the entire year of 2020. By January 2021, the COVIVAT researchers had received more detailed external data, i.e. monthly numbers of (temporary) unemployment by gender, age groups, sector and daily wage categories, provided by the RVA. An important improvement relative to the external data previously used in Marchal et al. (2021), was that the external data referred to more detailed subpopulations and were available on a monthly basis, *conditional upon the status in the previous month*. Moreover, the external data also split the subpopulations by (categories of) days of temporary employment. While these data clearly represented a substantive improvement, limitations of the data were that i) the numbers for October – November were provisional, and those for December 2020 were lacking; ii) the lower threshold of the upper wage threshold was fairly low, at the wage ceiling for the maximum unemployment benefit[7], and iii) the numbers only referred to the absolute numbers of affected (temporary) unemployed. In order to calculate the likelihood that an individual observation in the subpopulation would be affected by temporary unemployment or unemployment, these monthly numbers were therefore divided by the weighted number of employees in each category as observed from the EU-SILC: aggregate external data on the total number of employees in each category were at the time not available for these more fine-grained subpopulations.

The more detailed data made it possible to forego the parametric model, and to randomly allocate temporary unemployment and unemployment status at the level of more fine-grained subpopulations, and conditional upon the status in the previous month. Only monthly transitions between employed, (fully) unemployed and temporary unemployed (further distinguished by the number of days of temporary unemployment) were allocated. The starting point of the random allocation was April 2020, since this was the first full month in which the COVID-19 measures were in full effect. Transitions were then allocated from April to May, from May to June and onwards, in line with the external data. A reverse transition from April to March was also added. In order to be able to allocate in line with these more fine-grained subpopulations in sufficient detail, the researchers inflated the EU-SILC with a factor 10 (accompanied by a proportionate correction to the individual weights used) to minimize rounding

[7] The upper wage threshold available in the RVA data was 105.95 euro per day (in a 6-day workweek, i.e. 126 euro when converted to a 5-day workweek). Based on external information that 16.4% of temporary unemployed had a prior wage above 134 euro (160 euro), a further calibration was adopted to include more variation in the income levels (cf. Capéau et al., 2021).

errors. As was the case in Marchal et al. (2021), the number of days worked in the EU-SILC was calculated based on the reported working hours at the moment of interview, so that no more days of temporary unemployment could be allocated than the number of days regularly worked. Thanks to the improved external data, the allocation of days of temporary unemployment now occurred by detailed subpopulation, in the same allocation step as previously described[8]. It was still the maximum possible number of days that were allocated per category. Finally, monetary variables were uprated in line with appropriate indices. Annual earnings from work were adjusted in line with the allocated days and months of (temporary) unemployment, while the EUROMOD microsimulation included the annual impact of the temporary unemployment benefits, the long-term temporary unemployment premium and the effect of the automatic stabilizers.

The KULeuven team generously shared its approach with the UAntwerpen COVIVAT team, that used it for **policy note 10 (published in December 2021, by Derboven et al. (2021)).** This note adopted a month-by-month perspective. Exactly the same approach was used to identify those becoming (temporary) unemployed. However, since the interest of Derboven, Neelen, Vanderkelen, Verbist, and Marchal (2021) was on the change in monthly incomes, rather than on the annual income shock, the monthly statuses were used to adjust monthly earnings, and to calculate the effect of the COVID-19 policy measures in each month. Main differences with Capéau et al. (2021) therefore related to the scope of the simulations in EUROMOD, that in Derboven et al. (2021) also included regional income support benefits. In addition, the paper focused on slightly different groups of interest. The modeling of flex-workers was not included in the random allocation. Self-employed on the other hand were included in the analysis, by using random allocation in order to assign the bridging right to self-employed EU-SILC observations. The external aggregated data used to assign the bridging right were provided by the RSVZ, and were received by early February 2021. Unfortunately, information was less detailed than the information available for affected employees. Percentages of those receiving a bridging right were only available (and hence applied) by sector, gender and age group. Moreover, there was no information at the subpopulation level on the transitions from bridging right back to self-employed activity. The random allocation hence assumed that states were relatively constant, i.e. those who were assigned a bridging right in the previous month, were most likely to continue to receive bridging right. As was the approach in Marchal et al. (2021), incomes from self-employment were set to zero if one was in receipt of the bridging right.

In April 2022, **Capéau et al. (2022) reported in COVIVAT Working Paper No. 5,** a detailed comparison of two different nowcasting methods. Both methods built on random allocation, yet one method showed the results of a more broad-brush allocation (in line with the public availability of external administrative data right at the onset of the COVID-19 crisis), whereas the alternative allocation built on more fine-grained external data, as well as more detailed modelling of income losses specifically for the self-employed. The more detailed comparison case modeled transitions for employees, in line with the approach developed in Capéau et al. (2021), taking account of sector, gender, age, wage-category and status in the previous month. The necessary external aggregate administrative data by subpopulation are the same as those used in Capéau et al (2021), that were provided by the RVA, and

[8] An additional extension of the nowcasting method applied in Capéau et al. (2021) was the attention devoted to the situation of non-standard workers. Specifically, effects for those working under the flexi-job system were estimated. Publicly available statistics from the RSZ for flex-workers per sector were used to assign flex-worker status to observations in the EU-SILC who had an employment of at least 4/5th in the first quarter. Of this group, observations were randomly picked in line with external data in order to assign who would lose their flexi-job in the second quarter, while these same observations would also lose their flexi-job in the last quarter. In the third quarter of 2020, every flex-worker was assumed to regain their flexi-job. Hours worked in all flexi-jobs were also adjusted accordingly: 55 hours worked in the first quarter of 2020; 51 hours for the other three.

converted into percentages by relating them to the subpopulation sizes reported in the EU-SILC. For the self-employed, the analysis reported in Capéau et al. (2022) brings in far more detail, both into the stratified sampling procedure, as well as in the adjustment of self-employed incomes. Regarding the former, the identification of self-employed eligible for bridging right is still based on external data on the share of self-employed receiving a bridging right per sector, derived from RSVZ data. However, the assumption of full overlap is relaxed, meaning that the allocated statuses are recalibrated in line with aggregate external data on the transitions (for all self-employed, not available by sector) from bridging right to self-employed activity (and vice versa) from one month to the other. The impact of the COVID-19 crisis on self-employment earnings is also modelled in far more detail, taking account of variation in fixed costs and heterogeneity in turnover losses at the sectorial level[9].

Finally, the COVIVAT team at UAntwerpen received in May 2022 aggregated administrative data from the *Datawarehouse Kruispuntbank Sociale Zekerheid (KSZ)*. The KSZ data comprised final (i.e. not provisional) aggregate monthly transition statistics for employees as well as the self-employed, for March - December 2020. These allowed for a number of further changes to the random allocation procedures summarized above, that resulted in the working paper by **Neelen et al. (2022)**[10]**.** For one, the data on the number of (temporary) unemployed by subpopulation for September-November and December 2020 were final. Second, the adopted wage categories reached higher into the wage distribution, with the top threshold at 175 euro per (5-day workweek work)day. Third, the external data included information on the denominator, making it possible to calculate the (temporary) unemployment probability by subpopulation fully on external data, rather than by relating the numbers of those affected to the observed populations in the EU-SILC. Fourth, the transition probabilities for self-employment were now available by (2019) income category. Finally, information had become available on the overlap between those who became (temporary) unemployed in April and November 2020, offering an opportunity to re-anchor the monthly transitions to better proxy those who were hit by the social distancing measures of both COVID-19 waves in 2020.

After the COVIVAT project was concluded, **Wizan and Marchal (forthcoming)** further assessed and revised the method applied in Neelen et al. (2022) as additional input to the FAST project. Specifically, they updated the underlying income data to SILC-2020 (2019 income reference year), instead of using the SILC-2018 (2017 income reference year)[11]. Also, the authors finetuned the modelling of a number of COVID-19 social policies. The authors included the Walloon premiums (water, gas and electricity) in December, and updated the long-term temporary unemployment premium to be more accurately based on the RVA's calculations, simulating separately the premium for part-timers. During this revision, Wizan and Marchal (forthcoming) also revised certain methodological choices. Specifically, in

[9] Capéau et al. (2022) do so by adding this extra information to the underlying EU-SILC data, based on aggregate statistics at the sectorial level on cost-income and income-turnover ratios. They further divided costs into fixed and variable costs based on estimates of the share of fixed costs in turnover. Capéau et al. (2022) further assumed fixed costs to be constant during 2020, while variable costs changed in proportion to their turnover for every month. They used information on the impact of the COVID-19 crisis on the turnovers of self-employed provided by the Economic Risk and Management Group (ERMG). Seven categories of turnover losses/gains could subsequently be allocated, and certain months had extra corrections in turnover loss (see Capéau et al., 2022 for a more detailed description). The losses in turnover were then used to generate a percentage change in turnover, which was further used to adjust the gross self-employment income. Furthermore, fixed costs were deducted, as well as the variable costs in proportion to the turnover for every month, in order to come to their final gross self-employment income. They also made a second income concept, where the regional compensation measures were added. This adjustment of the gross incomes of the self-employed allowed them to better model the distributional impact of the COVID-19 shock on their incomes.

[10] Subsequently, the data were used for an analysis of income volatility during 2020 in Wizan et al. (2023).

[11] The impact of this change is reported in section 3.2.3.

the case of dual statuses (i.e. observations who reported to have been both employees and self-employed throughout the base year), the authors decided to prioritize the allocation of the bridging right, due to the small numbers of self-employed in the SILC, and slightly revised the derivation of monthly incomes from the annual SILC income data, in case of discrepancy between the self-reported monthly labour market statuses (i.e. PL210A-L) and the number of months in a given labour market status (e.g. PL070, PL080, etc.). Finally, during this revision, the authors also addressed a number of errors in the original conversion of annual to monthly incomes as done in Derboven et al. (2021) and Neelen et al. (2022), that resulted in an overestimation of the level of monthly and annual earnings in both the baseline and shock scenario[12]. For the post-hoc assessment of the accuracy of projected annual incomes (section 3.3.1.5), we will therefore focus on the results as obtained by the revised nowcasting version by Wizan and Marchal (forthcoming). In line with the scope of this paper, we will focus on the original nowcasting exercises reported in Derboven et al. (2021) and Neelen et al. (2022) for post-hoc comparisons of those affected by COVID-19 (as the revised allocation by Wizan and Marchal (forthcoming) only found minor discrepancies).

In sum, the nowcasting approaches adopted throughout the COVIVAT project changed from a parametric approach, modeled on the Corona study and calibrated using publicly available recipiency statistics, to assess the situation in April 2020, to a non-parametric approach that built on random allocation by subpopulation, building on purpose-provided aggregate (but fine-grained) month-to-month transition rates. In the following sections, we assess the impact of some of the key changes in the COVIVAT approaches, and compare selected nowcasting projections with post-hoc available information from both the EU-SILC and administrative data. Revisiting all the underlying choices and allocation practices falls outside the scope of the analysis. Rather, we opt to focus on those changes that prima facie may possibly have had a large impact, and – importantly – of which the underlying microdata are available to the researchers.

We first assess the impact of two technical issues (section 3.2), before we embark on a more complete comparison of the findings from various nowcasting approaches with results obtained from the EU-SILC survey and analyses on administrative data (section 3.3).

3.2 Prima facie assessment

This section assesses the impact of selected choices made in the nowcasting process. Specifically, we compare the shares of affected employees and self-employed in the different nowcasting approaches (section 3.2.1) and we assess the impact of the choice to inflate the EU-SILC data in order to have sufficiently high numbers of observations in individual subpopulations used for the random allocation (section 3.2.2); and we explore the impact of the year the underlying income distribution refers to (section 3.2.3).

3.2.1 Shares of affected workers in April 2020, various nowcasting approaches

Table 4 below compares the shares of affected employees and self-employed in three different nowcasting approaches: the parametric approach (Marchal et al. 2021, calibrated on publicly available RVA (and RSZ) data, the non-parametric approach building on purpose-built RVA data (here as used in Derboven et al., 2022), and the non-parametric approach that became possible after the Datawarehouse was able to provide linked information (here as used in Neelen et al., 2022).

[12] Specifically, average monthly earnings were erroneously inflated in both baseline and COVID-19 scenario relative to the actual number of months worked in the baseline data. Also, the annual to monthly conversion to earnings did not take account of special statuses such as student and domestic worker. Finally, not all observations that were allocated a transition into newly employed states were assigned new earnings.

Recall that the main differences between these approaches were:

- The Corona-study-based parametric nowcasting estimated probabilities based on gender, age, educational attainment, occupation, work regime and sector. The results were calibrated using external recipiency statistics by sector, age group and gender. The precise days of temporary unemployment were allocated in a second step (see section 3.1).
- The RVA data allowed for non-parametric monthly labor market status allocations by gender, age groups, sector and daily wage categories (and, less relevant for April 2020, previous month's labour market status). Labor market status changes were allocated towards employment, temporary unemployment, including the number of days (in 6-day categories) and regular unemployment. The lower bound of the upper wage group was limited to 105.95 euro per day (in a 6-day work week). A further distinction was made, for April, into wages above 134.62 euro (Capéau et al. 2021). For the self-employed, the RSVZ data allowed for a monthly allocation of self-employed taking up the bridging right by sector, gender and age group. The RSVZ data included information on bridging right beneficiaries and total number of self-employed by subpopulation. The total numbers of employees by subpopulation was not available in the RVA data, meaning that the shares affected by temporary and full unemployment were calculated on the subpopulation sizes available in the SILC.
- The KSZ data provided information on the monthly work status (working, fully unemployed or categories of days temporary unemployment) by gender, age, daily wage, sector and previous month's work status. The more detailed KSZ strata were combined in subpopulations of two genders, two age categories (< 40 and >= 40), four daily wages (<= €125, €125-€150, €150-€175 and > €175) and twelve sectors. In addition, the data also included information on the number of self-employed in different subpopulations transitioning into the bridging right, by previous work status (self-employed or bridging right), gender, age group, sector and (2019) income group (<28,000; 28000-40000; >40,000). While the external aggregate data for self-employed were available by age group, we did not use this information in our allocation approach: the number of self-employed aged below 40 present in the EU-SILC was insufficient to allocate meaningful transitions. The KSZ data did include information on the overall size of the subpopulation.

Table 4 below lists the external numbers used, and the obtained allocated numbers and shares, in the different nowcasting methods, for April 2020. The number of employees are based on the reported labor market statuses in EU-SILC 2018, for the respective months of April and March. The reported labor market statuses were used as starting point for the allocated transitions to temporary unemployment[13].

Overall, the allocated numbers and shares of temporary unemployed are well in line with the external numbers, be it consistently lower. The allocation (or calibration, in the case of Marchal et al. 2021) by subpopulation can lead to small losses in the identification of likely affected, specifically in smaller subpopulations where the number of underlying observations that can be selected becomes fairly limited. The various nowcasting exercises remedied this in multiple ways. For one, the subpopulations applied were generally larger than what would have been possible given the availability of the external statistics (see Table 1), in order to prevent very small or empty cell sizes. In Neelen et al. (2023), certain combinations of age, gender, sector and income level were combined. In addition, as described in section 3.1, Capéau et al. (2021) suggested to use an inflated EU-SILC (with a factor 10, with a related rescaling of the individual weights) to secure sufficient observations in the underlying subpopulations

[13] Moreover, these variables were also used to convert the annual incomes available in SILC into monthly proxies.

and correct for rounding errors. The numbers cited for Derboven et al. (2021) and Neelen et al. (2022) in the table below also apply this approach. In section 3.2.2, we zoom in on the impact that this inflation may have had.

It is worth remarking that, on top of the uncertainty that comes with the assumption that the monthly labor market statuses reported for 2017 closely resemble no-COVID April 2020 (or March), the SILC survey does not aim to be representative at the level of the different subpopulations that have been used for the various nowcasting exercises, specifically the number of employees at the sectoral level in each month, further divided by gender and age (and even wage level)[14].

Table 4. Shares and totals of temporary unemployed, external data and allocated, different nowcasting approaches, April 2020

External data source		Number of temporary unemployed	Number of employees	Share
RVA, public	External	1,170,458	3,957,963 (source: RSZ 1/2020)	30
	Allocated (Marchal et al., 2021)	1,117,309	4,010,118 (refers to labour market statuses reported for March)	28
RVA, purpose-built	External	1,142,607	n.a. (SILC: 3,993,322)	29
	Allocated (Derboven et al., 2022)	1,030,498	3,993,320	26
KSZ	External	1,142,761	4,047,229	28
	Allocated (Neelen et al., 2023)	1,052,567	3,993,320	26

While Table 4 shows overall a close approximation between the overall numbers of employees in administrative data (that are as close as possible to April 2020), and the reported labor market status for April (2017), evidently issues may arise when one zooms in on more precise characteristics. Throughout this paper, we explore whether this might have led to substantively different conclusions. Panel A of Figure 1 below already compares where in the (pre-COVID) individual earnings distribution those affected by temporary unemployment are located, in each of the three nowcasting approaches discussed here. While the general picture is relatively similar for the three approaches (most of those affected find themselves in the lower half of the earnings distribution), some differences are apparent. The parametric allocation used in Marchal et al. (2021), building on – among other characteristics – education level, further calibration by recipiency statistics by sector, age group and gender, places a higher share of affected in the first quintile of the pre-COVID earnings distribution, whereas the non-parametric allocations by (among other things) wage level, locate more of those affected in the second quintile. The allocation building on wage information higher up the wage distribution places more affected individuals in the fourth and fifth quintile.

In Table 5, we show the numbers and shares of affected self-employed, as identified in the different nowcasting exercises. Affected self-employed are defined as those (identified to be) receiving a bridging right. A first observation is that, regardless of the nowcasting approach, the external administrative data used for the nowcasting show large differences – specifically, the KSZ relative to the RSVZ. This leads to widely varying shares of affected self-employed, according to the administrative

[14] This also means that when the EU-SILC information is used to identify the size of the underlying subpopulation, rather than take this information from external administrative data, the applied shares of affected on that subpopulation may be (generally) higher than when external data would have been used, effectively leading to a closer approximation of the external absolute numbers for that subpopulation.

sources: around 50% of the self-employed versus around 35%, both for April 2020. This is due to the different definitions employed in the administrative data. The KSZ data request asked for the number of self-employed by (categories of) previous earnings, gender, sector and age, and for the number of bridging right beneficiaries by those same characteristics, as well as the previous month's labor market status. The RSVZ data did not include previous earnings level, but did allow to distinguish between self-employed in "hoofdberoep" (main activitiy) or as "nevenactiviteit" (supplementary activity). Since most of the bridging right receipt was concentrated among the self-employed in "hoofdberoep", the nowcasting exercises building on the RSVZ data used the percentages for self-employed in "hoofdberoep". The KSZ data request was not drafted to include the same distinction between both categories of self-employed[15].

Second, the total number of self-employed in the external data is much higher than the numbers reported in the SILC, even when we take account of the uncertainty surrounding those estimates (see note to table). This may point to an actual underrepresentation in the survey data, or to the fact that some of the self-employed legally registered and hence present in the administrative RSVZ and KSZ data do not primarily identify themselves (anymore) as self-employed when asked in a survey. Regardless of the reason, this discrepancy between the administrative and survey records means that in the EU-SILC data, there will be less observations for each subpopulation, which naturally affects the degree of detail we can incorporate into our construction of subpopulations and allocation and transition methods. This subsequentially also affects the level of confidence with which we can perform our analysis for the self-employed.

Table 5. Shares and totals of bridging right beneficiaries, external data and allocated, different nowcasting approaches, April 2020

		Number of bridging right beneficiaries	**Number of self-employed**	**Share**
RSVZ, public	External	389,606	762,386 (main activity only)	52
	Allocated (Marchal et al., 2021)	277,483	542,616	51
RSVZ, purpose-built	External	389,996	753,093 (main activity only)	52
	Allocated (Derboven et al., 2022)	267,943	549,474	49
KSZ	External	381,030	1,052,716 (main *and* supplementary activity)	36
	Allocated (Neelen et al., 2023)	193,856	549,474	35

Note: the relatively low numbers of self-employed present in the SILC lead to fairly large confidence intervals around these estimates. E.g. the point estimate of allocated bridging right recipients in Marchal et al. (2021) falls within the bounds of [218946; 336020], the total number of self-employed within [438118; 647114].

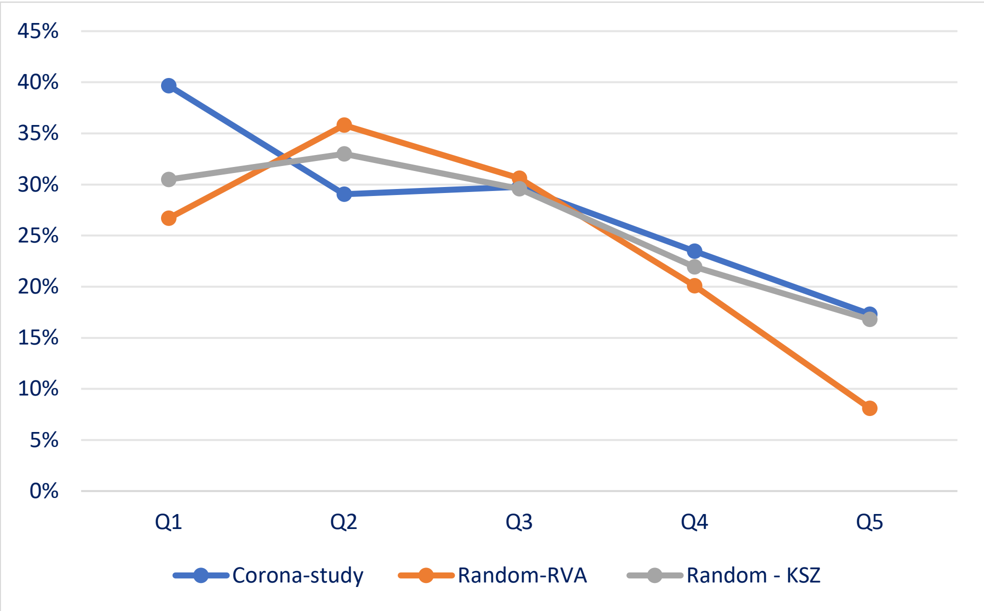
Evidently, these differences also show in the allocated shares and numbers of bridging right beneficiaries. For all three approaches, the shares of beneficiaries are well in line with the external allocation percentages used, but those do translate in far fewer numbers of bridging right recipients. The discrepancy is especially pronounced in Neelen et al. (2023), where the discrepancy in the total

[15] Note that the EU-SILC definition of a self-employed also does not unequivocally allow to make the same distinction. Information is limited to whether self-employment is seen as a fulltime or parttime occupation by the respondent, which does not necessarily amount to the same legal distinction of hoofdberoep and bijberoep. Both in Derboven et al. (2022) and Neelen et al. (2023), the allocation was performed on all individuals reporting a self-employed activity in each respective month.

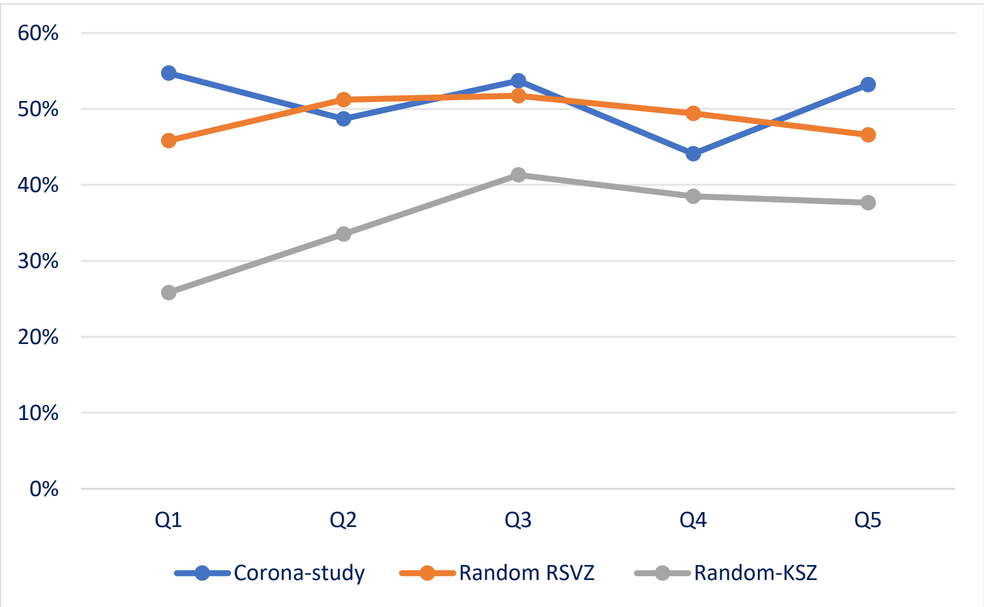
number of self-employed as well as bridging right beneficiaries between external administrative data and survey data was the largest.

Figure 1. Estimated share of employees/self-employed experiencing a change in employment status to temporary employment/bridging right, by quintiles of pre-COVID individual earnings, April 2020

Panel A. Employees



Panel B. Self-employed



Source: Marchal et al. (2021), Derboven et al. (2022), Neelen et al. (2023)

Panel B of Figure 1 then plots the share of affected self-employed by baseline pre-COVID (monthly) earnings quintile in each nowcasting approach. A number of observations stand out. First, the lower shares in the external KSZ data (which show the percentages for *all* self-employed, not only those self-employed as "hoofdberoep"), are also apparent in the graph. Second, we do observe the impact of the income information that was included in the KSZ data (and absent from the RSVZ and Corona-study information). There is virtually no (pre-COVID) income gradient in affected self-employed in the nowcasting exercises building on the Corona-study and the random RSVZ allocation. The KSZ allocation, that included information by 2019 income status, does show an income gradient, in the sense that self-employed that reported lower earnings in 2019 were less often affected than Q3 – Q5. Since we did not request detailed data by legal status of the self-employed, we cannot assess any further to what extent this is due to the fact that (perhaps) self-employed in *bijberoep* were overrepresented in the smaller income groups, who perhaps did not bother to apply for the bridging right, or who may not have been eligible.

3.2.2 Inflating the EU-SILC input data

As outlined in the previous sections, all COVIVAT nowcasting methods were either calibrated or allocated in line with externally available administrative aggregate statistics on benefit recipiency. The nowcasted shares of (temporary) unemployed and affected self-employed by subpopulation were in line with these external aggregates. To prevent the small EU-SILC sample sizes of the subpopulations from underestimating the overall number and shares of temporary unemployed, the subpopulations were generally larger than the actual detail present in the aggregate external statistics (see for instance the discrepancy in Table 1 between the external statistics available to the researchers, and the actual level of detail included in the transitions). Neelen et al. (2022) also combined specific subpopulations (for instance assessing the agriculture and industry sector in combination) to guarantee sufficiently large numbers of EU-SILC observations in the underlying group.

Here, we explore to what extent the EU-SILC inflation did indeed lead to a more limited loss of likely affected observations. To that end, we work with the most recent update and revision of the approach applied in Neelen et al. (2022) – the revision performed by Wizan and Marchal (forthcoming), in which the underlying microdata were updated to those closest to 2020 (see also section 3.2.3 below).

Table 6. Number of temporary unemployed and bridging right beneficiaries, April 2020, various inflation factors of the EU-SILC

	Number of temporary unemployed	**% of employees**	**Number of bridging right beneficiaries**	**% of self-employed**
External (KSZ)	1,142,761	28.2	381,030	35.8
Allocated (Neelen et al., 2023) (inflation factor 10)	1,052,567	26.4	193,856	35.3
Allocated (Wizan and Marchal, forthcoming) (inflation factor 10)	1,050,453	24*	196,303	34*
Allocated (inflation factor 0)	1,044,130	23*	177,864	32*
Allocated (inflation factor 20)	1,045,426	24*	197,333	34*

Note: expressed relative to annual labor market status, rather than the monthly.

Table 6 shows that the total numbers of those who are identified as likely affected (in terms of receiving temporary unemployment benefits and bridging right beneficiaries) are generally closer to the external numbers and shares at higher inflation factors. This is especially so for the self-employed.

In any case, for both the self-employed and the temporary unemployed, there does not really seem to be a large gain from a further duplication by a factor 20 instead of 10[16].

3.2.3 Updating the nowcasting with more recent input data

An obvious check that has by now become possible, is to assess the sensitivity of the nowcasting results to the underlying version of the EU-SILC that is being used. To this end, we compare selected nowcasting results with an alternative nowcasting on a more recent "origin" file, the EU-SILC 2020 (with incomes referring to 2019). This is closer to the period under focus, so it requires less assumptions on the uprating of incomes and the changes in labor market status that took place from the reference period to the onset of the COVID-19 pandemic.

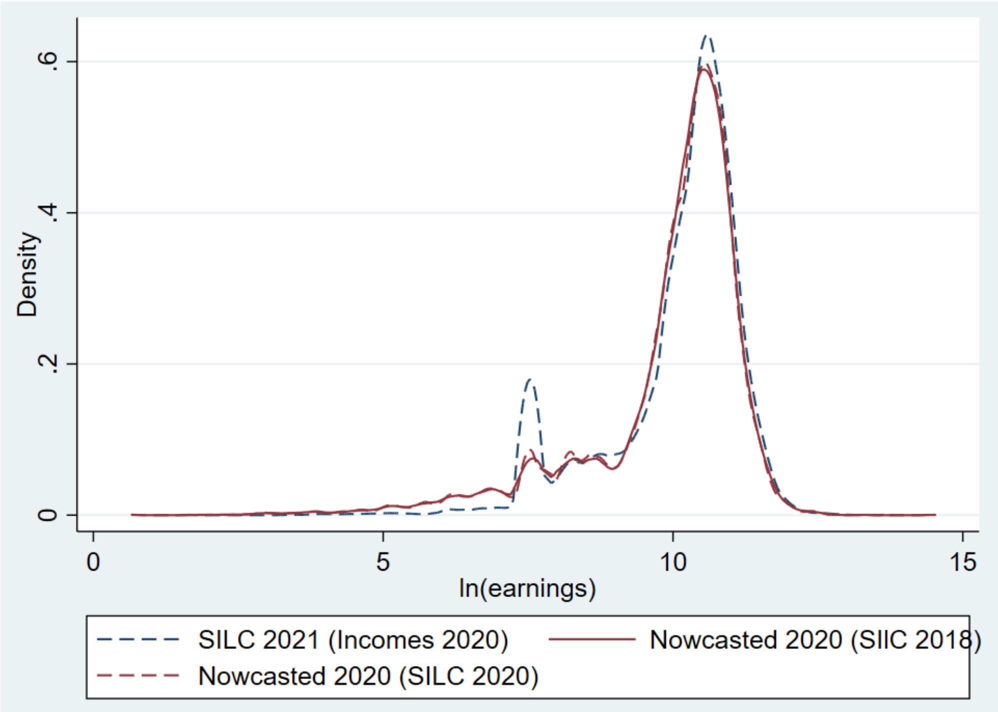
It is precisely this approach that was adopted by Wizan and Marchal (forthcoming) (cf. section 3.1). Figure 2 shows the earnings distribution (panel A) and income distribution (panel B) after simulation in EUROMOD, using the nowcasted data with input file EU-SILC 2020, with monthly labor market statuses and incomes for 2019 (dotted line) versus the nowcasted data with EU-SILC 2018 (solid line) as input file. For reference, we included the distribution as observed in the EU-SILC 2021 (incomes 2020). Where we can observe some limited differences for earnings between the two datafiles, this is much less the case for disposable income[17].

[16] But do note that we apply here the approach adopted in Neelen et al. (2022), which already sought to combine as much as possible logically connected sectors and other groups, in order to prevent as much as possible disproportionate losses of identified affected observations.

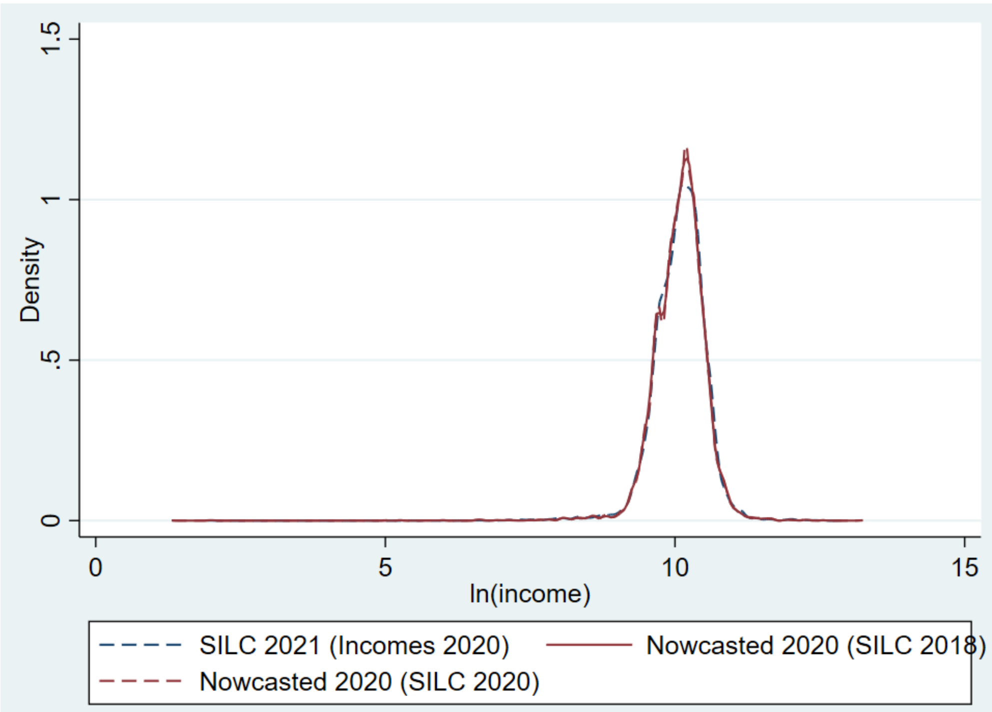
[17] The main difference in earnings is caused by the minimum wage correction (the bump at the bottom of the income distribution). While all three distributions show a bump around the level of the minimum wage (as EUROMOD requires the reported earnings to be in line with what is legally required), the impact of this minimum wage correction is more outspoken in the EU-SILC 2021 earnings distribution. This is likely the case because COVID-19 made it harder to correctly identify the hours worked, and hence whether or not the minimum wage correction should in fact be applied.

Figure 2. Earnings distribution and net disposable income distribution, nowcasting cf. method Wizan and Marchal (forthcoming) on EU-SILC 2018 and EU-SILC 2020 input data, versus post-hoc observed distribution in EU-SILC 2021 (incomes 2020)

Panel A. Comparison of earnings distribution, nowcasting input data for 2017 and 2019, versus observed earnings distribution



Panel B. Comparison of net disposable income distribution, nowcasting input data for 2017 and 2019, versus observed net disposable income distribution



Source: own calculations on EU-SILC 2021 (after simulation of all tax benefit rules in EUROMOD), and nowcasting data from Wizan and Marchal (forthcoming) and Neelen et al. (2022)

3.3 Post-hoc validation

We now compare the nowcasted data with post-hoc available observational data covering 2020. In contrast to section 2.2.2, the closer look on the COVIVAT data for which we have access to the underlying microdata rather than the published results, allows us to apply a more in-depth comparison. This comparison not only spans the EU-SILC data, but also includes a comparison with findings from administrative microdata that have since been published by Vinck et al. (2023).

3.3.1 Comparison with EU-SILC and BE-SILC

The EU-SILC 2021 data allow for a comparison of the overall income distribution from survey data for 2020 with the nowcasted data. The EU-SILC is designed to accurately measure (annual) incomes and living standards for a representative sample of the population, in a cross-national comparable way for the different EU Member States. It builds on nation-specific questionnaires, that are designed in such a way as to allow the construction of cross-nationally comparable user databases. However, the information of the nation-specific questionnaires sometimes include additional information, that gets aggregated or combined in specific ways for the cross-national comparable version. While so far we have used the harmonized EU-SILC files for the analysis reported in section 3.3.1.1-4, we benefit from the added insights possible from the underlying national data[18]. Specifically, in 2021, the national questionnaire (which we, for brevity, call BE-SILC throughout this paper) included a COVID-19 module. In section 3.3.2, we repeat the post-hoc validation with a comparison to findings from publications that build on administrative microdata that have since become available.

In the next paragraphs, we build on the COVID-19 module to assess which respondents (post hoc) reported to have been temporary unemployed, or a bridging right beneficiary throughout 2020. The module also inquired after other COVID-support that was received during 2020. Other information is derived from the general EU-SILC files, including the information on annual earnings and other income components. Please note that most of the information in EU-SILC refers to the annual level. The nowcasting exercises used in this section built on a monthly nowcasting, and were also primarily (intended to be) used by the researchers to assess the monthly impact of the COVID-19 pandemic and the related social measures. To enable the comparison with the EU-SILC data, we constructed an annual version of these nowcasted data.

3.3.1.1 Shares and absolute numbers

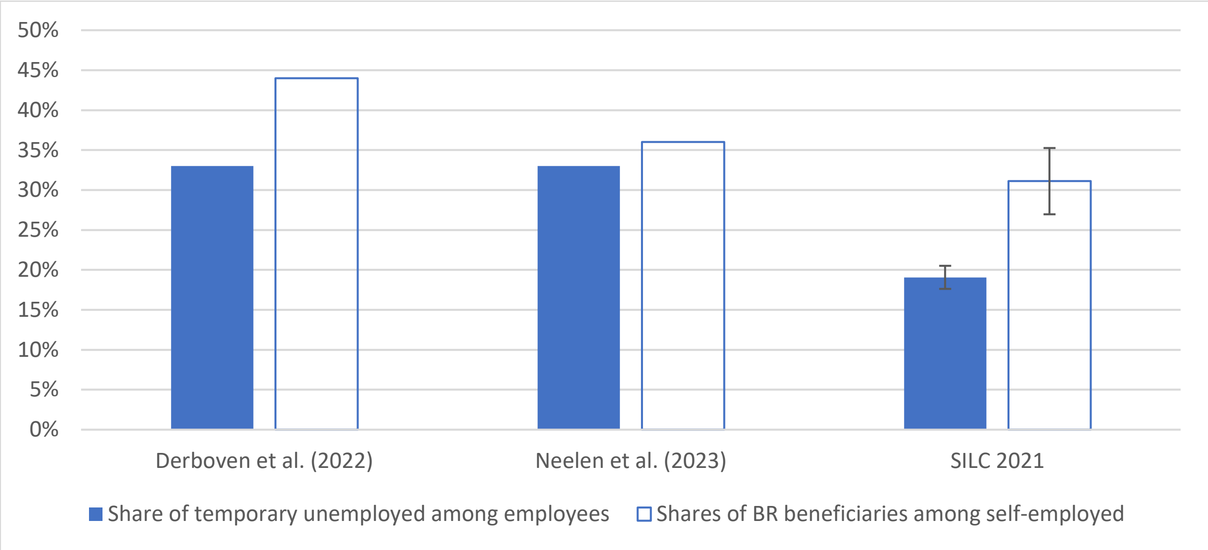
Figure 3 below compares the nowcasted numbers of temporary unemployed and bridging right beneficiaries to those observed in the (module of) BE-SILC. In general, the shares of both temporary unemployed and bridging right beneficiaries in the BE-SILC are lower than the ones nowcasted in the different approaches (33% of temporary unemployed in Derboven et al. (2021) and Neelen et al. (2022), versus 19% in the BE-SILC; and 44 and 36% of bridging right beneficiaries in Derboven et al. and Neelen et al., versus 31% in SILC). Evidently, this also translates to different overall numbers of affected. The BE-SILC observes around 900,000 temporary unemployed throughout 2020, as opposed to over 1,000,000 in the nowcasted data. The numbers of bridging right beneficiaries in the BE-SILC and Neelen et al. are close (both around 193,000), but are higher in Derboven et al. (at 267,943). The exact cause of the discrepancy is hard to single out (and in fact, there might be several causes). Evidently, the nowcasted estimates depend on numerous assumptions (see sections 3.1), and should be seen as a "best possible approximation" in times when data are scarce. Additionally, they push at the limits of the underlying sample. On the other hand, the discrepancy with total numbers of temporary unemployed in the BE-SILC could reflect recall bias, when relatively large shares of the

[18] The researchers gratefully acknowledge access to the national survey data provided by Statbel..

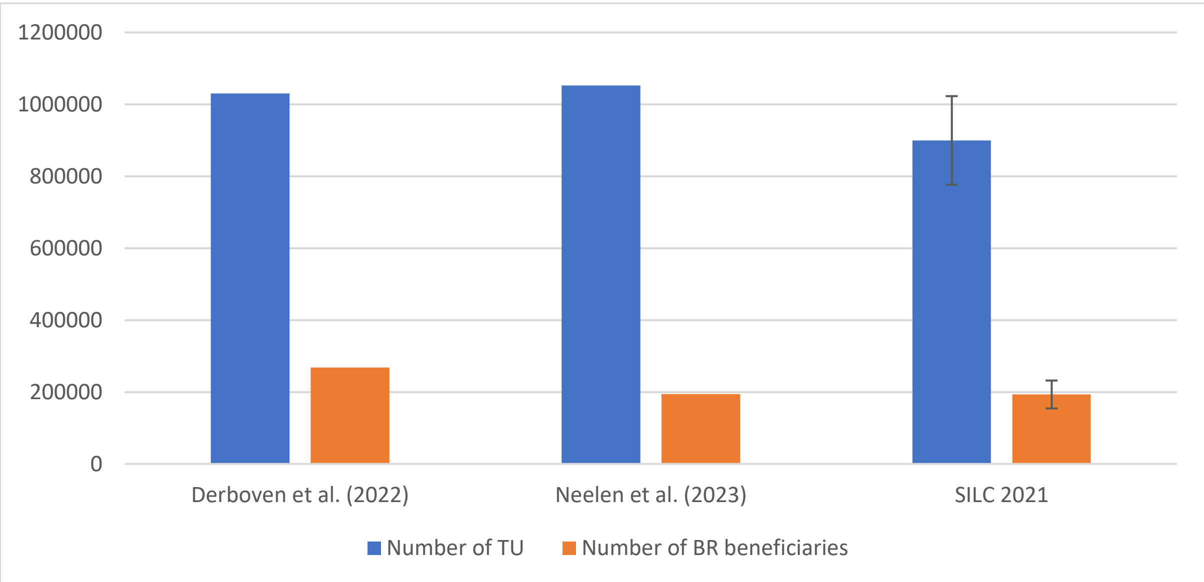
temporary unemployed in 2020 were only so for a number of days, at the start of the pandemic (see section 3.3.2.2).

Figure 3. Shares and totals of temporary unemployed and bridging right beneficiaries, as nowcasted and reported in the BE-SILC, at least once in 2020

Panel A. Shares



Panel B. Totals



Note: Marchal et al. (2021) not included in this section – only projections for April 2020 available.

Source: Derboven et al. (2022, Neelen et al. (2023), and own calculations on BE-SILC 2021, Statbel

3.3.1.2 Socio-demographic characteristics

We zoom in on the socio-demographic characteristics of the temporary unemployed and the bridging right beneficiaries. Specifically, we look at age (in six categories), gender, citizenship, sector, whether or not individuals rented their dwelling, education level, family type and region, and assess to what extent these characteristics are different for the subset of temporary unemployed and bridging right beneficiaries versus all employees and self-employed.

Note that the different nowcasting exercises built to varying extent on these socio-demographic characteristics. Marchal et al. (2021) built on a parametric model that included gender, age, educational attainment, occupation, work regime and sector. The socio-demographic characteristics of family type, tenant, and region hence do not directly derive from the model, but reflect the associations between these different characteristics with the model parameters. Similarly, the allocation used in Neelen et al. (2022) and Derboven et al. (2021) built on (broader) age categories, gender, sector and earnings/wages. Also here, an over- or underrepresentation of other socio-demographic characteristics (such as tenant, education, citizenship, family type, …) stems from the underlying associations.

3.3.1.2.1 Temporary unemployed

To assess whether the temporary unemployed differ substantially from the overall group of employees on specific socio-demographic characteristics, we compare the prevalence of those characteristics among the temporary unemployed with their prevalence among the broad group of employees[19].

Those who reported to have been temporary unemployed in 2020 in the BE-SILC additional module, are more often male, non-EU citizens, tenants and with low and middle education levels (columns 7 and 8 of Table 7). Temporary unemployed were overrepresented in various sectors, including mining, manufacturing and utilities, construction, wholesale and retail and accommodation and food services. Unsurprisingly, they were underrepresented in health care, as in education and public administration, and financial and insurance services. The data do not show clear differences in terms of affected age groups, family types or regions (Table 7 and 8).

Generally, the same profile emerges from the nowcasted data, with one exception. The nowcasted data generally identified younger persons (age group 18-24 in Marchal et al. (2021), and 25 – 34 in Derboven et al. (2021) and Neelen et al. (2022)) as more often temporary unemployed. This discrepancy is puzzling, as age is precisely one of the characteristics used in the various nowcasting processes, be it within somewhat broader categories. The projected characteristics regarding ownership, family type, education level and citizenship are in line with those observed in the BE-SILC, even though these characteristics were not part of the allocation.

[19] Tables B - E in appendix includes the confidence intervals surrounding these estimates.

Table 7. Socio-demographic characteristics, comparison between post-hoc BE-SILC and various nowcasting approaches – differences between temporary unemployed and employees

		Derboven et al		**Neelen et al.**		**BE-SILC 2021**		**Marchal et al**	
		% TU	% EE	%TU	%EE	%TU	%EE	%TU	%EE
Age	< 18	0.0	0.1	0.0	0.1	0.0	0.1	0.1	0.0
	18-24	6.7	6.2	6.7	6.2	4.8	4.8	7.0	4.1
	25-34	29.7	26.5	30.6	26.5	26.7	26.7	26.7	26.3
	35-49	37.3	38.4	37.1	38.4	40.2	39.0	38.6	38.6
	50-64	26.0	28.5	25.3	28.5	27.2	29.1	27.1	30.6
	>=65	0.3	0.3	0.3	0.3	1.0	0.3	0.4	0.4
Gndr	Female	39.4	48.5	41.0	48.5	41.9	50.1	41.5	48.3
	Male	60.6	51.5	59.0	51.5	58.1	49.9	58.5	51.7
Citizen	Belgium	86.4	89.3	87	89.3	87.9	90.1	86.7	89.9
	EU	8.3	6.8	7.8	6.8	6.5	6.4	8.2	6.7
	non-EU	5.3	4	5.1	4	5.6	3.5	5.1	3.4
Sector	Other	0	0	0	0	0.7	0	0	0
	A. Agriculture					0.1	0.4	0.2	0.2
	B-E. Mining, manufacturing and utilities	23.2	15.5	24.9	15.5	19.5	15.6	21.9	15.3
	F. Construction	10.9	5.4	10.9	5.4	9.9	4.9	11.1	5.2
	G. Wholesale and retail	20.1	10.5	15.9	10.5	18.2	9.8	17.5	10.2
	I. Accomodation and food services	5.5	2.7	6	2.7	6.1	1.8	6.8	2.5
	H - J. Transport, storage, information and communication	8.7	8.9	8.7	8.9	7.8	8.9	8	9.1
	K. Financial and insurance services	1.3	3.9	1.7	3.9	1.1	3.3	1.7	3.9
	L - N. Real estate, professional, scientific and administrative services	17.4	9.9	14.7	9.9	16.7	10.2	16.4	9.6
	O. Public administration and defence	0	11.3	1.4	11.3	2.4	10.4	0.2	11.5
	P. Education	1.5	12.8	2.7	12.8	3.7	13.2	2.5	13.3
	Q. Human health and social work	7.1	15.4	8.6	15.4	8.7	17.2	8.3	15.3
	R-U. Arts, entertainment and recreation	4.3	3.8	4.4	3.8	5.3	4.4	5.4	3.8
tenant	no	52.8	56.5	52.6	56.5	51.7	57.3	51.9	57
	yes	47.2	43.5	47.4	43.5	48.3	42.7	48.1	43
educ	low	9	6.7	8.8	6.7	4	2.7	8.2	6.8
	middle	58.6	45.2	56.1	45.2	60.9	42.7	65.8	44.5
	high	32.4	48.2	35.1	48.2	35.1	54.5	26	48.7

* Marchal et al. referred to the situation in April 2020, i.e. it describes the socio-demographic characteristics of those who were assigned temporary unemployment status in April 2020. BE-SILC 2021 describes the socio-demographic status of those who reported to have been temporary unemployed in 2020. Similarly, Derboven et al. and Neelen et al. refer to those who were assigned temporary unemployment status at least once in 2020.

Source: Marchal et al. (2021), Derboven et al. (2022, Neelen et al. (2023), and own calculations on BE-SILC 2021, Statbel

Table 8. Socio-demographic characteristics - bis, comparison between post-hoc BE-SILC and various nowcasting approaches – no substantial differences between temporary unemployed and employees

	Derboven et al		Neelen et al.		BE-SILC 2021		Marchal et al*	
	% TU	% EE	% TU	% EE	% TU	% EE	% TU	% EE
Family type								
couple with children	35.6	36.6	34.7	36.6	36.6	38.3	35.0	36.8
couple without children	32.5	31.9	32.3	31.9	32.0	31.2	33.4	33.1
single parent	2.1	2.5	2.1	2.5	3.9	3.6	2.3	2.3
single	13.4	13.6	14.3	13.6	14.1	13.1	13.1	14.3
other	16.3	15.4	16.7	15.4	13.3	13.8	16.2	13.4
Number of children								
0	59.1	58	59.9	58	57.5	55.8	59.1	58.5
1	19.7	19.2	19.1	19.2	17.8	18.9	19.7	18.5
2	14.1	15.3	13.9	15.3	17.4	18.5	13.9	15.5
3 or more	7.1	7.6	7.2	7.6	7.3	6.8	7.3	7.5
Region								
Brussels	10.4	9.4	10.2	9.4	10.5	9.5	10.1	9.2
Flanders	60.7	62.1	61.8	62.1	61.3	61	62.3	62.6
Wallonia	28.8	28.5	28	28.5	28.2	29.5	27.6	28.2

* Marchal et al. referred to the situation in April 2020, i.e. it describes the socio-demographic characteristics of those who were assigned temporary unemployment status in April 2020. BE-SILC 2021 describes the socio-demographic status of those who reported to have been temporary unemployed in 2020. Similarly, Derboven et al. and Neelen et al. refer to those who were assigned temporary unemployment status at least once in 2020.

Source: Marchal et al. (2021), Derboven et al. (2022, Neelen et al. (2023), and own calculations on BE-SILC 2021, Statbel

3.3.1.2.2 Bridging right beneficiaries and self-employed

Tables 9 and 10 below show the same socio-demographic characteristics, but this time zooming in on the target population of the bridging right beneficiaries and the total group of self-employed. For this group, the BE-SILC data does show an age gradient: bridging right beneficiaries are overrepresented among the 25 – 34 age group. This result was also projected in Marchal et al. (2021), but not in Derboven et al. (2021) and Neelen et al. (2022). In Neelen et al. (2022), to enable allocation to sufficiently large subpopulations when also considering age, sector and income level, the age cut-off used was below and above 40 years. Bridging right beneficiaries, according to the BE-SILC, did resemble the overall population of self-employed fairly well in terms of citizenship, gender, and home-ownership (especially when taking account of the uncertainty surrounding these estimates, see Table F in appendix for an indication). Unsurprisingly, they are overrepresented in certain sectors, not in the least accommodation and food services, and the Arts. Bridging right beneficiaries are somewhat more often middle educated (and less often high educated).

The nowcasting approach adopted in Marchal et al. (2021), building on a parametric model that did include finer age groups, as well as education level, shows a similar overrepresentation among the middle-education and the younger self-employed. Differences in socio-demographic characteristics are less pronounced in the projections in Derboven et al. (2021) and Neelen et al. (2022).

Table 9. Socio-demographic characteristics, comparison between post-hoc BE-SILC and various nowcasting approaches – differences between bridging right beneficiaries and self-employed

		BE-SILC		Derboven et al.		Neelen et al. (2022)		Marchal et al.	
		% BR beneficiaries	% self-employed	% BR beneficiaries	% self-employed	% BR beneficiaries	% self-employed	% BR beneficiaries	% self-employed
Age	< 18	0.0	0.0	0.0	0.1	0.0	0.1	0.0	0.0
	18-24	1.2	2.3	2.0	3.3	0.9	3.3	1.3	0.9
	25-34	26.9	18.5	18.4	17.6	18.4	17.6	20.8	16.5
	35-49	36.9	37.3	44.4	40.6	42.2	40.6	38.6	41.7
	50-64	32.5	39.9	33.3	36.5	36.9	36.5	36.8	38.7
	>=65	2.4	2.0	1.9	2.0	1.6	2.0	2.4	2.2
Gender	Female	35.8	32.2	33.3	34.4	32.5	34.4	33.4	33.8
	Male	64.2	67.8	66.7	65.6	67.5	65.6	66.6	66.2
Citizenship	Belgium	84.7	86.7	85.2	88.9	86.0	88.9	83.1	87.2
	EU	8.4	8.6	11.5	8.7	10.9	8.7	13.7	10
	non-EU	6.8	4.7	3.3	2.4	3.2	2.4	3.3	2.8
Sector	Other	0.3	0.0	0.3	0.0	0.0	0.0	0	0.3
	A. Agriculture	2.5	8.0					3.5	6.5
	B-E. Mining, manufacturing and utilities	6.6	6.2	8.5	12.1	7.7	12.1	5.9	5.5
	F. Construction	13.0	12.7	15.8	13.4	16.6	13.4	15.8	13.9
	G. Wholesale and retail	11.0	10.7	16.7	14.5	15.3	14.5	15.5	14.5
	I. Accomodation and food services	15.2	9.1	10.7	8.6	12.1	8.6	10.9	8
	H - J. Transport, storage, information and communication	5.9	7.1	7.2	6.5	6.0	6.5	6.4	6.7
	K. Financial and insurance services	0.0	2.1	2.5	4.3	2.3	4.3	2.6	4.1
	L - N. Real estate, professional, scientific and administrative services	16.4	22.5	17.4	23.0	19.3	23.0	17.2	21.9
	O. Public administration and defence	0.4	0.4	0.7	0.3	0.5	0.3	0.4	0.9
	P. Education	3.7	1.8	2.2	1.3	1.5	1.3	2.8	2
	Q. Human health and social work	15.2	12.9	13.1	11.6	14.0	11.6	13.5	12.1
	R-U. Arts, entertainment and recreation	9.7	6.6	4.9	4.5	4.6	4.5	5.3	3.6
tenant	no	49.6	51.9	54.4	53.2	55.0	53.2	48.1	52.7
	yes	50.4	48.1	45.6	46.8	45.0	46.8	51.9	47.3
education	low	2.1	1.8	6.6	5.2	6.7	5.2	6.7	6
	middle	46.8	41.7	44.6	43.1	43.5	43.1	49.3	42.1
	high	51.0	56.5	48.7	51.8	49.8	51.8	44	51.8

Note: BR: bridging right

Source: Marchal et al. (2021), Derboven et al. (2022, Neelen et al. (2023), and own calculations on BE-SILC 2021, Statbel

In table 10, we zoom in on differences regarding family type and region. The BE-SILC data show bridging right beneficiaries to more often live in a couple household with children. Similarly, there appears to be an overrepresentation of those located in Brussels. Derboven et al. (2021) and Neelen et al. (2022) find similar results with regard to family type, be it that the difference is far less outspoken. The overrepresentation of bridging right beneficiaries in Brussels relative to the self-employed is not evident from any of the nowcasted data.

Table 10. Socio-demographic characteristics, comparison between post-hoc BE-SILC and various nowcasting approaches – differences between bridging right beneficiaries and self-employed

		BE-SILC		Derboven		Neelen		Marchal et al.	
		% BR beneficiaries	% self-employed	% BR beneficiaries	% self-employed	% BR beneficiaries	% self-employed	% BR beneficiaries	% self-employed
Family type	couple with children	44.7	37.6	44.1	38.5	41.0	38.5	39.6	39.7
	couple without children	27.9	35.2	35.1	37.3	37.2	37.3	38.3	39.3
	single parent	1.9	1.3	1.9	1.6	2.2	1.6	1.7	1.8
	single	15.7	14.7	12.1	13.2	13.2	13.2	13.3	12.5
	other	9.8	11.2	6.8	9.3	6.4	9.3	7.2	6.7
Number of children	0	50.9	59.4	52.1	58.3	54.8	58.3	56.7	56.9
	1	17.0	16.3	20.1	18.3	18.2	18.3	18.1	18.3
	2	21.6	16.0	17.6	14.7	17.6	14.7	16.8	16.1
	3 or more	10.5	8.2	10.1	8.6	9.5	8.6	8.5	8.7
Region	Brussels	16.8	11.3	13.3	11.0	13.5	11.0	13.9	12.3
	Flanders	56.6	63.0	57.1	59.1	57.1	59.1	55.9	57.8
	Wallonia	26.6	25.7	29.6	29.8	29.4	29.8	30.2	29.8

Note: BR: bridging right

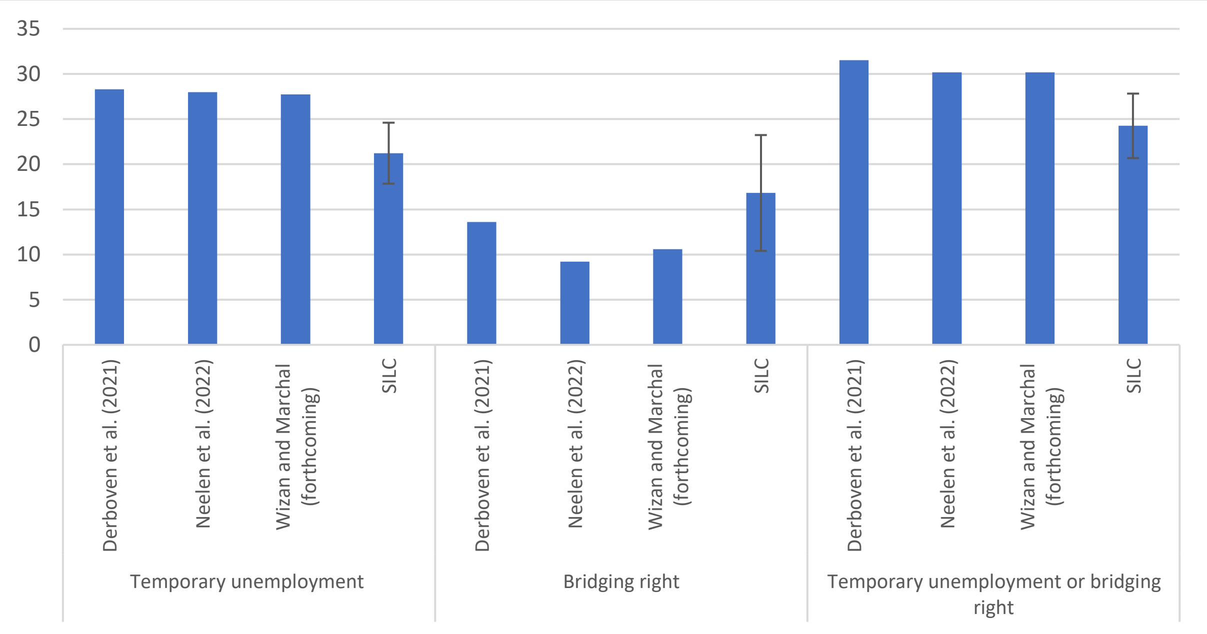
Source: Marchal et al. (2021), Derboven et al. (2022, Neelen et al. (2023), and own calculations on BE-SILC 2021, Statbel

3.3.1.3 Household buffers

Figure 4 below shows the share of the temporary unemployed that live in a household in which at least one other person was temporary unemployed, at least once throughout 2020. It shows the same for the bridging right beneficiaries, and for the group of temporary unemployed and bridging right beneficiaries combined.

The BE-SILC data (again based on the self-reported status in the module) show that 24% of those affected (defined as having been temporary unemployed, or received a bridging right) lived in a household in which at least one additional member was affected at some point in 2020. The nowcasted data put this concentration of risks within households somewhat higher, at (or just above) 30% of those affected. This representation evidently includes double counts, and at the same time does not take account of the added vulnerability of breadwinners.

Figure 4. The share among the temporary unemployed, those with a bridging right, and all affected together that lives in a household where at least one additional member was, throughout 2020, temporary unemployed, receiving a bridging right, or affected



Note: affected refers to either receiving a temporary unemployment benefit, or a bridging right.

Source: Derboven et al. (2022, Neelen et al. (2023), Wizan and Marchal (forthcoming) and own calculations on BE-SILC 2021, Statbel

Table 11 therefore reports findings at the household level. According to the BE-SILC, almost 20% of active households had at least 1 affected individual. In a quarter of the households with only one active individual, this individual was affected by temporary unemployment, bridging right, or both. Among households in which at least 2 earners were present, 7% saw several earners affected. In all three of the nowcasted projections, the share of affected households was higher, around 30% of all households. This reflects the discrepancy in shares and absolute numbers already discussed in section 3.3.1.1. This also translates into higher shares of affected households among single earner households (around 35%, rather than 25%), and higher shares of multiply affected more-earner households (around 15%, relative to 7%).

Table 11. Share of households with 0, 1 and 2 or more affected individuals, all active households and by number of active individuals present in the household

	Number of affected individuals	Number of active individuals in household: 1	Number of active individuals in household: 2 or more	All households
BE-SILC	0	75	65	81
	1	24	28	16
	2 or more		7	3
Neelen - non-parametric, re-anchored	0	64	43	71
	1	35	43	24
	2 or more		15	5
Derboven - non-parametric, monthly	0	63	42	71
	1	37	42	24
	2 or more		16	5
Wizan - non-parametric, recent input data	0	62	44	71
	1	37	42	24
	2 or more		14	5

Notes: Do not always sum to 100 due to rounding, and given small discrepancies between monthly labour market statuses (used for allocation affected or not, and annually reported les in SILC). Affected: BR or TU.

Source: Derboven et al. (2022, Neelen et al. (2023), Wizan and Marchal (forthcoming) and own calculations on BE-SILC 2021, Statbel

3.3.1.4 Other COVID support

As is clear from the description in sections 2.1 and 3.1, the nowcasting exercises generally built on allocating changes in labor market statuses that were derived from recipiency statistics, specifically full unemployment, temporary unemployment and bridging right. Earnings losses were then derived and calculated based on these allocated labor market status changes. These projected earnings losses were used to simulate the subsequent reaction of the tax benefit system. Eligibility to (temporary) unemployment support, and bridging right was taken as given, as it was in fact this beneficiary status that was allocated.

The simulated reaction of the tax benefit system included all legally applicable tax reactions (either through the withholding tax, on a monthly basis, or through the final personal income tax liabilities in annual assessments) and non-discretionary support included in EUROMOD. Importantly, Neelen et al. (2022), Derboven et al. (2021) and Wizan and Marchal (forthcoming) also included the other federal and regional COVID-19 social support measures, specifically the federal premium to means-tested benefit recipients, the Flemish energy and water premium, the Walloon water premium, the Brussels rental premium, and the increases in the child benefit system in Flanders and Brussels. Wizan and Marchal (forthcoming) additionally simulated the Walloon utility premiums available in December 2020, as well as long-term temporary unemployment for part-timers. A full overview of the generosity and eligibility conditions of these measures is provided in Wizan and Marchal (forthcoming). Receipt of these benefits was simulated if the household fulfilled the eligibility conditions, either through its changed labor market status, through the concurrent decrease in income, or through its overall status and income levels.

The BE-SILC module on the impact of COVID in 2020, included in the 2021 data collection, also includes a number of questions on receipt of these additional COVID-19 support measures.

Figure 5 below shows for each benefit that was simulated in the nowcasting exercises, the projected share of beneficiaries (relative to the relevant target populations) and the share as it was reported in the BE-SILC survey. We limit the comparison here to Wizan and Marchal (forthcoming), as it was the most recent nowcasting exercise, that included these additional support measures in high detail, and used the latest survey data as input, EU-SILC 2020.

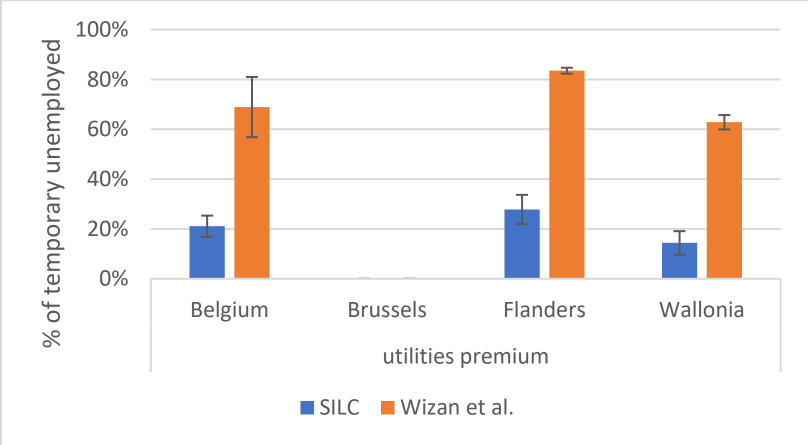
In general, the different panels of Figure 5 show that overall, the recipiency rates of these additional support benefits is much higher according to the nowcasted data, than it is reported in the BE-SILC.

Given the status of the BE-SILC module from which these data are derived (cf. 3.3.1), it is hard to draw stark conclusions from these observations.

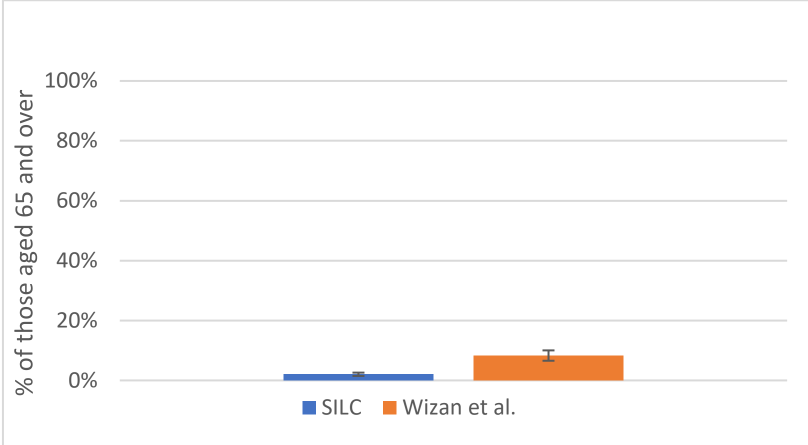
Specifically for the utilities premium in Flanders and Wallonia, and for the COVID-19 related supplement in the child benefit systems of Flanders and Brussels, the discrepancy is relatively large. Likely, the discrepancy derives from a combination of i) an overestimation in the nowcasted data, which are in fact simulations of “a perfectly functioning” welfare state, with no, or our best guesses referring to, non-take-up, and perfect implementation, with ii) a certain underreporting in the survey data. The latter explanation may be relatively plausible given the actual implementation of the Flemish utility premium, which was distributed automatically around mid-2020, with no separate application, and the nature of the (revised) child benefit supplement through the general child benefit system. In fact, a recipiency rate of less than 30% of the Flemish utility premium appears to be a substantial underestimation, given the almost categorical and automatic implementation of this benefit to everyone who had been temporary unemployed in the first COVID months.

Figure 5. Other COVID-19 support measures

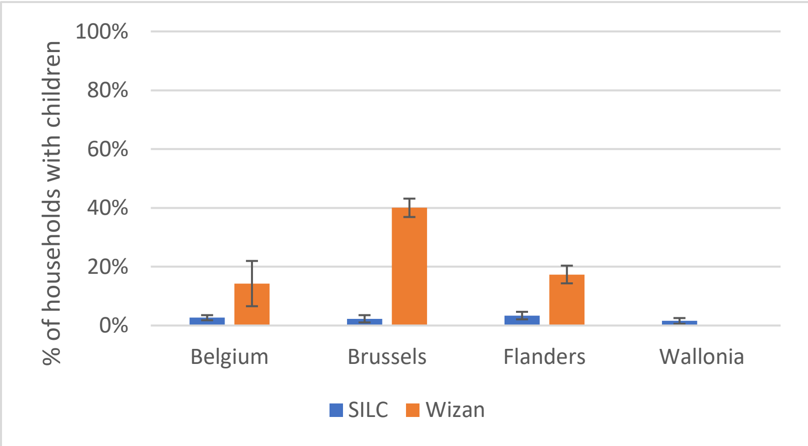
Panel A. Regional utilities premium



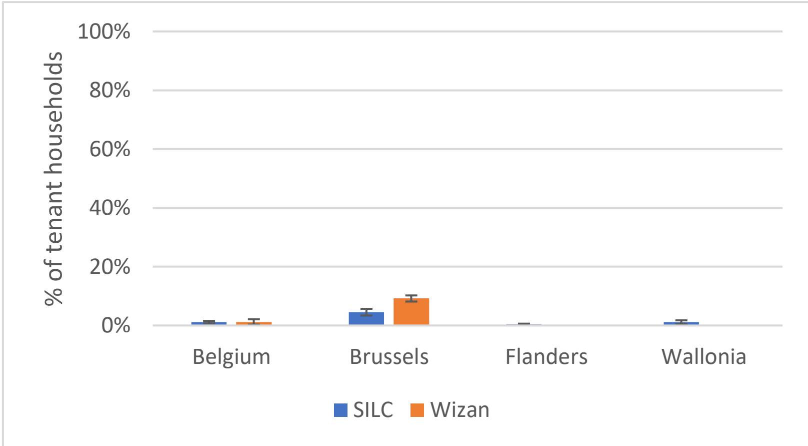
Panel B. Supplement means-tested benefits (income guarantee elderly only)



Panel C. COVID-19 related child benefit supplement



Panel D. COVID-19 related rent premium



Source: Wizan and Marchal (forthcoming) and own calculations on BE-SILC 2021, Statbel

3.3.1.5 Earnings and net disposable incomes

The nowcasted microdata allow to compare the actual levels and distribution of different projected income components for 2020 with the levels and distributions apparent from the EU-SILC 2021 data (referring to the situation in 2020).

We mentioned previously the discrepancy between the income concepts used in some of the nowcasting exercises, versus the income concept used in the EU-SILC. The EU-SILC is designed to measure annual incomes, whereas the nowcasting exercises discussed here focused on changes in monthly incomes throughout 2020. The focus on changes in monthly incomes (rather than annual incomes) made sense as both the severity of the lockdown measures, the shock on the labor market and the social protection measures fluctuated greatly from one month to the other. In addition, the external data that were used for nowcasting were also delivered to the researchers by month, including information on the labor market status in every previous month. For the post-hoc comparison, this implies that for the papers that only report on changes in monthly incomes, the reported findings cannot one on one be compared to the results that can be directly obtained from the EU-SILC. For this paper, we decided to derive an annual version of the monthly (nowcasted) microdata to allow for a comparison with the annual results of the EU-SILC.

In what follows, we show the nowcasted results using the 2020 EU-SILC (2019 incomes) as used by the most recent version in Wizan and Marchal (forthcoming), instead of the 2018 EU-SILC (2017 incomes) used in Neelen et al. (2022) and Derboven et al. (2021). Consequently, the updated nowcasting model is compared to the observed data of the EU-SILC 2021 (2020 incomes). Instead of using the raw EU-SILC data, we use the simulated version of the data, which means that we use the observed EU-SILC data as input data to EUROMOD. We do this to account for the discrepancy between simulated and observed data. Therefore, we can focus on the changes due to the allocated changes in labor market status and related assumed changes in income, rather than on discrepancies that stem from an idealistic (simulated) versus realistic (observed) working of the tax benefit system. In Figure 3 in section 3.2.3 we already showed the overall similarity between the earnings and net disposable income distribution. Tables 12 and 13 add additional detail by showing the mean differences in earnings, wages, self-employment income and equivalized disposable household income from the nowcasted results with the observed SILC data.

In general, and in line with what we showed previously in Figure 3, the projected earnings levels in the nowcasted data are lower than the earnings levels actually observed for 2020. On average, the difference amounts to 6% in earnings among the working age population. It is somewhat lower for wages, but especially outspoken for self-employment income.

Net disposable income is for both the nowcasted and the observed data well in line with one another (as was also evident from Figure 3). The larger earnings losses applied in the nowcasted data were fully accommodated by the generous extensions to the bridging right and the temporary employment systems. Overall, that leads to poverty rates being nearly equal between nowcasted and (simulated) observed data, at 10.21 and 10.13% for 2020. Also the Gini coefficient is virtually equal, at 0.214 and 0.215.

Table 12. Comparison results nowcasting 2020 (EU-SILC 2020 – incomes 2019) with simulated 2021 (EU-SILC 2021 – incomes 2020)

	Nowcasted data (Wizan and Marchal, forthcoming)	Observed data	Difference
Total sample			
Mean earnings	33350	35955	-7,81%
Mean employment income	33401	35816	-7,23%
Mean self-employment income	20930	23730	-13,38%
Mean eq. disposable hh income	25031	25270	-0,95%
Working age only			
Mean earnings	37846	40195	-6,21%
Mean employment income	38014	40140	-5,59%
Mean self-employment income	23430	26417	-12,75%
Mean eq. disposable hh income	27035	27211	-0,65%

Source: Wizan and Marchal (forthcoming) and own calculations on EU-SILC, Eurostat

Table 13. Comparison results Wizan and Marchal (forthcoming) to simulated 2020 (incomes 2020 as observed in EU-SILC 2021), working age population

		Wizan and Marchal (forthcoming)	**2020 incomes**
Mean earnings		37820	40120
Mean employment income		37998	40140
Mean self-employment income		23343	25533
Mean eq. disposable hh income		27921	28162
Median earnings		34243	36350
Median employment income		34582	36737
Median self-employment income		18866	20125
Median eq. disposable hh income		26893	27105
Mean earnings by quintile	Q1	5293	6412
	Q2	18756	20974
	Q3	30205	33176
	Q4	42075	44578
	Q5	71185	75873
Mean employment income	Q1	4789	5828
	Q2	18767	20806
	Q3	30472	33464
	Q4	42327	44872
	Q5	71107	75480
Mean self-employment income	Q1	933	785
	Q2	4884	5503
	Q3	15051	16792
	Q4	28334	31089
	Q5	56690	61464
Mean equivalized disposable income	Q1	12577	12648
	Q2	18721	19038
	Q3	23522	23642
	Q4	28657	29023
	Q5	40578	41225

Note: the quintiles refer to the quintiles based on the respective income type. Means and medians are calculated on positive, non-zero income values only. The working age population is defined as aged between 25 and 59.

Source: Wizan and Marchal (forthcoming) and own calculations on EU-SILC, Eurostat (2021)

3.3.2 Comparison to findings from administrative data

Vinck et al. (2022) obtained administrative microdata from the Datawarehouse KSZ that enabled zooming in on the trajectories of individuals throughout the entire year 2020, beyond the aggregate month-to-month transitions by stratum that were available to researchers for the nowcasting exercises. In addition, the microdata available to Vinck et al. (2022) include transitions to statuses other than unemployment, temporary unemployment, (self-) employment and bridging right, and also allow to assess whether people were left without access to an income support scheme, or had to fall back on social assistance. Their information also allows for assessing the cumulation of transitions at the household level, whereas the aggregate statistics were only available at the individual level. Vinck et al. (2022) reported their findings to the extent possible at the annual, at the quarterly, and at the monthly level[20].

While the data does not include information on income, it does allow for an in-depth post-hoc comparison on other dimensions. Below, we compare the main findings from Vinck et al. (2022) to the projections derived from the nowcasting exercises in the COVIVAT project. In line with the reported findings in Vinck et al. (2022), we compare the projected and observed numbers and shares of temporary unemployed annually and monthly (3.3.2.1), assess the differences in projected and observed temporary unemployment duration (3.3.2.2), explore the differences in socio-demographic characteristics (3.3.2.3), and the concentration of temporary unemployment at the household level (3.3.2.4).

3.3.2.1 Shares and absolute numbers

All COVIVAT papers included a check of the extent to which the overall allocated labor market statuses aligned with the external aggregate statistics that were used. Overall, these results were satisfactory, although some specific subgroups (such as those employed in the agricultural sector, or specific combinations of gender, sector and age) were in some cases less well proxied, due to an absence of relevant observations in the underlying EU-SILC data[21]. In section 3.3.1.1, we showed the allocated shares (at the annual level) and compared those to the external information used for the nowcasting (at the annual level – but note that in fact monthly aggregate statistics were used) and to the numbers reported in the (post-hoc observed) EU-SILC.

In this section, we repeat this exercise, but on a monthly basis. Table 14 shows the percentages in temporary unemployment and bridging right in every month from March 2020 to December 2020, as they have been allocated in the different exercises, and as they are included in the different external statistics used. We also include the percentages as reported by Vinck et al. (2022). These align very closely to the external KSZ numbers used for the allocation in Neelen et al. (2022). Indeed, the microdata used by Vinck et al. (2022) to estimate these percentages were based on (a sample of) microdata obtained from the KSZ, the same source that provided the aggregate external statistics for Neelen et al. (2022). Note that Vinck et al. (2022) only zoomed in on the situation of the temporary unemployed[22].

[20] Note that a quarterly and monthly comparison is not fully possible with the EU-SILC 2021. As such, the comparisons mentioned under paragraphs 3.3.1 and 3.3.2 are complementary.

[21] This issue also led to the implementation of an inflated EU-SILC, cf. 3.2.2.

[22] This also causes the next paragraphs to focus almost exclusively on the temporary unemployed, even though the nowcasting exercises did also project the impact on newly unemployed (and covered by the unemployment insurance scheme) and the self-employed benefiting from a bridging right.

Overall, differences are fairly small, especially between Derboven et al. and Neelen et al. (2022). The 'peak-to-peak' method presented in Neelen et al. approached the administrative data slightly better vis-à-vis the previous method for the months of April, May and September and most notably for November and December. For the other months (March and July until September), the peak-to-peak recalibration based on the KSZ data (slightly) lost some temporary unemployed in comparison with the old method.

Table 14. Comparison temporary unemployment and bridging right percentages according to administrative source data, and as reported in Vinck et al. and different nowcasting approaches from March 2020 to December 2020

Panel A. Temporary unemployment rates, % of employees

	March	April	May	June	July	August	September	October	November	December
As provided and applied in the nowcasting process										
KSZ	22.8	28.2	22.8	14	8.4	7.9	6.1	9.2	11.3	8.7
RVA (only numbers of temporary unemployed provided, denominator taken from EU-SILC)	24.8	30.2	24	14.8	9.6	8.5	6.7	9.9	10.2	n.a. (share for November used)
As reported										
Vinck et al. (sample of administrative microdata)	22.3	28	22.3	13.7	8.2	7.5	6	9.1	11.2	8.4
Derboven et al. (monthly allocation, based on RVA data)	20.5	25.8	20.6	13	8.9	7.9	6.3	9	9.6	9.4
Neelen et al. (monthly allocation with recalibration in November, based on KSZ data)	20.3	26.4	20.9	13	7.6	7	5.8	8.9	11.2	8.5

Panel B. Bridging right beneficiaries, % of self-employed

	March	**April**	**May**	**June**	**July**	**August**	**September**	**October**	**November**	**December**
As provided and applied in nowcasting process										
CBSS (all self-employed)	34.3	35.8	32.7	15.4	10.9	10.6	7.7	9.7	13.6	11.3
RSVZ (hoofdberoep only)	49	52	48	23	16	16	12	14	20	16
As identified after allocation										
Derboven et al. (RSVZ)	46	49	45	21	14	14	10	12	17	13
Neelen et al. (CBSS)	33	35	31	13	8	8	5	7	9	7

3.3.2.2 *Duration of temporary unemployment and repeated affectedness*

Neelen et al. (2022) already provided a first check of the accuracy of its nowcasting method (and for the method used in Derboven et al. (2021)) against the findings reported in Vinck et al. (2022). This comparison showed the share of those who were at least one day temporary unemployed in April 2020, who were also temporary unemployed in a consecutive months. We copy this comparison below in Table 15. The table points towards an underestimation by the peak-to-peak transition allocation of those who were also affected in August and September. In contrast, relative to the Derboven et al.

(2021), the peak-to-peak transition does seem to capture better the overlap between those who were affected in April as well as in November 2020. Differences in the other months remained limited.

Table 15. Comparison transition percentages administrative data, peak-to-peak and previous allocation; transitions from minimum one day temporary unemployment in April 2020 to temporary unemployment in May/…/December 2020

	May	**June**	**July**	**August**	**September**	**October**	**November**	**December**
Vinck et al. (2022)	74.40%	44.20%	26.40%	23.80%	19.00%	26.80%	33.80%	25.50%
Neelen et al. (2022) – peak-to-peak	74.50%	43.70%	24.20%	19.30%	14.10%	23.90%	35.30%	25.00%
Derboven et al. (2021)	74.50%	45.60%	29.80%	24.50%	19.10%	24.80%	25.60%	24.30%

Source: Table 8 in Neelen et al. (2022)

Neelen et al. (2022) also reported the quarterly temporary unemployment rates of Derboven et al. (2021) and Neelen et al. (2022) to those reported in Vinck et al. (2022)(see table 16 below). This exploration showed that the peak-to-peak allocation did a better job at proxying the shares of temporary unemployed who were temporary unemployed in the fourth quarter and the second quarter of 2020. The same holds true for the temporary unemployment percentages when affected in one, two or three quarters of 2020. In contrast, the peak-to-peak allocation reports a lower share of temporary unemployed who were affected in all four quarters. This reflects to some extent the lower numbers of affected employees in certain months as described above.

Table 16. Comparison quarterly temporary unemployment between administrative data, peak-to-peak and previous allocation

	Vinck et al.	Neelen et al.	Derboven et al.
Percentage temporary unemployed in quarter 4 ***and*** in quarter 2 of 2020	84%	72%	68%
Share of temporary unemployed that were temporary unemployed for:			
1 quarter in 2020	25%	30%	32%
2 quarters in 2020	34%	34%	31%
3 quarters in 2020	24%	23%	21%
4 quarters in 2020	17%	13%	16%

Source: Table 9 in Neelen et al. (2022)

Table 17 adds to the previous analysis by zooming in on the distribution of temporary unemployment duration. Vinck et al. (2022) did not report the overall distribution of temporary unemployment days over the entire population of temporary unemployed, but in the framework of the FAST project, Audenaert and Geerts Danau calculated, on the same data, a distributive summary that could be compared to the nowcasted data. This comparison shows the results of the approach adopted in the various nowcasting approaches, in which the maximum number of the allocated categories (1-6, 7-12; 13-19, 20-25 and 26) was attributed to those observations assigned membership of the temporary unemployed subpopulation (cf. section 3.1). Overall, even though on average the discrepancy in allocated number of days with actual duration of temporary unemployment remains limited, the nowcasted days are generally above the actually observed durations (with the exception of the maximum). Very short durations (i.e. below 6 days) are also not possible in the nowcasted data. Likely, this choice has resulted in the somewhat lower earnings as observed in section 3.3.1.5, as the reduction in earnings follows exclusively from the duration of (temporary) unemployment and bridging right in the nowcasted data considered here[23].

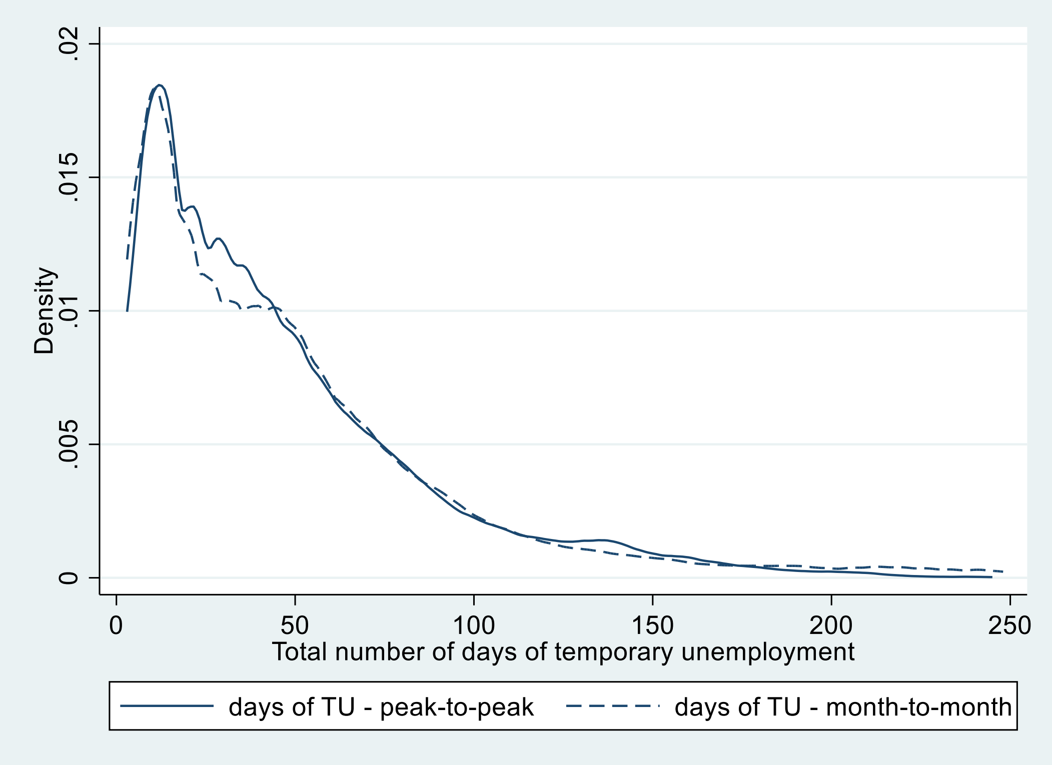
Table 17. Days of temporary unemployment, among temporary unemployed individuals (at least one day of temporary unemployment throughout 2020)

	Neelen et al. (2022)	**Derboven et al. (2021)**	**FAST WP1 (courtesy of Audenaert and Geerts Danau)**
	peak-to-peak	month-to-month	Sample of administrative data
average	46.68	48.1	43,15
min	6	6	1
D10	8	6	6
median	36	37	31
D90	102	103	97
max	245	248	259,5

Table 17 additionally shows that, overall, the re-anchoring of the allocated temporary unemployment status of those affected in November, to their prior status in April 2020 did not lead to large differences with the continuous allocated month-to-month transitions employed in Derboven et al. (2022). Figure 6 below provides some context as to why that is the case. Overall, the peak-to-peak allocation shows two small additional bumps, relative to the monthly allocation. A first bump appears from days 30 – 50, and a (very small one) around 130 days of temporary unemployment. In contrast, the line is somewhat lower at the tail end of the distribution. This reflects the impact of the re-anchoring that was done for November 2020, when the share of temporary unemployed was again at its peak (see Table 14, panel A). The underlying idea of this re-anchoring is that the temporary unemployed who should have been identified in the monthly allocation process, likely already had some experience with temporary unemployment previously. Hence, for November, the newly unemployed are not (proportionally) taken from the pool of temporary unemployed in October (as was done in Derboven et al.), but (proportionally) taken from those temporary unemployed in April. The months October and September were then recalculated, with reverse transitions, from those identified as temporary unemployed in November. That means that there is a stark cut between August and September (when the share of temporary unemployed was at a low of 6 – 8%, see Table 13). This stark cut led to some underestimation of the very long temporary unemployed, as is evident from Table 16. At the same time, the impact was fairly limited, and the peak-to-peak allocation did succeed in better capturing those affected for 2 and 3 quarters (Table 16).

[23] This means that the impact of the choice for allocating the upper bound of the temporary unemployment day categories on earnings is the nowcasted data, is not fully compensated by likely decreases in overtime and other work reductions that are covered in the observed incomes, but not in the nowcasted earnings of the nowcasting exercises considered here.

Figure 6. Comparison density temporary unemployment duration



Source: own calculations on data as nowcasted in Derboven et al. (2022) and Neelen et al. (2023)

3.3.2.3 Socio-demographic characteristics

Table 18 below compares the socio-demographic characteristics as observed by Vinck et al. (2022), to those of the groups identified as (likely) temporary unemployed in Derboven et al. (2021), Neelen et al. (2022), and in the module of the BE-SILC, at least once throughout 2020. Note that the data for the latter three are identical to those reported in section 3.3.1.2.1. However, we do add a further distinction to Derboven et al. (2021) and Neelen et al. (2022), by showing the socio-demographic characteristics of shorter-term and longer-term temporary unemployed separately. This distinction was also made by Vinck et al. (2022), and repeating it here allows for a more extensive comparison of the profiles of the different groups.

As in section 3.3.1.2, we stress here that the allocation processes applied in Derboven et al. (2021) and Neelen et al. (2022) were based on age, gender, previous wage and sector only (and evidently previous month's labor market status). Other socio-demographic characteristics reported here therefore stem from underlying associations that remain after the furthermore random allocation process. Given the random allocation process, it is unadvisable to zoom in on overly small or specific groups.

Vinck et al. (2022) found in their administrative microdata that certain groups were overrepresented among the temporary unemployed in 2020. Those were 25 – 34 year olds, men, and persons born outside of Belgium[24]. The overrepresentation of men among the temporary unemployed is specifically apparent for shorter-term temporary unemployed. The other two groups are mainly overrepresented among the longer-term temporary unemployed. Flemish people are overrepresented among shorter-

[24] We proxied this information for the nowcasted data and the BE-SILC 2021 data with "citizenship". The percentages in Table 17 hence do not refer to strictly the same underlying concept here.

term temporary unemployed, while those living in Brussels are overrepresented in longer-term temporary unemployment. Vinck et al. (2022) do not observe clear patterns of overrepresentation for family type and number of children.

The nowcasted data similarly show an overrepresentation of temporary unemployment in the age group 25 – 34, and among men. As in Vinck et al. (2022), the overrepresentation of the latter is explicitly outspoken in short-term temporary unemployment (operationalized in Vinck et al. (2022) as less than 52 days). An overrepresentation of those living in Brussels, and of foreign citizenship among the longer-term temporary unemployed is discernible, but one should take account of the uncertainty surrounding the estimates for these fairly small groups (see also Table B-E in annex).

Table 18. Socio-demographic characteristics, projected temporary unemployed population in Neelen et al. and Derboven et al., versus observed population in Vinck et al. and SILC, 2020

	Vinck et al.				**Neelen et al.**				**Derboven et al.**				**BE-SILC**	
	% TU			% of working population	% TU			% of working population	% TU			% of working population	% TU	% of working population
	all	1 - 52 days	> 52 days		all	1 - 52 days	> 52 days		all	1 - 52 days	> 52 days			
Age														
18-24	9.7	9.4	10.5	9.7	6.7	6.4	7.4	6.2	6.7	6.5	7.1	6.2	4.8	4.8
25-34	28.	27.6	29.4	25.8	30.	30.5	30.7	26.5	29.	29.0	31.2	26.5	26.7	26.7
35-49	37.	38.0	36.7	36.7	37.	36.7	37.7	38.4	37.	37.8	36.1	38.4	40.2	39.0
50-64	24.	24.9	23.4	27.7	25.	26.0	24.0	28.5	26.	26.4	25.3	28.5	27.2	29.1
>=65	0.0	0.0	0.0	0.1	0.3	0.3	0.2	0.3	0.3	0.3	0.3	0.3	1.0	0.3
Gender														
Female	41.	40.2	45.9	49.7	41.	39.0	45.3	48.5	39.	36.8	44.5	48.5	41.9	50.1
Male	58.	59.8	54.1	50.3	59.	61.0	54.7	51.5	60.	63.2	55.5	51.5	58.1	49.9
Family type														
couple with children	53.	55.0	50.8	52.5	34.	35.8	32.5	36.6	35.	36.3	34.4	36.6	36.6	38.3
couple without	20.	20.2	19.6	20.0	32.	32.0	32.8	31.9	32.	32.8	31.9	31.9	32.0	31.2
single parent	8.8	8.4	9.7	9.8	2.1	2.2	1.8	2.5	2.1	1.9	2.5	2.5	3.9	3.6
single	14.	13.9	16.6	15.3	14.	13.9	15.0	13.6	13.	13.0	14.4	13.6	14.1	13.1
other	2.7	2.4	3.3	2.4	16.	16.1	17.9	15.4	16.	16.0	16.8	15.4	13.3	13.8
Children														
0	37.	36.6	39.5	37.7	59.	58.7	62.3	58.0	59.	58.4	60.6	58.0	57.5	55.8
1	25.	25.7	25.3	24.4	19.	19.6	18.0	19.2	19.	19.8	19.5	19.2	17.8	18.9
2	25.	26.0	23.5	25.9	13.	14.3	12.9	15.3	14.	14.6	13.1	15.3	17.4	18.5
3 or more	11.	11.7	11.7	12.0	7.2	7.3	6.8	7.6	7.1	7.3	6.7	7.6	7.3	6.8
Region														
Brussels	8.2	6.5	12.6	9.0	10.	8.8	13.0	9.4	10.	8.8	13.7	9.4	10.5	9.5
Flanders	64.	67.2	57.7	61.5	61.	62.8	59.6	62.1	60.	62.8	56.7	62.1	61.3	61.0
Wallonia	27.	26.3	29.8	29.5	28.	28.3	27.4	28.5	28.	28.4	29.6	28.5	28.2	29.5
Country of birth/citizenship														
Belgium	77.	79.5	72.4	81.9	87.	87.5	86.0	89.3	86.	87.7	84.0	89.3	87.9	90.1
EU	9.5	9.2	10.4	7.4	7.8	7.6	8.3	6.8	8.3	7.7	9.4	6.8	6.5	6.4
non-EU	12.	11.3	17.2	10.7	5.1	4.8	5.7	4.0	5.3	4.7	6.5	4.0	5.6	3.5

Source : Vinck et al. (2023), Derboven et al. (2022, Neelen et al. (2023), and own calculations on BE-SILC 2021, Statbel

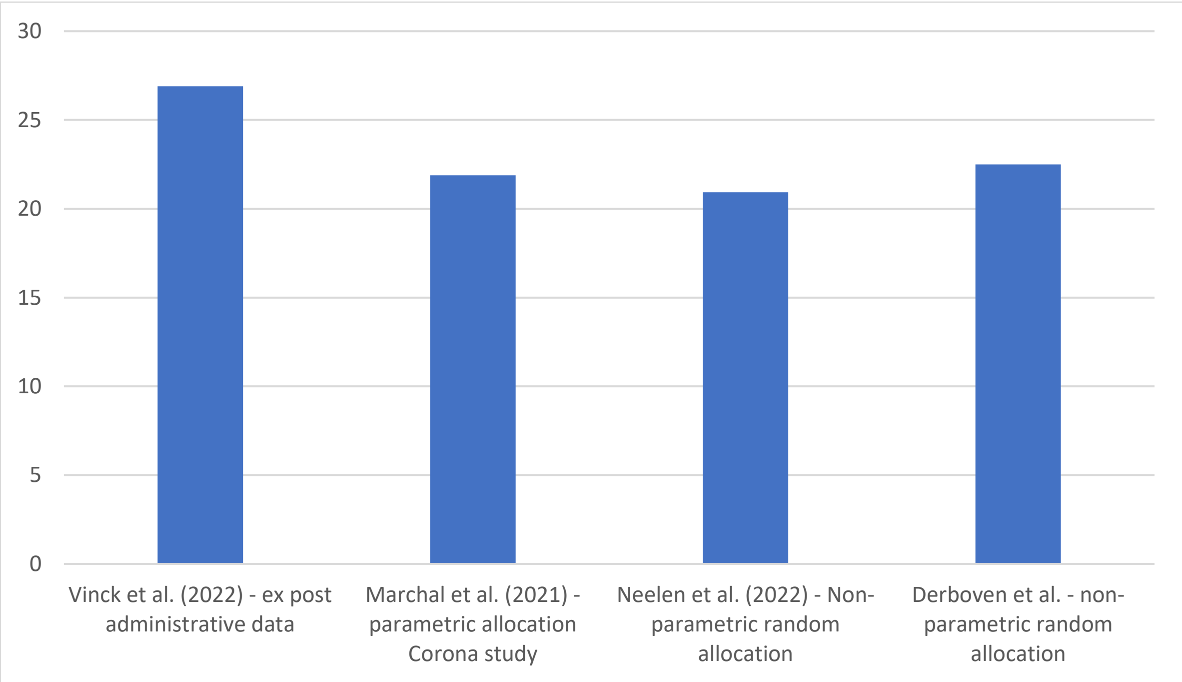
3.3.2.4 Household buffers

Vinck et al. (2022) showed to what extent temporary unemployment was buffered at the family level, by assessing to what extent temporary unemployment was clustered within families. They reported results for April 2020.

In section 3.3.1.3 above, we showed the concentration of temporary unemployment (and bridging right) at the household level, throughout 2020. In Figure 7 below, we follow the approach taken in Vinck et al. (2022), and focus on the clustering of temporary unemployment in April 2020, rather than throughout the whole of 2020. Vinck et al. (2022) reported that 26.9% of those that were temporary unemployed (at least one day) in April 2020, lived in a family in which one other adult member was temporary unemployed. The different nowcasting approaches projected this overlap in April 2020 to be somewhat lower, around 21 – 22.5 per cent of temporary unemployed[25].

The employed nowcasting approaches, that were in all cases focused on the individual level, and did not take family or household characteristics on board, therefore appear to have underestimated the clustering at the household level in April 2020.

Figure 7. Share of temporary unemployed individuals living in a household with at least one additional temporary unemployed member, April 2020



Source: Vinck et al. (2022), and own calculations on data as nowcasted cf. Marchal et al. (2021), Neelen et al. (2023) and Derboven et al. (2022)

[25] The percentages reported in section 3.3.1.3 for the clustering at the household level throughout 2020 are higher, around 28% in the different nowcasting approaches, and around 21% in the facultative BE-SILC module.

4 Discussion

4.1 General assessment

The nowcasting efforts summarized in section 2 of this paper all stemmed from highly motivated and conscientious researchers making the most of the data that was available at the time, to make estimates of the income distribution as swiftly as possible. It is therefore with some reservation that we set out to conduct a "hindsight" exercise. The aim of this exercise is not to criticize the work done, but to take stock of the different methods used and to distill lessons for the future, in the broader framework of the FAST project. When governments are in dire need of up-to-date information, what are viable options? Which data are needed, and what are realistic time frames? Which investments should be made upfront in order to have reliable short term estimates at hand during an upheaval? And the focus of this exercise: what turned out to be the margin of error, in light of those determinants? In combination with the results from the other BE-FAST work packages, this information should contribute to a timeline and a proposed approach for the future.

Based on the comparisons in this paper we can draw a fairly favorable general assessment.

First, the estimates of the various nowcasting approaches reported in section 2 (and also shown in more detail in deliverable 2.1) are, broadly speaking, very much in line with one another. Overall, these nowcasting exercises already indicated in an early stage that the welfare state did an outstanding job in mitigating the harsh impact of the pandemic on earnings. While there are evidently small differences in the degree of the projected decreases in net disposable incomes and their distribution, projected increases in inequality were negligible, and projected increases in poverty rates fairly small.

Second, the projected net disposable incomes as resulting from the various nowcasting exercises were very much in line with the net disposable incomes post-hoc observed in the SILC. While the nowcasting exercises projected small increases in poverty (relative to a hypothetical no-COVID baseline), the SILC data even show a decrease in poverty rates (both relative to a hypothetical no-COVID baseline, and versus 2019). Discrepancies in the overall distribution of (equivalized) net disposable incomes remain limited.

Third, the nowcasted data do seem to have overestimated the earnings losses. The fact that net disposable incomes were very much in line with those post-hoc recorded in the SILC, is therefore likely to an important extent due to the generosity of the welfare state intervention. We return to this issue in section 4.2.

Finally, the post-hoc comparison to administrative microdata, and the information in the BE-SILC, shows that the socio-demographic characteristics of those projected to be affected by temporary unemployment and bridging right, tend to be in line with those that turned out to have been affected.

4.2 Caveats and scope

Our post-hoc validation does point towards a number of issues and lessons learned that can be taken on board in future nowcasting exercises.

Most of the nowcasting approaches built on the (pre-COVID) EU-SILC sample. Using this sample had some advantages. It contained important information on socio-demographic characteristics that could be used for the parametric and non-parametric allocations used. Moreover, the EUROMOD microsimulation model, that was used to assess the impact of the COVID-19 social policy measures, is developed to calculate the impact of the European Member States' tax benefit systems on the EU-SILC data. While overall, the different nowcasting approaches performed rather well in assessing the impact of the welfare state, and in modelling the sizes and characteristics of the affected population, some problems arose that are related to the reliance on the EU-SILC data. These were especially relevant for the non-parametric allocation. Part of the underestimation of the overall numbers of affected is related to the absence of sufficient observations in the subpopulations used for random allocation. The different approaches mitigated this issue by using ad hoc broader subpopulations, and by inflating the underlying EU-SILC sample. We showed in this paper that this mitigation strategy was especially relevant to chart the impact on the self-employed. Still, the monthly allocations did stretch the EU-SILC beyond its intended uses. As the EU-SILC is not intended to be representative on the monthly level (let alone by sector, gender, age and wage level), the application of allocation percentages on such a fine-grained level likely contributed to an underestimation of overall numbers of affected.

A related issue refers to the difficulties in estimating the impact of the pandemic on the self-employed. In fact, the nowcasting approach adopted in Wizan and Marchal (forthcoming) leads to (almost) consistently lower projected self-employment earnings than observed from the EU-SILC 2021. While the nowcasting approaches assessed in detail in section 3 only adopted a fairly rudimentary (and generous) assumed change to self-employment incomes[26], the EU-SILC self-employment earnings are not substantially lower than those assumed here. This might reflect the ambiguity surrounding reported self-employment incomes (Horemans & Marx, 2017; Steyaert & Van Lancker, 2025). In addition, there are also important discrepancies between the numbers of self-employed recorded in the administrative data, and those observed in the EU-SILC. Likely, this means that the underlying baseline data already include quite a few uncertainties regarding the situation of the self-employed, which is only exacerbated in the nowcasting process.

An issue that should be taken on board in the future is that the nowcasting approaches might underestimate to some extent the clustering of the risks of being temporary unemployed and receiving a bridging right at the household level. We found a discrepancy between the clustering of these risks at the household level in the monthly administrative data, versus in the nowcasted data[27].

Finally, the nowcasting approaches assessed in somewhat more detail in section 3 appear to have, on average, underestimated 2020 earnings (cf. section 3.3.1.5), likely due to a slight overestimation of the number of days of temporary unemployment (cf. section 3.3.2.2). Surprisingly, this underestimation of overall earnings manifests even as the nowcasting exercises assessed here did not include estimates of reduced working hours outside the workings of the temporary and general unemployment scheme.

A final note refers to the ***scope*** of the nowcasting exercises developed to monitor the pandemic in 2020.

As is clear from the descriptions in this paper, most of the nowcasting exercises discussed here built on administrative beneficiary statistics on temporary unemployment, bridging right, and

[26] Monthly self-employment incomes were equaled to zero for the months individuals were projected to receive a bridging right benefit. This assumption negated the fact that bridging right could be combined with some remaining earnings, but, more importantly so, disregarded the fact that self-employed were likely still confronted with continuing costs. Even more so, this assumption disregarded the likely impact on self-employed that were not eligible to a bridging right. Capéau et al. (2022) did model the likely impact of disappearing profits and constant costs, while also including the impact of regional support benefits targeted at companies. This led to far more substantial decreases in self-employment earnings.

[27] It is worth noting that we also found a discrepancy in the other direction between the nowcasted data and the post-hoc reported statuses in the BE-SILC module. We suffice to highlight here that it should be considered to include the clustering at the household level in future exercises.

unemployment benefits. Transitions to statuses other than those three were not modelled, and hence their impact on the income distribution, nor the effectiveness of the welfare state in covering these alternative transitions, was not taken on board.

Hence, transitions that remained out of the remit of the nowcasting exercises are transitions into inactivity (i.e. not being covered at all), into health insurance benefits, social assistance benefits, or other forms of temporary leave covered by the welfare state. Similarly, it is conceivable that people remained in work, but at reduced hours and against reduced remuneration.

Geerts Danau, Audenaert, Vinck, and Van Lancker (2024) used the same administrative microdata as Vinck et al. (2022) to zoom in on the situation of very specific groups, with a focus on the size and socio-demographic characteristics of the under protected[28]. The authors define the under protected as those who did work in the last quarter of 2019, but lost their work during the pandemic, and did not rely on one of the support measures implemented on the government, nor on a general social insurance benefit. One is considered to be under protected if one fails to be covered by either work or the general safety net for at least one quarter in the period 2020 – 2021. Geerts Danau et al. (2024) calculate that this group amounts to a fairly small share of 3.5% of those working in the last quarter of 2019 (based on their sample). In terms of characteristics, people living in households with a low work intensity have a higher chance of being under protected, as are individuals who previously worked in blue-collar jobs, in smaller companies and in part-time jobs. Those who are at risk of being under protected are also relatively more often young, born outside of Belgium and living in Brussels.

The module of the Belgian SILC files offers additional information on the extent to which the nowcasting exercises' focus on temporary unemployment and bridging right may have missed part of the impact of the pandemic. Specifically, the federal and regional governments introduced a number of additional support measures, not directly targeted towards temporary unemployed and bridging right beneficiaries. For instance, during the pandemic, the options for deferred rent and mortgage payments were broadened. Evidently, whether or not one used such a measure gives additional insight in whether people experienced hardship due to the pandemic. Table 19 below gives an indication of the importance of these alternative support measures. Overall, the numbers of households indicating that they requested and benefited from deferred rent or mortgage payments is fairly limited. Still, 4.5% of tenant households, and 2.5% of owner-occupiers, benefited from some form of deferred payment related to living costs.

[28] Additionally, people experienced transitions to benefits other than temporary unemployment, bridging right or unemployment. Geerts Danau and colleagues (2024) find that 13.01% of those employed in the last quarter of 2019, received at least one quarter in the subsequent two years a benefit other than temporary unemployment and bridging right. However, this percentage also includes those transitioning to old age pensions, and those covered by unemployment, and therefore cannot be interpreted as a direct indication of the COVID-19 incited (temporary) exit routes not covered by the nowcasting.

Table 19. Number of beneficiaries observed in BE-SILC 2021

Measure	**Total number of beneficiaries (individuals or households)**	
Household level benefits		
Deferral of rent payment	17,348	[8481;26216]
Deferral of mortgage payment	45,573	[31474;59673]
Food aid	79,107	[48467;109747]
Individual level benefits		
Supplement in sickness benefit	55,836	[34188.96;77483.44]
Corona parental leave	72,225	[50722;93727]

Note: for the sake of completeness: 3,452,620 individuals report to having received the rail pass to boost national tourism in 2020.

Source: Own calculations on BE-SILC, Statbel (2021)

In Table 20, we show to what extent these indicators of hardship are in fact concentrated among the bridging right beneficiaries and temporary unemployed that formed the backbone of the different nowcasting exercises. Note that these estimates are based on very small numbers of observations. These estimates only serve to give an idea of the prevalence of those affected who fell outside the scope of the nowcasting exercises. Overall, around half of those reporting to have used deferral of housing cost payments also report having been temporary unemployed or a bridging right beneficiary at some point throughout 2020. Still, this also means that around half of this group (some 30,000 households) was not captured by the focus on temporary unemployment and bridging right dominant in the nowcasting exercises.

Table 20. Overlap between households with at least one person temporary unemployed or bridging right beneficiary, and receiving additional support measures, as reported in BE-SILC 2021

	Affected household	
	no	yes
deferral of rent	59.71 [33.49;81.2]	40.29 [18.64;66.5]
deferral of mortgage	40.24 [26.07;56.3]	59.76 [43.74;73.93]
food aid	91.5 [85.4;95.22]	8.48 [4.78;14.60]

Note: affected household used as shorthand for households with at least one person temporary unemployed or bridging right beneficiary

Source: Own calculations on BE-SILC, Statbel

Finally, Table 19 also listed a number of individual-level benefits. The nowcasting exercises did not model individual transitions to health insurance benefits and parental leave, nor did they estimate the financial impact of such a transition. While the prevalence of the number of people indicating they received a corona parental leave benefit is nowhere near the beneficiary numbers of the temporary unemployment and the bridging right cited elsewhere in this text, with around 72,000 persons, the group is fairly sizable.

Evidently, some limitation in scope is necessary in nowcasting exercises, and it makes sense to focus on the largest and likely more heavily affected groups. Still, the information from Geerts Danau et al. (2024) and from the statuses observed post-hoc in the BE-SILC data, do indicate that moderately substantial groups were covered by parental and health benefits. In addition, we observe that for the fairly large group of people that indicate having received food aid during COVID-19, there is only a very limited overlap with temporary unemployment or bridging right receipt.

4.3 Timeliness and availability of external statistics

We set out this exercise under the impression that it was the availability of external statistics on a sufficiently fine-grained level that was the delimiting factor for accurate nowcasted projections. While there is some truth to that assertion, the overall image that emerges is less clear-cut, for a number of reasons.

For one, often, the fine-grained statistics that were obtained from the administrations were aggregated to some extent in order to allow a meaningful allocation on the relatively small EU-SILC sample (see columns 5 and 6 of Table 1). In addition, nowcasting approaches differed in more than only the available aggregate external data used for the allocation, but also made different choices regarding baseline comparisons, the calculation of monthly and annual incomes, the precise policy measures modelled, and related modelling choices... Still, in spite of these different approaches and choices, the overall results in terms of earnings and income decreases, and overall impact on poverty rates and income inequality, are fairly similar. It should be mentioned however, that this similar impact to large extent stems from the substantial welfare state effort, that mitigated (actual and modelled) discrepancies in earnings decreases.

Based on the comparisons made in this paper, a direct allocation based on previous wages and earnings did lead to slightly different (income) groups projected to be affected by temporary unemployment and bridging right. Such information was (for employees) available with a number of months delay (available in January 2021, for March through November 2020, cf. Table 21 below). As described in Section 3.1, information for October – November 2020 was provisional at the time. However, later comparisons with final data obtained from the KSZ (Table 14, panel A) do not indicate large corrections[29]. For self-employed, information by previous earnings level was only available from the KSZ after 17 – 26 months (depending on the reference month in 2020 – all data were obtained in May 2022). The previous earnings level referred to the incomes in 2019.

In Table 21 below, we integrate findings from work packages 1 and 2 of the FAST project, and assess to what extent, according to the latest available information (cf. Geerts Danau et al., 2025), such information might be more swiftly available in the future[30].

Overall, we find that aggregated statistics derived from the data available at the public institutions were swiftly provided to researchers during 2020 and early 2021. This reflects once more the huge effort by public institutions and dedicated civil servants to act, as also evidenced by the efforts of the WG SIC group. The aggregate statistics were generally shared with no, or minimal, delay, relative to the best case scenario identified by Geerts Danau et al. (2025), bar practical challenges.

The table also shows other additional efforts taken during COVID-19. The last row reflects the aggregate statistics provided by the Datawarehouse in May 2022, for the nowcasting performed by

[29] Nor did the fact that the wage information obtained by the KSZ was based on wage categories somewhat higher in the wage distribution. To some extent, this might be due to the fact that Neelen et al. (2022) had to recombine some of the higher and more detailed wage categories in order to allow for a meaningful allocation on the SILC sample size. Such differences may therefore become more relevant when the underlying baseline data used for nowcasting is changed, cf. section 4.4. Furthermore, there was a (fairly small) impact of the reanchoring in Autumn 2020 (cf. section 3.3.2.2), but not to such an extent that it changed the overall image and interpretations.

[30] Note that Table 21, and the information in Geerts Danau et al. (2025), refer to the earliest available information of the data used in the different papers cited in column 1. At the "earliest available timing", these data may not necessarily be available to external researchers. With the exception of the final row, this information is not yet stable, and unmatched (i.e. data in phase 2 as discussed in Geerts Danau et al. (2025)).

Neelen et al. (2022). During the COVID pandemic, information on the bridging right was submitted to the Datawarehouse on an ad hoc basis, whereas previously, the Datawarehouse did not receive this information.

Geerts Danau et al. (2025) provide information on whether similar data would, currently, be available at the Datawarehouse. The information used by the Datawarehouse to provide the aggregate statistics are, according to Geerts Danau et al., only available with a certain delay. It should however be noted that this delay is related to the data delivery frequency. The RSZ data that are used to build the variable for the previous month's work status, and prior wages, are only considered final at the end of the calendar year, and submitted in the third quarter of the following year. This means that a shock that occurs in January, will only be available at the Datawarehouse after 12 months, and two quarters. For data referring to December, the timing is more expedient, in the third quarter of the following year. Data originating from the RVA run through a similar process, but are only submitted in Q4 (October).

That means that data similar to those used for Neelen et al. (2022) would, currently, based on 'earliest possible' exercise by Geerts Danau et al. (2025), be available at the Datawarehouse in the fourth quarter of the subsequent year[31]. In the future, it therefore might be conceivable that more detailed aggregate statistics are available at (somewhat) shorter notice, at least for in-house analyses by the Datawarehouse.

[31] The exercise of Geerts Danau et al. (2025) builds on the current timing and delays, and should not be interpreted as the earliest possible in 2020 – 2022. At the time, a huge effort was ongoing, in which, contrary to usual practice, intermediary temporary and ad hoc files were submitted to the Datawarehouse.

Table 21. Publication date and period of analysis of the different papers

Paper	Period of Analysis	Description external statistics	Availability external statistics 2020 (to researchers)	Availability external statistics at public institution for social security cf. Geerts Danau et al. (FAST WP1)
Thuy et al. (2020)	March - April - May 2020 (monthly impact)	E: linked RVA-RSZ data, detailing TU by occupational status (2), gender (2), daily wage level (cont.) and parity committee SE: BR, general recipient numbers	Available Jul 2020 T+2m, counting from May	E: link RVA/ONEM -NISS/RSZ/ONSS outside scope Geerts Danau et al., wage-, and working time data (DmfA data) available at NISS at t+4m, personnel register (Dimona data) , at RVA/ONEM at t+1m SE: t+1.5m
Marchal et al., (2021)	April 2020	E: TU, by sector (21), age group (5 years), gender, province, region, occupational status (2) SE: BR, by occupation code (>60), age group (5 years), region, type of SE and gender	Published online, *Retrieved* Nov 2020	E: t+1m SE: t+1,5m
Capéau et al. (2021)	March - December 2020 (annual impact)	E: TU by gender, age group (4), sector (22), daily wage (5) and numbers of days in TU (5) + monthly info on transitions	Available Jan 2021 (t+2m)	E: t+1m; stable (for TU) in t+6m, for U in t+1m
Christl et al. (2021)	2020 (annual impact)	E: TU by sector (up to August) SE: BR by sector (Q1-Q2)	Available Sept 2020 (t+1m)	E: t+1m SE: t+1,5m
Derboven et al. (2021)	March - December 2020 (monthly impact)	E: TU by gender, age group (4), sector (22), daily wage (5) and numbers of days in TU (5) + monthly info on transitions SE: BR by occupation code (>60), age group (5 years), region, type of SE and gender (M/F)	Available Jan 2021 (TU), Feb 2021 (BR) (t+2m)	E: t+1m; stable in t+6m SE: t+1,5m
Capéau et al. 2022 (- detail)	March - December 2020 (annual impact)	E: TU by sector SE: BR by sector	Available	n.a. (generally t+0/1)
Capéau et al. 2022 (+ detail)	March - December 2020 (annual impact)	E: TU by gender, age group (4), sector (22), daily wage (5), number of days in TU (5), LM status previous month SE: BR by sector (and aggregate transitions)	Available Jan 2021 (TU), Feb 2021 (BR) (t+2m)	E: t+1m; stable in t+6m SE: t+1,5m
Neelen et al. (2022)	March - December 2020 (monthly impact)	E: TU by gender, age group (4), sector (22), daily wage (5), number of days in TU (5), LM status (7) + monthly transitions SE: BR by gender, age, sector, income (2019), LM status (2) + monthly transitions	Available May 2022 (DWH KSZ) (t+17m, counting from December 2020)	Availability at Datawarehouse, linked at individual level (phase 4, section 4.1): SE: NISS/RSVZ/ONSS, bridging right: ad hoc, COVID-19: t + 12 months E: RVA/ONEM, temporary unemployment: t + 1 year+ 10 months (4th quarter) NISS/RSZ/ONSS: wages: t + 1year + 3rd quarter Previous month's labour market status: t + 1 year + 3rd quarter

Note: We thank Joanna Geerts Danau for valuable input in drafting this table. [a] Note that the 1 year refers to the frequency of data delivery. Data are delivered to the DWH at the end of the calendar year. This means that data for January will have a delay of 12 months + 3 quarters. Data for December on the other hand only have a delay of 3 quarters.

4.4 Ways forward

In section 4.1, we stress that overall, the nowcasting exercises performed for Belgium in 2020 were usually not far of the mark. Results were very much in line with one another, and also, in line with post hoc observed outcomes, both in survey and in administrative data.

Evidently, there are differences, but those remain fairly limited. To some extent, the limited differences in net disposable incomes are due to the large welfare state efforts deployed throughout 2020. Even when nowcasted projections over- or underestimated likely earnings losses, both the projected and actual welfare state intervention still succeeded in limiting the impact on net disposable incomes. Still, in terms of total numbers of affected, and their socio-demographic characteristics, the nowcasting exercises closely align to the actually observed profiles.

We highlighted a number of issues that the different nowcasting exercises ran into. Specifically, some of the detail that was available in external aggregate administrative statistics could not be taken on board in the actual nowcasting, specifically for the self-employed, but also for specific combinations of education levels and sectors in higher wage categories for employees (leading to an allocation on fairly broad wage categories, even in the final allocation). Similarly, the allocations by categories of days of temporary unemployment are likely related to an overestimation of earnings losses[32].

Furthermore, the scope of the nowcasting exercises was limited to temporary unemployment, unemployment and bridging right, even though post hoc available administrative data and survey data hint at the importance that also other types of benefits might have played, specifically, health benefits and parental benefits. Finally, we should note that neither the parametric nor the non-parametric nowcasting exercises took account of the household level. Our post-hoc comparison provides some indication that this might have led to an underestimation of the concentration of affected individuals at the household level (although likely not to such an extent that it led to different assessments regarding the distribution of net disposable household incomes).

The EU-SILC sample size made it far from evident to include more labor market status transitions. For the future, one should however consider how using alternative input data, such as the standing BELMOD sample, makes way for an expanded scope of labor market transitions included. The ongoing project 'Nowcasting BELMOD', which aims to develop a nowcasting procedure for the BELMOD input data set, is a very relevant step in this respect. Given the size of the BELMOD input data (473,583 households, as compared to 6,787 in the EU-SILC for 2019), this would allow for a much more fine-grained analysis of the impact of shocks on specific groups. In this project different approaches are investigated to keep the BELMOD input dataset as up-to-date as possible. The first method implemented is a parametric approach, where transitions between employed, self-employed, and unemployed are based on information from the EAK. This method is based on the approach used by Eurostat for the Flash estimates of income inequalities and poverty indicators. A second method, also involving transitions, is a non-parametric approach that utilizes aggregated data from the Datawarehouse Labour Market and Social Protection from the KSZ. This approach allows for more transitions than the first one and, as a result, contains temporary unemployment and atypical employment such as flexi-jobs, temporary work, and seasonal work. Both transition-based methods are subsequently compared with each other and with a nowcasting procedure that consists solely of reweighting. Within this project, nowcasting is being performed on an annual basis. The size of the

[32] This could in the future however be addressed also without changing the underlying nowcasting approach, by having more detailed information on distribution of the number of days of temporary unemployment within each category.

underlying sample would enable a more finetuned allocation of numbers of days of temporary unemployment, and hence also a more accurate proxy for earnings losses.

In the future, BELMOD and the nowcasting of BELMOD, will therefore likely allow for more fine-grained assessments during crises. Importantly, the work done by Geerts Danau et al. (2025) may help in updating BELMOD during crisis situations, as it gives an overview of the most expedient timing of preliminary information useful for nowcasting. Currently, BELMOD focuses on annual incomes, but it is conceivable that also quarterly projections are made during times of crisis. The underlying information for labor market status in BELMOD builds indeed on quarterly available register data.

Finally, our findings, and specifically those reported in section 4.2, do give rise to some further qualifications. The exercise done for this paper was very much a backward looking exercise, focusing on the last crisis. Due to the nature of that crisis, and – not in the least – the type of policy measures developed to mitigate the impact of that crisis, the nowcasting exercises focused on projecting incomes, building on the extensive infrastructure (including survey data and the EUROMOD microsimulation model) built up over the previous years to allow for such an analysis. The nowcasting exercises analyzed here all very much entailed an income-based assessment, built around the administratively available support. Still, other types of shocks are equally possible, at the individual or aggregate level, with their own specifically tailored policy responses.

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6 Annex

Table A. Distribution of COVID-19 impact on net disposable income over the income distribution

	Nowcasted 2020, relative to no-COVID baseline[a]	**Observed 2020, relative to hypothetical no-COVID baseline**[b]
Thuy et al. (2020)	Progressive	Progressive
Almeida et al. (2021)	Highest losses in D10	Highest losses in Q1 and Q5
Capéau et al., (2021)	Progressive	Highest losses Q1 (all E) Highest losses in Q1 (but also Q4 and Q5) (affected E)
Christl et al. (2021)	Progressive	Highest losses in Q1 and Q5 (small differences)
Eurostat (2021) – 2020 FE	Slightly regressive	Progressive
Capéau et al., 2022 (- detail)	Progressive	Highest losses in Q1 and Q5 (small differences)
Capéau et al., 2022 (+ detail)	Slightly regressive	Highest losses in Q1 and Q5 (small differences)

[a] As constructed and reported in the different nowcasting exercises. [b] EU-SILC 2021 (incomes 2020), used as input data in EUROMOD to eliminate differences due to simulated versus observed data, as compared to EU-SILC 2020 (2019 incomes), uprated to a no-COVID 2020 using EUROMOD.

Note: the distributive patterns reported in the nowcasting exercises (column 2) are not comparable to the distributive patterns reported in column 3, and are shown for illustrative purposes only. The nowcasting exercises tend to consider the average impact by quintile based on the net disposable equivalent household incomes in the baseline scenario. Column 3 builds on two separate data files, and therefore considers the decrease in average income by quintile, with the quintiles re-calculated in the observed and the hypothetical baseline scenario.

Source: own calculations on EUROMOD and EU-SILC, Eurostat

Table B. Socio-demographic characteristics of temporary unemployed, as per allocation done in Marchal et al. (2021)

		% temporary employed		% employees	
Age	< 18	0.1	[0;0.7]	0.0	[0;0.2]
	18-24	7.0	[5.5;9.1]	4.1	[3.4;5]
	25-34	26.7	[24;29.6]	26.3	[24.7;27.9]
	35-49	38.6	[35.4;41.8]	38.6	[36.8;40.4]
	50-64	27.1	[24.6;29.7]	30.6	[29;32.2]
	>=65	0.4	[0.2;1]	0.4	[0.2;0.7]
Gender	Female	41.5	[38.6;44.4]	48.3	[46.9;49.6]
	Male	58.5	[55.6;61.4]	51.7	[50.4;53.1]
Family	couple with children	35.0	[31.8;38.3]	36.8	[34.9;38.9]
	couple without children	33.4	[30.2;36.8]	33.1	[30.8;35.6]
	single parent	2.3	[1.7;3.2]	2.3	[1.9;2.8]
	single	13.1	[10.8;15.8]	14.3	[12.1;16.7]
	other	16.2	[13.9;18.8]	13.4	[12.1;14.9]
children	0	59.1	[55.6;62.6]	58.5	[56.4;60.5]
	1	19.7	[17.1;22.5]	18.5	[16.9;20.2]
	2	13.9	[11.8;16.3]	15.5	[14.1;17]
	3 or more	7.3	[5.6;9.3]	7.5	[6.5;8.7]
Region	Brussels	10.1	[2.8;30.3]	9.2	[2.6;27.7]
	Flanders	62.3	[52.1;71.5]	62.6	[53.9;70.5]
	Wallonia	27.6	[21.9;34.1]	28.2	[23.6;33.4]
Citizen	Belgium	86.7	[82.7;89.8]	89.9	[86.8;92.4]
	EU	8.2	[6.3;10.7]	6.7	[5.1;8.7]
	non-EU	5.1	[3.2;8]	3.4	[2.3;4.9]
Sector	Other	0	[0;0]	0	[0;0]
	A. Agriculture	0.2	[0.1;1]	0.2	[0.1;0.4]
	B-E.	21.9	[18.3;26]	15.3	[13.8;17]
	F. Construction	11.1	[9.2;13.3]	5.2	[4.5;6]
	G. Wholesale and retail	17.5	[15.2;20.1]	10.2	[9.3;11.3]
	I. Accomodation and food services	6.8	[5;9.3]	2.5	[1.8;3.3]
	H - J.	8	[6.6;9.7]	9.1	[8.3;10.1]
	K. Financial	1.7	[1;2.8]	3.9	[3.2;4.7]
	L - N	16.4	[14.1;18.8]	9.6	[8.5;10.8]
	O. Public administration	0.2	[0.1;0.6]	11.5	[10.3;12.8]
	P. Education	2.5	[1.7;3.7]	13.3	[12.2;14.5]
	Q. Human health	8.3	[6.8;10.1]	15.3	[14.1;16.7]
	R-U. Arts,	5.4	[3.9;7.6]	3.8	[2.8;5]
tenant	no	51.9	[47.2;56.6]	57	[53.5;60.4]
	yes	48.1	[43.4;52.8]	43	[39.6;46.5]
educ	low	8.2	[6.7;10]	6.8	[5.9;7.7]
	middle	65.8	[62.2;69.3]	44.5	[42.2;46.9]
	high	26	[22.9;29.3]	48.7	[46.4;51.1]

Table C. Socio-demographic characteristics of temporary unemployed, as per allocation done in Neelen et al. (2022)

		% temporary employed		% employees	
Age	< 18	0.0	[0;0.3]	0.1	[0;0.5]
	18-24	6.7	[5.6;8.1]	6.2	[5.3;7.2]
	25-34	30.6	[28.6;32.7]	26.5	[24.9;28.1]
	35-49	37.1	[35;39.2]	38.4	[36.6;40.2]
	50-64	25.3	[23.4;27.3]	28.5	[27.1;30.1]
	>=65	0.3	[0.1;0.6]	0.3	[0.2;0.6]
Gender	Female	41.0	[39.3;42.8]	48.5	[47.4;49.6]
	Male	59.0	[57.2;60.7]	51.5	[50.4;52.6]
Family type	couple with children	34.7	[32.1;37.4]	36.6	[34.6;38.6]
	couple without children	32.3	[29.7;35]	31.9	[29.7;34.3]
	single parent	2.1	[1.7;2.6]	2.5	[2;2.9]
	single	14.3	[12;16.9]	13.6	[11.7;15.8]
	other	16.7	[14.8;18.7]	15.4	[14;16.9]
Number of children	0	59.9	[57.2;62.5]	58	[55.9;60]
	1	19.1	[17;21.3]	19.2	[17.5;20.9]
	2	13.9	[12.3;15.6]	15.3	[13.9;16.8]
	3 or more	7.2	[6;8.6]	7.6	[6.5;8.8]
Region	Brussels	10.2	[2.9;30.3]	9.4	[2.8;27.5]
	Flanders	61.8	[52.1;70.6]	62.1	[53.5;70]
	Wallonia	28	[22.8;33.9]	28.5	[23.8;33.7]
Citizenship	Belgium	87	[83.6;89.8]	89.3	[86.2;91.7]
	EU	7.8	[6.1;10.1]	6.8	[5.1;8.9]
	non-EU	5.1	[3.7;7.1]	4	[2.9;5.4]
Sector	A-E. Agriculture, mining, manufacturing and utilities	24.9	[22;28.1]	15.5	[13.9;17.3]
	F. Construction	10.9	[9.3;12.7]	5.4	[4.6;6.4]
	G. Wholesale and retail	15.9	[14.5;17.5]	10.5	[9.5;11.5]
	I. Accomodation and food services	6	[4.5;7.9]	2.7	[2;3.6]
	H - J. Transport, storage, information and communication	8.7	[7.7;9.8]	8.9	[8;9.8]
	K. Financial and insurance services	1.7	[1.3;2.2]	3.9	[3.2;4.7]
	L - N. Real estate, professional, scientific and administrative services	14.7	[13.1;16.5]	9.9	[8.8;11.2]
	O. Public administration and defence	1.4	[1.1;1.7]	11.3	[10.1;12.5]
	P. Education	2.7	[2.3;3.3]	12.8	[11.7;14]
	Q. Human health and social work	8.6	[7.7;9.6]	15.4	[14.2;16.8]
	R-U. Arts, entertainment and recreation	4.4	[3.4;5.8]	3.8	[2.9;4.9]
	Other	0	[0;0]	0	[0;0]
tenant	no	52.6	[48.7;56.5]	56.5	[53;59.9]
	yes	47.4	[43.5;51.3]	43.5	[40.1;47]
education	low	8.8	[7.6;10.1]	6.7	[5.8;7.6]
	middle	56.1	[53.1;59]	45.2	[42.8;47.6]
	high	35.1	[32.5;37.9]	48.2	[45.8;50.5]

Table D. Socio-demographic characteristics of temporary unemployed, as per allocation done in Derboven et al. (2022)

		% temporary employed		% employees	
Age	< 18	0.0	[0;0.1]	0.1	[0;0.5]
	18-24	6.7	[5.6;8]	6.2	[5.3;7.2]
	25-34	29.7	[27.6;32]	26.5	[24.9;28.1]
	35-49	37.3	[35;39.6]	38.4	[36.6;40.2]
	50-64	26.0	[23.9;28.1]	28.5	[27.1;30.1]
	>=65	0.3	[0.1;0.9]	0.3	[0.2;0.6]
Gender	Female	39.4	[37.6;41.2]	48.5	[47.4;49.6]
	Male	60.6	[58.8;62.4]	51.5	[50.4;52.6]
Family type	couple with children	35.6	[33;38.3]	36.6	[34.6;38.6]
	couple without children	32.5	[29.7;35.4]	31.9	[29.7;34.3]
	single parent	2.1	[1.6;2.8]	2.5	[2;2.9]
	single	13.4	[11.4;15.8]	13.6	[11.7;15.8]
	other	16.3	[14.4;18.3]	15.4	[14;16.9]
Number of children	0	59.1	[56.4;61.8]	58	[55.9;60]
	1	19.7	[17.5;22.1]	19.2	[17.5;20.9]
	2	14.1	[12.5;15.9]	15.3	[13.9;16.8]
	3 or more	7.1	[5.9;8.6]	7.6	[6.5;8.8]
Region	Brussels	10.4	[3;30.2]	9.4	[2.8;27.5]
	Flanders	60.7	[51.1;69.6]	62.1	[53.5;70]
	Wallonia	28.8	[23.4;35]	28.5	[23.8;33.7]
Citizenship	Belgium	86.4	[82.5;89.6]	89.3	[86.2;91.7]
	EU	8.3	[6.3;10.7]	6.8	[5.1;8.9]
	non-EU	5.3	[3.6;7.8]	4	[2.9;5.4]
Sector	A-E. Agriculture, mining, manufacturing and utilities	23.2	[20.5;26.2]	15.5	[13.9;17.3]
	F. Construction	10.9	[9.3;12.8]	5.4	[4.6;6.4]
	G. Wholesale and retail	20.1	[18.2;22]	10.5	[9.5;11.5]
	I. Accomodation and food services	5.5	[4.1;7.3]	2.7	[2;3.6]
	H - J. Transport, storage, information and communication	8.7	[7.7;9.9]	8.9	[8;9.8]
	K. Financial and insurance services	1.3	[1;1.7]	3.9	[3.2;4.7]
	L - N. Real estate, professional, scientific and administrative services	17.4	[15.4;19.7]	9.9	[8.8;11.2]
	O. Public administration and defence	0	[0;0]	11.3	[10.1;12.5]
	P. Education	1.5	[1.2;1.9]	12.8	[11.7;14]
	Q. Human health and social work	7.1	[6;8.3]	15.4	[14.2;16.8]
	R-U. Arts, entertainment and recreation	4.3	[3.3;5.5]	3.8	[2.9;4.9]
	Other	0	[0;0]	0	[0;0]
		0	[0;0]	0	[0;0]
tenant	no	52.8	[48.6;56.9]	56.5	[53;59.9]
	yes	47.2	[43.1;51.4]	43.5	[40.1;47]
education	low	9	[7.7;10.5]	6.7	[5.8;7.6]
	middle	58.6	[55.7;61.4]	45.2	[42.8;47.6]
	high	32.4	[29.9;34.9]	48.2	[45.8;50.5]

Table E. Socio-demographic characteristics of temporary unemployed, BE-SILC 2021

		% temporary employed		% employees	
Age	< 18	0.0	[0;0]	0.1	[0;0.2]
	18-24	4.8	[3.5;6.5]	4.8	[4.1;5.5]
	25-34	26.7	[23.5;30.2]	26.7	[24.9;28.7]
	35-49	40.2	[37.1;43.4]	39.0	[37.3;40.8]
	50-64	27.2	[24.4;30.2]	29.1	[27.5;30.6]
	>=65	1.0	[0.5;2]	0.3	[0.2;0.5]
Gender	Female	41.9	[38.5;45.2]	50.1	[49;51.3]
	Male	58.1	[54.8;61.5]	49.9	[48.7;51]
Family type	couple with children	36.6	[33.5;39.9]	38.3	[36.4;40.2]
	couple without children	32.0	[28.9;35.4]	31.2	[29.4;33]
	single parent	3.9	[2.8;5.6]	3.6	[3.1;4.2]
	single	14.1	[12;16.4]	13.1	[11.9;14.4]
	other	13.3	[11.3;15.7]	13.8	[12.6;15.2]
Number of children	0	57.5	[53.9;61.1]	55.8	[53.7;57.8]
	1	17.8	[15.2;20.7]	18.9	[17.5;20.5]
	2	17.4	[15;20.1]	18.5	[17;20.1]
	3 or more	7.3	[5.7;9.3]	6.8	[5.9;7.9]
Region	Brussels	10.5	[5.3;19.8]	9.5	[5;17.5]
	Flanders	61.3	[54.5;67.7]	61	[55.6;66.1]
	Wallonia	28.2	[23.3;33.6]	29.5	[25.7;33.6]
Citizenship	Belgium	87.9	[84.9;90.4]	90.1	[88.4;91.5]
	EU	6.5	[4.9;8.7]	6.4	[5.4;7.7]
	non-EU	5.6	[4;7.7]	3.5	[2.7;4.5]
Sector	Other	0.7	[0.2;1.8]	0	[0;0]
	A. Agriculture	0.1	[0;0.8]	0.4	[0.2;0.7]
	B-E. Mining, manufacturing and utilities	19.5	[16.5;22.9]	15.6	[14.1;17.2]
	F. Construction	9.9	[7.9;12.3]	4.9	[4.2;5.7]
	G. Wholesale and retail	18.2	[15.7;21]	9.8	[8.9;10.7]
	I. Accomodation and food services	6.1	[4.5;8.1]	1.8	[1.4;2.3]
	H - J. Transport, storage, information and communication	7.8	[6.2;9.8]	8.9	[8;9.9]
	K. Financial and insurance services	1.1	[0.6;1.8]	3.3	[2.7;4]
	L - N. Real estate, professional, scientific and administrative services	16.7	[14.2;19.5]	10.2	[9.3;11.1]
	O. Public administration and defence	2.4	[1.5;3.7]	10.4	[9.4;11.4]
	P. Education	3.7	[2.6;5.3]	13.2	[12.1;14.4]
	Q. Human health and social work	8.7	[6.8;10.9]	17.2	[16;18.5]
	R-U. Arts, entertainment and recreation	5.3	[3.9;7.1]	4.4	[3.7;5.1]
tenant	no	51.7	[47.7;55.7]	57.3	[54.7;59.8]
	yes	48.3	[44.3;52.3]	42.7	[40.2;45.3]
education	low	4	[2.9;5.3]	2.7	[2.3;3.3]
	middle	60.9	[57;64.7]	42.7	[40.2;45.2]
	high	35.1	[31.4;39]	54.5	[51.9;57.2]

Source: Own calculations on BE-SILC, Statbel

Table F. Socio-demographic characteristics of bridging right beneficiaries and self-employed, BE-SILC 2021

		% BR beneficiaries		% self-employed	
Age	< 18	0.0	[0;0]	0.0	[0;0]
	18-24	1.2	[0.4;3.7]	2.3	[1.3;4.2]
	25-34	26.9	[20.6;34.4]	18.5	[15.6;21.8]
	35-49	36.9	[29.9;44.5]	37.3	[33;41.8]
	50-64	32.5	[27;38.5]	39.9	[35.8;44.2]
	>=65	2.4	[0.9;6]	2.0	[1.1;3.5]
Gender	Male	64.2	[57.1;70.7]	67.8	[64.2;71.2]
	Female	35.8	[29.3;42.9]	32.2	[28.8;35.8]
Family type	couple with children	44.7	[37.4;52.3]	37.6	[32.8;42.6]
	couple without children	27.9	[22.3;34.4]	35.2	[30.5;40.3]
	single parent	1.9	[0.9;4]	1.3	[0.7;2.3]
	single	15.7	[11.6;20.9]	14.7	[11.7;18.4]
	other	9.8	[6.1;15.2]	11.2	[8.3;14.9]
Number of children	0	50.9	[43.5;58.3]	59.4	[54.3;64.3]
	1	17	[12.5;22.6]	16.3	[13;20.2]
	2	21.6	[15.9;28.6]	16	[13;19.7]
	3 or more	10.5	[5.9;18]	8.2	[5.6;12]
Region	Brussels	16.8	[9;29.2]	11.3	[6;20.2]
	Flanders	56.6	[46.1;66.5]	63	[55.2;70.2]
	Wallonia	26.6	[18.6;36.5]	25.7	[20.2;32]
Citizenship	Belgium	84.7	[76.4;90.5]	86.7	[82;90.3]
	EU	8.4	[5.4;13]	8.6	[6.5;11.3]
	non-EU	6.8	[2.9;15.3]	4.7	[2.5;8.7]
Sector	Other	0.3	[0;2.4]	0	[0;0]
	A. Agriculture	2.5	[0.9;6.9]	8	[5.1;12.4]
	B-E. Mining, manufacturing and utilities	6.6	[4.1;10.5]	6.2	[4.7;8.3]
	F. Construction	13	[8.7;19.1]	12.7	[9.9;16]
	G. Wholesale and retail	11	[6.7;17.7]	10.7	[7.8;14.5]
	I. Accomodation and food services	15.2	[8.9;24.8]	9.1	[5.8;13.9]
	H - J. Transport, storage, information and communication	5.9	[3.6;9.6]	7.1	[5.3;9.5]
	K. Financial and insurance services	0	[0;0]	2.1	[0.9;4.6]
	L - N. Real estate, professional, scientific and administrative services	16.4	[12.4;21.3]	22.5	[18.8;26.7]
	O. Public administration and defence	0.4	[0.1;1.6]	0.4	[0.1;1.3]
	P. Education	3.7	[1.7;8.2]	1.8	[0.9;3.5]
	Q. Human health and social work	15.2	[10.1;22.1]	12.9	[9.8;16.8]
	R-U. Arts, entertainment and recreation	9.7	[6.3;14.6]	6.6	[4.7;9.2]
tenant	no	49.6	[41.6;57.6]	51.9	[46.9;56.8]
	yes	50.4	[42.4;58.4]	48.1	[43.2;53.1]
education	low	2.1	[0.8;5.8]	1.8	[1;3.1]
	middle	46.8	[39.6;54.2]	41.7	[36.5;47.1]
	high	51	[43.6;58.4]	56.5	[51.1;61.7]

Source: Own calculations on BE-SILC, Statbel

Table G. Socio-demographic characteristics of bridging right beneficiaries and self-employed, Derboven et al. (2022)

		% BR beneficiaries		% self-employed	
Age	< 18	0.0	[0;0]	0.1	[0;0.7]
	18-24	2.0	[1;4]	3.3	[1.9;5.4]
	25-34	18.4	[14.4;23.2]	17.6	[13.9;22]
	35-49	44.4	[39.7;49.1]	40.6	[36.3;44.9]
	50-64	33.3	[28.8;38.2]	36.5	[32.2;41]
	>=65	1.9	[1;3.4]	2.0	[1.2;3.5]
Gender	Female	33.3	[29.1;37.8]	34.4	[30.9;38.2]
	Male	66.7	[62.2;70.9]	65.6	[61.8;69.1]
Family type	couple with children	44.1	[38.5;49.8]	38.5	[33.7;43.5]
	couple without children	35.1	[30.5;40.1]	37.3	[32.9;41.9]
	single parent	1.9	[1;3.4]	1.6	[0.8;3.2]
	single	12.1	[8.9;16.2]	13.2	[10;17.4]
	other	6.8	[4.7;9.8]	9.3	[7;12.3]
Number of children	0	52.1	[47;57.3]	58.3	[53.5;63]
	1	20.1	[16.7;24.1]	18.3	[15;22.2]
	2	17.6	[14.5;21.2]	14.7	[12.1;17.9]
	3 or more	10.1	[7.2;14.2]	8.6	[6.2;11.7]
Region	Brussels	13.3	[4.3;34.1]	11	[3.6;29.2]
	Flanders	57.1	[45.8;67.7]	59.1	[48.9;68.6]
	Wallonia	29.6	[22.2;38.3]	29.8	[22.8;38]
Citizenship	Belgium	85.2	[79.1;89.8]	88.9	[84.1;92.4]
	EU	11.5	[8;16.3]	8.7	[5.9;12.7]
	non-EU	3.3	[1.8;5.9]	2.4	[1.3;4.4]
Sector	Other	0.3	[0.1;1]	0	[0;0]
	A. Agriculture				
	A-E. Mining, manufacturing and utilities	8.5	[6.1;11.8]	12.1	[8.9;16.3]
	F. Construction	15.8	[12.5;19.7]	13.4	[10.5;16.9]
	G. Wholesale and retail	16.7	[13.2;20.9]	14.5	[11.3;18.3]
	I. Accomodation and food services	10.7	[7.5;15]	8.6	[6.1;12.1]
	H - J. Transport, storage, information and communication	7.2	[5.3;9.8]	6.5	[4.6;8.9]
	K. Financial and insurance services	2.5	[1.4;4.3]	4.3	[2.4;7.6]
	L - N. Real estate, professional, scientific and administrative services	17.4	[14.2;21]	23	[19.2;27.4]
	O. Public administration and defence	0.7	[0.2;2.8]	0.3	[0.1;1.2]
	P. Education	2.2	[1.3;3.8]	1.3	[0.7;2.4]
	Q. Human health and social work	13.1	[10.3;16.5]	11.6	[9.1;14.5]
	R-U. Arts, entertainment and recreation	4.9	[3.2;7.2]	4.5	[3;6.6]
tenant	no	54.4	[48.8;60]	53.2	[47.6;58.7]
	yes	45.6	[40;51.2]	46.8	[41.3;52.4]
education	low	6.6	[4.6;9.3]	5.2	[3.7;7.2]
	middle	44.6	[40;49.4]	43.1	[38.2;48.1]
	high	48.7	[44.1;53.4]	51.8	[46.6;56.9]

Table H. Socio-demographic characteristics of bridging right beneficiaries and self-employed, Marchal et al. (2021)

		% BR beneficiaries		% self-employed	
Age	< 18	0.0	[0;0]	0.0	[0;0]
	18-24	1.3	[0.6;3.2]	0.9	[0.4;1.9]
	25-34	20.8	[15.9;26.7]	16.5	[13;20.7]
	35-49	38.6	[32.8;44.8]	41.7	[37.3;46.2]
	50-64	36.8	[30.7;43.4]	38.7	[34;43.6]
	>=65	2.4	[1.2;4.6]	2.2	[1.3;3.9]
Gender	Female	33.4	[27.8;39.5]	33.8	[30.1;37.7]
	Male	66.6	[60.5;72.2]	66.2	[62.3;69.9]
Family type	couple with children	39.6	[33.4;46]	39.7	[34.6;45.2]
	couple without children	38.3	[31.9;45]	39.3	[34.6;44.1]
	single parent	1.7	[0.8;3.7]	1.8	[0.9;3.4]
	single	13.3	[9.3;18.7]	12.5	[9.4;16.5]
	other	7.2	[4.5;11.3]	6.7	[4.6;9.7]
Number of children	0	56.7	[50.6;62.6]	56.9	[52;61.6]
	1	18.1	[13.6;23.7]	18.3	[15;22.2]
	2	16.8	[12.7;21.8]	16.1	[13.3;19.3]
	3 or more	8.5	[5.3;13.3]	8.7	[6.2;12.1]
Region	Brussels	13.9	[4.9;33.9]	12.3	[4;32]
	Flanders	55.9	[44.6;66.6]	57.8	[47.1;67.9]
	Wallonia	30.2	[22.6;39.1]	29.8	[22.6;38.2]
Citizenship	Belgium	83.1	[76.4;88.2]	87.2	[81.9;91.1]
	EU	13.7	[9.8;18.8]	10	[7;14.1]
	non-EU	3.3	[1.6;6.6]	2.8	[1.5;5.2]
Sector	Other	0	[0;0]	0.3	[0.1;0.9]
	A. Agriculture	3.5	[1.8;6.7]	6.5	[4.1;10.2]
	B-E. Mining, manufacturing and utilities	5.9	[3.6;9.5]	5.5	[3.6;8.2]
	F. Construction	15.8	[11.7;21]	13.9	[11;17.3]
	G. Wholesale and retail	15.5	[11.2;21]	14.5	[11.3;18.5]
	I. Accomodation and food services	10.9	[7.4;15.9]	8	[5.6;11.5]
	H - J. Transport, storage, information and communication	6.4	[4.1;10.1]	6.7	[4.8;9.3]
	K. Financial and insurance services	2.6	[1;6.7]	4.1	[2.3;7.2]
	L - N. Real estate, professional, scientific and administrative services	17.2	[12.9;22.7]	21.9	[18.2;26.1]
	O. Public administration and defence	0.4	[0.1;1.7]	0.9	[0.3;2.5]
	P. Education	2.8	[1.5;5.2]	2	[1.2;3.4]
	Q. Human health and social work	13.5	[9.8;18.3]	12.1	[9.6;15.2]
	R-U. Arts, entertainment and recreation	5.3	[3.3;8.4]	3.6	[2.3;5.5]
tenant	no	48.1	[41;55.3]	52.7	[47.2;58.2]
	yes	51.9	[44.7;59]	47.3	[41.8;52.8]
education	low	6.7	[4.4;10]	6	[4.3;8.5]
	middle	49.3	[42.9;55.8]	42.1	[37.6;46.8]
	high	44	[37.7;50.5]	51.8	[47.2;56.4]

Table I. Socio-demographic characteristics of bridging right beneficiaries and self-employed, Neelen et al. (2022)

		% BR beneficiaries		% self-employed	
Age	< 18	0.0	[0;0]	0.1	[0;0.7]
	18-24	0.9	[0.3;2.2]	3.3	[1.9;5.4]
	25-34	18.4	[14.3;23.4]	17.6	[13.9;22]
	35-49	42.2	[37.4;47.2]	40.6	[36.3;44.9]
	50-64	36.9	[31.8;42.4]	36.5	[32.2;41]
	>=65	1.6	[0.9;2.9]	2.0	[1.2;3.5]
Gender	Female	32.5	[28.2;37.1]	34.4	[30.9;38.2]
	Male	67.5	[62.9;71.8]	65.6	[61.8;69.1]
Family type	couple with children	41.0	[35.6;46.7]	38.5	[33.7;43.5]
	couple without children	37.2	[32.2;42.4]	37.3	[32.9;41.9]
	single parent	2.2	[1;4.6]	1.6	[0.8;3.2]
	single	13.2	[9.7;17.8]	13.2	[10;17.4]
	other	6.4	[4.2;9.6]	9.3	[7;12.3]
Number of children	0	54.8	[49.5;59.9]	58.3	[53.5;63]
	1	18.2	[14.7;22.3]	18.3	[15;22.2]
	2	17.6	[14.5;21.2]	14.7	[12.1;17.9]
	3 or more	9.5	[6.6;13.3]	8.6	[6.2;11.7]
Region	Brussels	13.5	[4.8;32.5]	11	[3.6;29.2]
	Flanders	57.1	[46.2;67.3]	59.1	[48.9;68.6]
	Wallonia	29.4	[22.1;38]	29.8	[22.8;38]
Citizenship	Belgium	86	[80.5;90.1]	88.9	[84.1;92.4]
	EU	10.9	[7.6;15.4]	8.7	[5.9;12.7]
	non-EU	3.2	[1.6;6]	2.4	[1.3;4.4]
Sector	Other	0	[0;0]	0	[0;0]
	A. Agriculture				
	B-E. Mining, manufacturing and utilities	7.7	[5.5;10.7]	12.1	[8.9;16.3]
	F. Construction	16.6	[13.3;20.6]	13.4	[10.5;16.9]
	G. Wholesale and retail	15.3	[12;19.4]	14.5	[11.3;18.3]
	I. Accomodation and food services	12.1	[8.5;17]	8.6	[6.1;12.1]
	H - J. Transport, storage, information and communication	6	[4.2;8.6]	6.5	[4.6;8.9]
	K. Financial and insurance services	2.3	[1.3;4]	4.3	[2.4;7.6]
	L - N. Real estate, professional, scientific and administrative services	19.3	[15.6;23.6]	23	[19.2;27.4]
	O. Public administration and defence	0.5	[0.2;1.6]	0.3	[0.1;1.2]
	P. Education	1.5	[0.9;2.6]	1.3	[0.7;2.4]
	Q. Human health and social work	14	[10.9;17.8]	11.6	[9.1;14.5]
	R-U. Arts, entertainment and recreation	4.6	[3;7]	4.5	[3;6.6]
tenant	no	55	[49.4;60.5]	53.2	[47.6;58.7]
	yes	45	[39.5;50.6]	46.8	[41.3;52.4]
education	low	6.7	[4.7;9.6]	5.2	[3.7;7.2]
	middle	43.5	[38.8;48.3]	43.1	[38.2;48.1]
	high	49.8	[44.9;54.7]	51.8	[46.6;56.9]