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SOUTHMOD – simulating tax and benefit policies for development

Imputation methods for adjusting SOUTHMOD input data to income losses due to the COVID-19 crisis

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Abstract: This note sets out two different methods on how to adjust incomes in the microdata underlying the standard SOUTHMOD models to reflect a sudden shock, in this case the COVID-19 shock, as done in the accompanying working paper by Lastunen et al. (2021). The note first describes how industry-specific GDP shocks are calculated. Next, it describes how these shocks are randomly allocated to individuals' incomes in the microdata. Using the World Bank Phone Survey for Uganda, an alternative, regression-based method is described that models labour market transitions in a more detailed manner as it takes into account individuals' characteristics. The method could easily be replicated for other countries provided such alternative microdata eventually become available. We further track and compare variables between the survey data underlying the UGAMOD input data, the 2016/17 Uganda National Household Survey, and the World Bank Phone Survey for Uganda.

Key words: imputation, income loss, World Bank Phone Survey, UGAMOD, COVID-19

JEL classification: C18, C63, C81

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Related publications: at the end of the paper, after the references

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1 Introduction

One of the major challenges for evaluating the distributional effects of the COVID-19 pandemic is the lack of up-to-date microdata with detailed information on household characteristics and (disposable) income. In general, income data collected from surveys usually become available only with a time lag, often of up to two years, and survey years are not necessarily the same for different countries. However, if suitable microdata on gross incomes can be generated, disposable incomes can be simulated through microsimulation techniques as employed in the working paper this note refers to.

The data availability limitations mentioned above pose a challenge, and not only for research on developing countries. Cantó Sanchez et al. (2021), for example, estimate the impact of the COVID-19 crisis and governments' policy response on household incomes in Europe. The authors apply different techniques to update the labour market status and income of individuals in survey data for Belgium, Italy, Spain, and UK during the first month of the crisis to account for the COVID-19 shock, to make up for the lack of comprehensive microdata following households and their incomes across time. Christl et al. (2021) who conduct a similar exercise for Germany discuss the two main approaches used to implement labour shocks in the microdata, namely static and dynamic approaches. The first approach typically consists of updating the individual observations in the microdata to match more recent labour market or other aggregate statistics. The latter approach is based on the use of new labour market information at the individual level to update the microdata.

In this technical note, we explain how we develop and apply the static (random allocation method) to create updated datasets to analyse the distributional effects of the COVID-19 pandemic and related tax-benefit measures for selected African countries: Ghana, Mozambique, Tanzania, Uganda, and Zambia. For the case of Uganda where World Bank Phone Survey (WBPS) provides survey data on individuals' labour market outcomes throughout the pandemic are available, we further compare the static approach to a dynamic transition approach, specifically a regression-based method.

This technical note is structured as follows:

- **Short background and definition of datasets** underlying the tax-benefit microsimulation models.
- **Estimation of sectoral GDP shocks:** due to lack of aggregate labour market data, we turn to sectoral GDP data to approximate the size of the COVID-19 shock on the labour force in each sector of the economy. Both approaches employed, explained later, use the estimated sectoral GDP shocks to proxy overall income loss of workers in each sector.
- **Random allocation method:** this method is employed to produce the benchmark results in the related cross-country comparative working paper by Lastunen et al. (2021). The main reason being that at the time of writing nationally-representative microdata collected during the pandemic is only available for Uganda.
- **The WBPS Uganda:** we discuss the main characteristics and variables of interest for our purposes and discuss different approaches to construct income loss in the data. Furthermore, we compare the WBPS to the 2016/17 Uganda National Household Survey (UNHS), which underlies UGAMOD.

- **Transition method (regression-based):** this imputation method uses individual-level microdata from the WBPS for Uganda, the only country out of the countries analysed in Lastunen et al. (2021) that had released the necessary data at the time of writing.[1] We use this approach in the main research paper as a sensitivity analysis for Uganda to check the robustness of the random-allocation method.
- **Comparison between random-allocation and regressions-based method:** we close with a comparison between the random-allocation method and the regression-based approach.

2 Short background on survey data underlying the standard SOUTHMOD tax-benefit microsimulation models and relationship with external data

SOUTHMOD tax-benefit microsimulation models are based on nationally-representative household surveys with rich information on household characteristics, different types of incomes and consumption.

For the purposes of the related working paper we need to adapt the datasets to reflect households' situation just before the COVID-19 pandemic struck in those countries (thus March 2020), and the situation throughout 2020, the focus of our analysis. This leaves us in a nutshell with two datasets:

- **Pre-crisis dataset: no shock scenario**
  - Most recent country-specific standard microdatasets used in the respective country's tax-benefit microsimulation model are uprated and re-weighted so that they match with population projections for the first quarter of 2020.
- **Crisis dataset: COVID-19 scenario**
  - COVID-19 effects are implemented through labour market shocks using either a static or a dynamic approach. Deviations of sectoral GDP in 2020 from pre-COVID-19 in 2017–19 are used as proxies for income losses.
  - The data cover the whole year of 2020, thus including also the first quarter of 2020 when the pandemic had yet not affected the countries under consideration.

For Uganda — the country used as an example in this note — the survey underlying UGAMOD, the tax-benefit microsimulation model for Uganda, is the 2016/17 Uganda National Household Survey (UNHS).

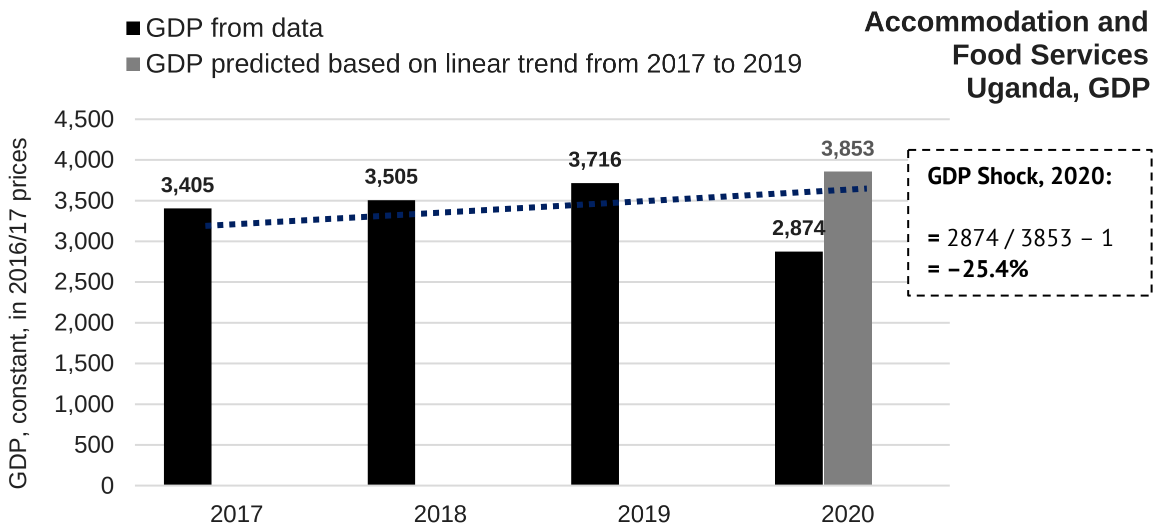
3 Estimating sectoral GDP Shocks

Estimating the deviation of 2020 GDP from pre-COVID trend. First, we gather annual or quarterly industry-level GDP data from each country under consideration for years 2017 to 2020 (see Table 1 in related working paper by Lastunen et al. (2021)). After annualizing the GDP figures, we then compute the economic shock in 2020; i.e., the deviation of 2020 GDP for each industry

[1] Note that similar surveys are under way or have been conducted in all other countries, but data has not (yet) been released (in full) at the time of writing.

from its pre-COVID-19, 2017–19 linear trend, accounting for inflation. Figure 1 shows the calculation of this shock for the accommodation and food services sector in Uganda (-25.4 per cent). The shocks calculated for each industry in each country are shown in Figure 2, and in the Appendix we present the GDP shocks for all countries.

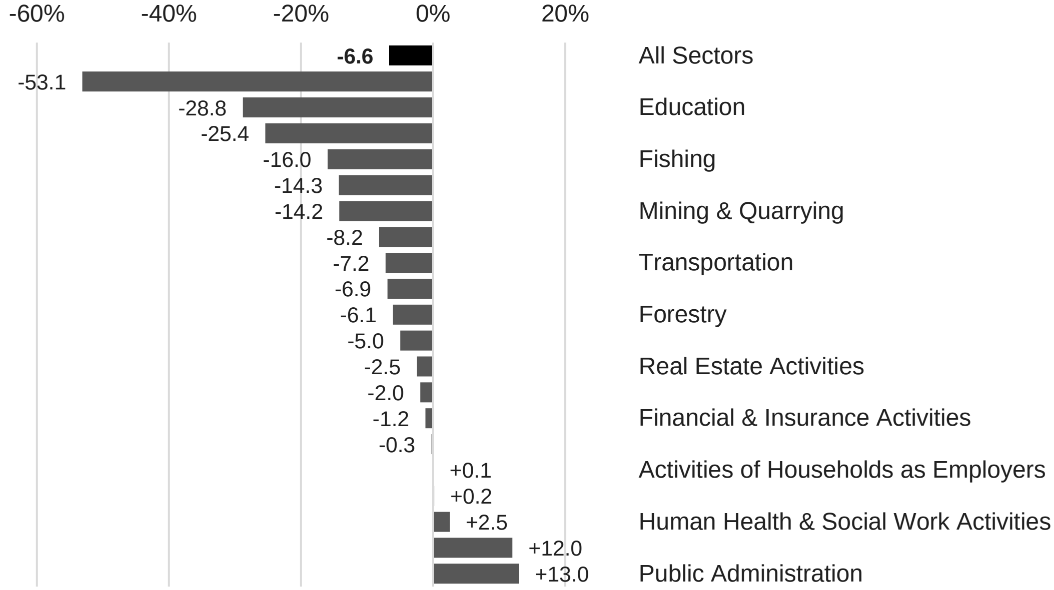
Figure 1. Example of the computation of the GDP shock: accommodation and food services, Uganda



Source: authors' elaboration based on national GDP data (quarterly GDP at constant 2016/17 prices up to Q4/2020, Uganda Bureau of Statistics, National Accounts, March 2021).

Industry matching: we then match the industry categories available for the shock estimates (available for 10–30 industries) with the industry categories available in the underlying survey data and hence pre-crisis datasets (available for hundreds of narrowly-defined industries; most countries follow the ISIC system). An individual industry in the 'shock data' can in most cases be directly matched with several 4-digit ISIC industries in the pre-crisis dataset.

Figure 2. Industry-level GDP shocks in 2020, Uganda (industry classification as in UNHS)



Source: authors' elaboration based on national GDP data (quarterly GDP at constant 2016/17 prices up to Q4/2020, Uganda Bureau of Statistics, National Accounts, March 2021).

4 Imputation of income loss via random allocation of shocks

The next step is **distributing industry-level shocks to the individual level.** In each industry, we reduce total labour income (employment, self-employment, and agricultural income) by the same percentage as indicated by the GDP shock estimate for that sector (only negative shocks are considered). This is achieved by assigning a certain number of workers to unemployment with zero income in the corresponding sector. For instance, a -25.4 per cent GDP shock in the accommodation sector in Uganda means that labour income is reduced by 25.4 per cent in that sector, with randomly selected workers losing their labour income.

Given the many industries with a limited number of workers, we need to guarantee an exact match between a given industry-level shock value to labour income lost in that sector by cutting incomes for employees that remain employed by a given (small) portion. Note that the main assumptions here are two-fold: factor shares remain constant because of the pandemic and all adjustment occurs at the extensive margin (i.e., complete employment and income loss for specific workers instead of partial income loss for a larger number of workers). The latter assumption is tested for Uganda in the next section, using more detailed data on income transitions during the crisis.

4.1 Detailed steps for 'shocking' individual incomes

1. Calculate total labour income for each worker. For workers in the agriculture/fishing sector (still with les=1, 2 or 3), and for those with no other types of employment income, we include general employment income, self-employment income, *and farm income*. For workers in other sectors, we exclude farm income. The idea is that shocks from COVID-19 to, say, the financial sector, do not influence farm incomes earned by workers who primarily work in the financial sector.
2. Some respondents are assigned to an industry despite not being in the labour market (variable les≠1/2/3) and/or not earning any labour income. We assume that these individuals do not work in any industry (at least in any meaningful way): the value for belonging to any industry is removed for these respondents.
3. We then calculate (A) the total labour income *earned* in an industry, and (B) the total labour income *lost* in an industry due to COVID-19. The latter comes from multiplying (A), total income earned, by the %-shock estimated for a given industry. Only negative shocks are considered. Industries for which positive output shocks are estimated are assumed to be unaffected by COVID-19.
4. Next, considering only workers who are in the labour market and have positive labour incomes, we randomly choose individuals to become unemployed with zero incomes based on the COVID-19 shock in each industry. This is achieved by
    a. randomizing workers within each industry;
    b. calculating the *cumulative* total labour income for each respondent within the industry (multiplying by survey weights); and
    c. assigning a 'lose_job' flag for workers for which this *cumulative* total labour income falls below the total labour income *lost* in an industry due to COVID (calculated in step 6).
5. As a result, a specific share of workers in each industry are assigned to become unemployed in a way that *the total income lost in an industry* is as close to *the output shock estimated for that industry* as possible. The remaining adjustment is to reduce incomes to zero for the newly unemployed workers who previously had positive incomes. Note again that farm income

is only adjusted for workers in the agricultural sector or those with no other types of income working in other sectors.

6. Given that many industries have a small number of workers, we need to guarantee an exact match between (A) a given industry-level output shock and (B) labour income lost in that industry. This is achieved by cutting incomes for employees that remain employed (after the employment adjustment) by a certain amount.
7. For an exact match, we first calculate the percentage difference between the income that *should* be lost due to COVID-19 (based on the shock estimate for each industry) to the income lost after the initial employment adjustment in each industry. This is usually around 0–5 per cent depending on the industry.
8. Employment income, self-employment income and farm income are reduced for the still-employed workers (with positive incomes) by that percentage. Again, since farm income is only included in the total income calculations when it is earned by those in the agricultural sector, farm income is only reduced also here (in the final stage) for the workers in that industry. This final income adjustment is done regardless of labour market status.

5 The WBPS for Uganda

5.1 Brief overview of the WBPS for Uganda

The WBPS is a monthly phone interview with a national sample of households interviewed in the latest round of the Uganda National Panel Survey (UNPS) 2019/20 (wave 8). Towards this end, the WB is leveraging the Living Standards Measurement Study – Integrated Survey on Agriculture (LSMS-ISA) programme to support the high-frequency phone survey for some countries, as in the case of Uganda. For other countries, different World Bank departments are responsible to provide technical assistance. These surveys are financed by the US Agency for International Development and in collaboration with the World Bank Poverty and Equity Global Practice (GP). The main goal is to track responses to and socioeconomic impacts of the COVID-19 pandemic in Uganda.

The first case of COVID-19 in Uganda was confirmed on 22 March. Nevertheless, the government of Uganda had already implemented the first policies aiming to curb the spread of the disease on 18 March, including a 14-day quarantine requirement for incoming travellers, cancellation of conferences and public events.

Currently there are four rounds of the survey available for Uganda; a fifth was conducted in March of 2021 but has not yet been concluded. Table 1 shows the dates of the data collection and the sample size across the five rounds:

Table 1: Characteristics of data collection in the WBPS, by survey round

Round	Starting date	Number of days	Sample size
Round 1	3 June 2020	16	2,225
Round 2	30 July 2020	20	2,189
Round 3	14 September 2020	16	2,169
Round 4	29 October 2020	16	2,129
Round 5	March onwards 2021	-	-

Source: WBPS Uganda.

5.2 Main characteristics of the variables of interest

- The data is nationally representative.
- The sample of the WBPS is a subsample of households covered in the Uganda National Panel Survey (UNPS) 2019/20 (wave 8). UNPS 2019/20 interviewed 3,098 households, of which 2,333 were in urban areas, and 745 in rural areas. The UNPS asks households to provide a phone number either belonging to one of its household members or a phone number of a reference person. In wave 8, 2,386 households provided a phone number (UBOS 2021).
- To obtain a nationally-representative sample for the COVID-19 Impact Survey, a sample size of approximately 1,800 successfully interviewed households was targeted. However, in phone surveys it is common that either respondents do not respond to enumerators calls (non-response) or the number provided is not valid (anymore, non-contact). Therefore, all households of the 2019/20 round of the UNPS that had phone numbers for at least one household member, or a reference individual were ultimately included to the initial sample for the WB phone survey (UBOS 2021).
- 2,245 households were reached, and 2,227 households accepted to participate in the interview, which is 72 per cent of the UNPS 2019/20 sample. Out of the 2,227 households interviewed in round 1, 2,199 (93 per cent) were interviewed in round 2; 2,147 (91 per cent) in round 3; and 2136 (90.5 per cent) in round 4.
- The survey is directed at the respondent who reports information on their own behalf and for the rest of the household. Table 3 below shows that almost 70 per cent of respondents are household heads. Despite this fact, the use of sample weight guarantees that the data is representative.

  For the purpose here, it is particularly worth noting that the data provide information on employment and industry at the respondent level while the information on income variation is reported on the household level only.

Table 2 presents the main variables of interest for our purpose across survey rounds and the level at which they are reported (respondent, household member, household). The data further has information on whether the respondent lives in a rural or urban area and in which region of the country they live. The data also allows to distinguish between formal and informal sectors.

Table 2: Summary of main variables

Variable	Round 1 Jun 2020	Round 2 Jul 2020	Round 3 Sep 2020	Round 4 Oct 2020	Level
Employment status at the time of interview	x	x	x	x	Respondent
Employment status before COVID-19 outbreak (March 2020)	x				Respondent
Industry	x	x	x	x	Respondent
Reason for the job loss	x	x	x	x	Respondent
Type of work: family farm, self-employment, employee for someone else	x	x	x	x	Respondent
Income variation:					
… relative to March (the month of the Covid-19 outbreak)	x				Household
… relative to the last interview		x	x	x	Household
… over the last 12 months				x	Household
Socioeconomic characteristics such as sex, age, and status in the household	x	x	x	x	All household members

Source: WBPS Uganda.

5.3 Information on job loss and modelling of job loss

- Information is asked only for the respondent themself, not for any other household member, for each round of the survey.
- Respondent reports whether they held a job in the week preceding the interview.[2]
- In round 1 there is a retrospective question on employment status before the crisis hit (March 2020).
- Respondent reports reasons for job loss, including COVID-19 and related lockdown measures.
- When showing results for job loss for each round, we use information on job status in the current round and whether the status has changed compared to the situation a week earlier.
- When taking a longer term, yearly perspective: We restrict the data to those who reported that they had a job before COVID-19 hit (thus in March 2020, retrospective information from round 1). We then categorize any job loss due in any of the rounds as losing one's job, even if the respondent was back in a job in a later round. This approach is taken mainly regarding COVID-19-related job loss in combination with information on income loss (see later).

[2] Specifically, the question is worded as follows: "Last week, that is from Monday up to Sunday, did you do any work for pay, do any kind of business, farming or other activity to generate income, even if only for one hour?"

5.4 Information on income variation

- No income values are reported; only the direction of variation of household income is reported (increase, decrease, or constant), thus no levels of income changes are reported.
  - In rounds 1, 2, 3, 4, information on whether the household level income stayed the same, increased, reduced, or was entirely lost in the last four weeks, is reported.
  - In round 4, information is reported on whether household income stayed the same, increased, or reduced in the last 12 months.
- Variation of household income is split into three types of income (respective variable names used in SOUTHMOD in parentheses):
  - agricultural income (-> yag),
  - self-employment income (-> yse), and
  - employment income (-> yem).
- No information on income variation is available at the level of the respondent or any other household members.
- No reasons for income changes are reported.

5.5 Descriptive statistics

Table 3 shows the distribution of respondents by relationship with the household head. Most of the respondents are the household head him/herself or the household head's spouse. In round 1, 66 per cent of the household heads are male, and 93.1 per cent of the spouses are women. Household heads are 47.8 years old on average, while spouses are on average 41.3 years old. Furthermore, 73.46 per cent of respondents live in rural areas. 4.63 per cent live in the capital area of Kampala, 22.18 per cent in the Central region, 24.61 per cent in the Eastern region, 23.53 per cent in the Northern region, and 25.06 per cent in the Western region.

Table 3: Relationship of respondents with household head across rounds, age and gender structure in round 1

Respondent's relationship to the household head	R 1	R 2	R 3	R 4	Round 1		
					Male (in %)	Age*	Number of jobs
Head	67.6	68.3	69.0	68.4	66.0	47.8	1390
Spouse	18.3	18.2	18.3	18.0	6.9	41.3	377
Own child	12.8	12.2	11.6	12.1	57.2	14.0**/19.5***	264
Step child	0.0	0.1	0.2	0.2	100.0	20.0	1
Grand Child	0.9	0.9	0.7	1.0	38.9	11.3	18
Brother\sister	0.1	0.0	0.0	0.1	0.0	31.5	2
Niece\nephew	0.1	0.1	0.1	0.1	50.0	19.0	2
Parent	0.0	0.0	0.0	0.0	0.0	89.0	1

Notes: * a table with the distribution of the respondents' age is available by request. ** Average across the sample. *** Average restricting the sample to those aged 10 or older.

Source: WBPS Uganda.

Table 4 shows the distribution of respondents across different types of work. The numbers show that most respondents are working on a family farm (row 3), followed by respondents working as an employee (rows 2, 4, 5), and self-employed individuals (row 1).

Table 4: Distribution (%) of the respondents across different types of work

Type of work	Round 1	Round 2	Round 3	Round 4
(1) In your own business	19.39	22.94	19.27	18.50
(2) In a business operated by a household or family member	4.15	3.00	2.55	3.09
(3) In a family farm, raising family livestock or fishing	57.61	56.41	63.62	59.96
(4) As an employee for someone else	18.62	14.24	14.47	12.93
(5) As an apprentice, trainee, intern	0.23	3.41	0.09	5.51

Source: WBPS Uganda.

Table 5 provides the industry breakdown for respondents' economic activity. The respondents are only those with employment at the time of the interview. Most respondents work in agriculture, wholesale, and retail trade, followed by the education and the services sector. Discussion of how we deal with missing information in the main industry variable and impute the information from previous rounds and information on job changes is available from the authors on request.

Table 5: Distribution (%) of respondents by industry

Industry	Round 1	Round 2	Round 3	Round 4
Agriculture	61.76	56.41	58.54	57.93
Mining, Energy, Utilities	1.33	1.09	1.20	1.10
Manufacturing	3.83	5.53	4.93	4.90
Construction	3.90	2.95	3.87	3.67
Services	4.67	5.58	5.69	5.72
Public Administration	1.48	1.86	1.79	1.87
Education and Science	8.83	10.27	8.83	11.08
Wholesale and Retail Trade	13.47	15.83	14.74	13.33
IT, Tech and Finance	0.72	0.49	0.42	0.41

Source: WBPS Uganda.

Table 6 presents descriptive statistics on respondents' job loss in three parts. The first part shows for each round the number of respondents reporting that they held a job and the number of those without a job. The second part of the table shows the self-reported causes of the job loss. Aggregating these answers, COVID-related reasons explain 75.61 per cent of job losses reported in round 1.

The last part of the table presents the job dynamics across rounds. In round 1, 17.56 per cent of respondents lost their job, and 13.21 per cent reported that they lost their job due to COVID-19. As of round 2, thus after June, relatively less job losses are reported in the following rounds. Similarly, the share of job losses attributed to COVID-19 decreases across rounds from 13.2 per cent to 3.42 per cent.

Looking across time, 90.80 per cent of respondents who initially reported having a job, also had a job in October 2020, disregarding what respondents' status was between these points in time (second last row of Table 6). When considering the job status of respondents in each round simultaneously, 70.80 per cent of respondents in a job pre-COVID, reported having a job every single round up till October (last row of Table 6).

Table 6: Job dynamics and reasons for job loss

Did you work in the last week?	**R1**	**R2**	**R3**	**R4**
Yes	1528	1665	1651	1609
No	326	163	162	163
Why did you stop working?	**(% of those who lost job in round)**			
Business / gov't closed due to COVID-related legal restrictions	**60.47**	**40.96**	**22.75**	**2.73**
Business / gov't closed for another reason	2.36	1.95	8.67	4.62
Laid off while business continues	0.37	0.00	0.28	0.00
Furlough	8.35	2.15	0.20	0.00
Vacation	0.00	0.69	0.00	3.11
Ill / quarantined	**10.14**	**27.47**	**28.02**	**43.16**
Need to care for ill relative	1.01	5.68	8.06	7.77
Seasonal worker	3.27	3.67	10.60	0.63
Retired	0.95	0.00	3.50	0.00
Not able to go to farm due to movement restrictions	**0.90**	**0.17**	**0.00**	**0.00**
Not able to farm due to lack of inputs	0.19	0.16	0.00	0.00
Not farming season	2.37	5.49	3.14	20.47
Lack of transportation	3.51	0.14	0.00	0.00
Do not want to be exposed to the virus	**4.09**	**0.00**	**0.00**	**0.00**
Other (please specify)	2.01	11.47	14.78	17.51
Was COVID-19 the reason of the job loss?	**(% of those who lost job in that round)**			
No	24.39	31.40	49.91	54.12
Yes	75.61	68.60	50.76	45.88
Job dynamics	**R 1**	**R 2**	**R 3**	**R 4**
Share of respondents who lost job, per round	**(in %)**			
In general	17.56	8.91	8.93	9.19
Due to COVID-19	13.21	4.37	3.03	2.43
Share of respondents who had a job pre-COVID-19 …				
and in round 4 (in %)	90.80			
and consistently across each round (in %)	70.80			

Note: all statistics were obtained using sample weights.

Source: WBPS Uganda.

Altogether, the data suggest that while initially people experienced sizable job losses, many recovered their jobs or found new jobs, and over time only a small share of those who lost their job attribute it to the COVID-19 pandemic and/or related policy measures.

The upper panel of Table 7 shows that in round 4, 83.3 per cent of respondents report household income from agriculture, a third reports household income from wage employment, and a little more than half report income from self-employment.

The lower panel of Table 7 shows how household incomes for different types of income varied across industries. For this exercise we combine information on industry at the respondent level with information on income changes at the household level. We focus on information on income changes as provided in round 4 since it relates to income variation regarding the last 12 months and not only to the time of the previous interview.

For lack of information on household members' industry, we assign income variation on the household level to the industry reported by the respondent. For example, if a respondent is in construction and reports variation in incomes from wage and self-employment income, we will assign both those variations to the construction industry.

Income from agriculture is a special case: we assign variation in agricultural income (yag) strictly to the agricultural sector in its three types (yag, yem and yse). As has been previously done to the input data, we let other industries override agriculture. Thus, if a respondent has positive agricultural income but assigns themself to the services sector, the person will be assigned to the service sector. However, the agricultural income will not be used to account for their total income.

As income variation is reported for three different types of incomes (yag, yem, and yse), it is important to bear in mind that a respondent might provide information on income variation for one, two, or three types of income.

Table 7 shows that the largest decrease in household income from wage employment is observed in wholesale and retail trade; 57.7 per cent of respondents in that industry reporting household income from wage employment, report a decrease in income, whereas 22.7 per cent report unchanged income, and the rest (19.6 per cent) an increase of income from that type of income. The smallest decrease in wage employment income is observed in public administration with 7.6 per cent of respondents reporting a decrease out of all respondents with household wage income and the respondent's industry being public administration. For self-employment income the largest decrease is registered in mining, energy, and utilities with more than three quarters of respondents reporting a decrease in income, followed by manufacturing (61.1 per cent), agriculture (60.8 per cent), IT, tech, and finance (58.4 per cent), and wholesale and retail trade (56.1 per cent). Altogether, variations for income from self-employment are larger in size than for income from wage employment.

Table 7: Variation in household income types, across types of income and by respondent's industry

Type of income[1]	Agricultural (yag)			Wage (yem)			Self-empl. (yse)		
Share of respondents with positive household income in round 4, by type of income (in %):	83.3			33.6			53.1		
	Share of respondents reporting income change of … out of all respondents reporting this type of income and specific industry (in %)								
Income variation in the last 12 months: Industry:[2]	Same	Above	Below	Same	Above	Below	Same	Above	Below
Agriculture	34.2	26.4	39.4	33.5	16.0	50.5	10.8	28.4	60.8
Mining, Energy, Utilities[3]				74.7	4.5	20.8	0.0	24.5	75.5
Manufacturing				48.7	36.7	14.7	4.2	34.7	61.1
Construction				29.3	35.2	35.6	0.0	47.5	52.5
Services				47.4	16.5	36.1	4.9	47.8	47.3
Public Adm.				92.4	0.0	7.6	5.0	66.9	28.2
Education and Sci.				64.0	8.7	27.3	14.0	35.4	50.6
Wholes./Retail Trade				22.7	19.6	57.7	11.5	32.4	56.1
IT, Tech and Finance[3]				78.3	2.9	18.8	5.0	36.6	58.4

Note: (1) Income changes as recorded at the household level. Income change as reported for the last 12 months. (2) Industry as reported by the respondent. (3) Mining, energy, utilities, and IT, Tech and Finance suffer from very low case numbers, also see next table.

Source: WBPS Uganda, round 4.

Next, we want to break income changes down by industry regardless of the type of income to produce the share of respondents who experienced a decrease in household income by industry (Table 8: columns 1, 2). We proceed in two steps:

1. First, we identify the change in total household income across the different income types for each respondent:
   a. If the respondent's industry is agriculture, their total household income variation may be composed of changes in agricultural income (yag), self-employment income (yse), and/or wage (yem).
   b. If the industry is not agriculture, their total household income variation is composed of changes in self-employment and/or wage employment income (yse and yem respectively).
2. Second, if the respondent reported a reduction in at least one of their income types in the last 12 months, we define overall income as reduced. A potential concern could be that some respondents could report an increase in one income type and a decrease in another income type. This occurs in 0.71 per cent of the sample only and in such cases, we consider the total household income as being reduced.

Column 1 in Table 8 shows the total number of respondents with at least one income type by industry. Mind that Mining, Energy, and Utilities and the IT, Tech and Finance sectors suffer from low case numbers. Column 2 shows the share of respondents who saw a reduction in at least one income source. For example, 55.2 per cent of respondents working in agriculture and 39.3 per cent working in services reported a decrease in household income in the last 12 months.

Variations in income may or may not be related to job loss due to COVID-19 and related lockdown measures. To identify income losses that are related to COVID-19 as compared to general income losses that might have occurred anyway, we combine the above analysis on income loss by industry with the information on COVID-19 related job losses (Table 8: column 3).

Table 8. Share of respondents with reduced household income and job loss over last 12 months, by industry

		Share of respondents with decreased household income (in %)	
	Number of observations	Disregarding job loss and reasons thereof (wide definition)	Restricted to those respondents who experienced job loss (narrow definition)
	(1)	(2)	(3)
Agricultural employment (yag), wage employment (yem) and self-employment (yse)			
Agriculture	1028	55.2	7.0
Wage employment (yem) and self-employment (yse)			
Mining, Energy, Utilities	17	60.8	1.9
Manufacturing	68	48.4	5.7
Construction	41	34.6	1.9
Services	86	39.3	11.6
Public Administration	27	15.9	4.6
Education and Science	128	39.2	14.6
Wholesale and Retail Trade	256	53.2	19.5
IT, Tech and Finance	10	42.2	32.1

Source: WBPS Uganda, rounds 1 through 4. Information on income variation from round 4; information on lob loss and industry rounds 1 through 4.

For that purpose, we identify respondents who had a job pre-COVID-19 and reported a job loss because of COVID-related reasons in at least one of the four rounds. If the respondent reported a job loss and an income reduction over the last 12 months in round 4, they are is classified as having lost household income due to COVID-19 ('Reduced because of COVID'). Everyone else including those who reported a job loss but not an income loss is not classified as suffering an income loss due to COVID-19.

Column 3 in Table 8 shows that the share of those with a reduction in income coinciding with a job loss due to COVID-19 is much lower than the share of those reporting an income reduction (column 2) across all industries. In agriculture, for example, only 7 per cent reported a job loss due to COVID-19 and related reasons together with an income reduction in the last 12 months; by contrast, 55.2 per cent of all respondents active in agriculture (regardless of job loss) reported a decrease in income. The difference in shares of respondents experiencing income losses between columns 2 and 3 is least pronounced for the wholesale and trade, services, and public sector.

Column 3 shows a narrow view of COVID-19-specific income decreases, no spillover effects of the COVID-19 measures to other parts of economic activity are captured. On the other hand, column 2 is too broad as it includes all other income reductions beyond the direct and indirect impacts of COVID-19 and related measures.

5.6 Comparison of the WBPS with the UGAMOD pre-crisis input data

In this section we compare the WBPS and with the pre-crisis input data of UGAMOD. Specifically, we focus on variables of interest for this exercise, most importantly industry and the type of income.

Table 9 shows that the shares of respondents by industry, type of income and region compare well across the two datasets.

Table 9: Main variables of interest across WBPS and the reweighted, pre-crisis UGAMOD input dataset, share of respondents (in %)

	Pre-crisis UGAMOD input data	WBPS
Industry		
Agriculture	71.9	67.98
Manufacturing	3.14	3.67
Construction	1.89	2.75
Wholesale and Retail Trade	9.12	13.03
Education	2.09	1.11
Others	11.86	11.46
Type of income		
Family Farm	59.71	63.00
Own Business	16.35	17.75
Employee	23.93	19.25
Region		
Central	21.64	22.18
Eastern	28.53	24.61
Northern	25.34	23.53
Western	24.5	25.06
Kampala[1]		4.63

Note: [1] In the World Bank Phone Survey, the capital Kampala is considered separately, but in the official regional division of the country Kampala is part of the Central region.

Source: WBPS round 1 with imputations from other rounds for industry.

Table 10 shows the share of households reporting a specific type of income. We split Table 10 into two parts to show two alternative options when comparing across datasets given that the datasets are structured differently.

For the WBPS, the respondents report different income types on the household level. For the pre-crisis UGAMOD input dataset, we have information on income types at the individual level. We treat households with more than one income type at the level of different household members in the following manner: consider households with at least one individual with a positive income for each of the three income types. For example, in household 1 the head has positive agriculture income, and in household 2, the spouse has positive agriculture income. In both cases, the household will be considered as having agricultural income.

Provided the different structure of the two surveys, we show in the top panel of Table 10 information for all respondents in the WBPS versus all household members in the UGAMOD pre-crisis input dataset. In the bottom panel, we restrict both datasets of the household heads.

Table 10: Distribution (%) of households by income source

	WBPS				UGAMOD pre-crisis input dataset
	Round 1	Round 2	Round 3	Round 4	
	All respondents				All household members
Agriculture Income (yag)	78.7	84.1	83.8	83.3	63.3
Employment Income (yem)	31.3	32.5	33.8	33.6	25.4
Self-Empl. Income (yse)	47.3	52.3	51.4	53.1	46.0
	Household heads				Household heads
Agriculture Income (yag)	65.2	69.5	68.9	68.8	63.3
Employment Income (yem)	25.7	26.6	28.1	27.2	19.0
Self-Empl. Income (yse)	38.1	42.0	41.5	43.4	39.1

Note: Each household can have more than one income source. It explains the fact that the columns do not sum up to 100%.

Source: WBPS Uganda.

6 Imputation of income loss via modelling of labour market transitions (regression-based method)

Our approach consists of the following steps:

1. Organize the WBPS data so that we have at hand the following variables for each employed adult respondent in both datasets (specifically, those that were assigned to an industry and job in March 2020, i.e., pre-COVID in the WB data):
    a. *Definition of the share of respondents experiencing an income reduction (12-month change, all or different types of income)*: the survey asked, for each income source, and whether the household experienced an income reduction (1), or if the income stayed the same or increased (0);

       We employ the wide definition of income reduction thus considering all income losses that coincided with a job loss regardless of whether that loss was due to COVID-19 or not (wide definition, as presented in Table 8: column 2). Restricting the sample to respondents who experienced a job loss due to COVID-19 (Table 8: column 3), the shares of workers with reduced incomes appear unrealistically small. In our exercise, even if reducing their incomes by 100 per cent, does not achieve a reduction of each industry's wage sum equal to the sectoral GDP shock.

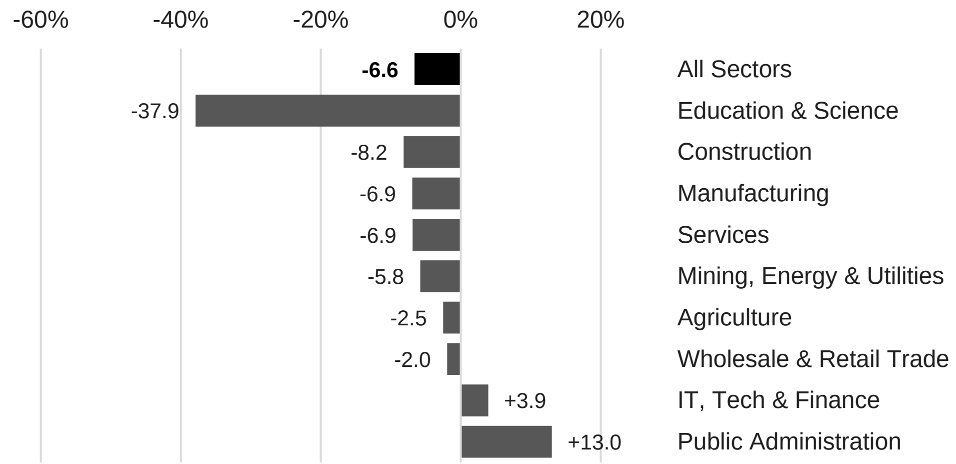
    b. *Harmonization of other variables across the WBPS and the UGAMOD input data:* Industry as well as other household characteristics that are common in both the

WBPS and UGAMOD input data.

2. Run a binomial logit model using the WBPS data to estimate the probability of income loss given different characteristics, using as:
    a. *Dependent variable,* the 12-month change in income (1 if reduced, 0 otherwise); and
    b. *Regressors:*
        i. age (e.g. in 10-year brackets);
        ii. female dummy;
        iii. urban dummy;
        iv. industry dummies;
        v. education dummies *(if comparable across datasets);*
        vi. interaction between the female dummy and education;
        vii. region/district variable *(if comparable across datasets);*
        viii. formal/informal dummy.

    These regressors largely match those used by Jara et al. (2021) and Barnes et al. (2021), with the exception of trade, occupation, and baseline earnings quintile which are not available in the WBPS.
3. Estimate the appropriate coefficients for the right-hand side variables (12-month earnings drop relative to baseline outcome of no earnings drop).
4. Use the coefficients from the model to predict the probabilities of (some) income loss for *adult respondents* in the 2020 pre-crisis UGAMOD input data. But, before reducing incomes for appropriate workers in the input data, we need to obtain overall labour income losses by industry. The current idea would be to make industry-level drops in overall labour income proportional to industry-level output shocks (2020 deviations in GDP from 2017–19 trend, *if negative*). This data is available for most SOUTHMOD countries as of 14 April 2021. For Uganda, these shocks are shown in Figure 2. Essentially, we calculate the total labour income loss across industries based on the corresponding percentage shocks.
5. For Public administration and IT, Tech and Finance sectors, we define no income changes. The share of individuals working in those industries and captured in the WBPS is too small (1.48 per cent and 0.72 per cent, respectively), and incorporating an income increase based on the GDP sectoral shocks brings another layer of complexity to the imputation procedure. Furthermore, it seems unlikely that these positive output shocks would have translated within such short time span into income increases for workers given wage rigidities.

Figure 3: Industry-level GDP shocks in 2020, Uganda, industry classification as in WBPS



Note: these industry categories differ slightly from the categories used in the random allocation method due to limitations in the World Bank Phone Survey data.

Source: authors' elaboration based on national GDP data (quarterly GDP at constant 2016/17 prices up to Q4/2020, Uganda Bureau of Statistics, National Accounts, March 2021).

6. Incomes can be reduced for adult respondents either at the intensive or extensive margin. Given limited permanent job losses over the course of 2020 according to the WBPS, we apply intensive margin income reductions. Based on the probability of *some* income loss for each positive-earning adult estimated in the pre-crisis UGAMOD input data above, the next steps are the following:

    a. For each industry, assign positive earners in the input data to a status of 'some income loss', respecting the probabilities derived from the model. For example, someone with a predicted probability of income loss of 0.1 would have only a 10 per cent chance of being assigned to this status.

    b. In each industry, we order individuals with positive incomes by probability of losing income. Then we select individuals as losing (some) income starting from those with the highest probability of losing income until the share of individuals losing equals the percentage of respondents who lost income in each industry according to the WBPS. There are now many adults with the status of 'some income loss'.

    c. Then, we randomly reduce incomes for all these individuals within a sector using the beta distribution, so that the overall reduction in labour income in that sector matches the sectoral GDP shock in Figure 3. Therefore, new incomes can be any value between zero (total reduction) and the original income (no reduction). Specifically, after imputation, 50 per cent of the sample had income reduced between 0 and 2 per cent, and 25 per cent of the sample had incomes reduced by values between 75 per cent and 99 per cent.

       For respondents with income losses we adjust all income sources. Specifically, in an example of a respondent with total income reduction equal to 15 per cent):

        i. First, identify how many income sources the respondent has.

        ii. If they have only one income source, yem, for example, reduce yem by 15 per cent.

iii. If they have two (three) income sources, yem and yse (and yag), reduce each income source by 15 per cent;

7. Translation of income changes into consumption follows the approach set out in the technical note by Lastunen (2021):

    a. Consumption loss is proportional to the income changes across *all household members* weighted by their respective contribution to overall household income.

    b. Negative consumption values: proportional reduction can result in negative consumption values. To avoid that, we protect a minimum amount of consumption.

7 Comparison between the random allocation and the transition method (regression-based approach)

With the transition method 11.67 per cent of the total sample were selected to lose (some) income. Table 11 shows in column 1 the estimated GDP reduction in each sector (positive shocks set to zero). Column 2 shows the total income reduction in per cent based on the random allocation method, while column 3 shows results for the transition method (regression-based approach). Values in columns 1 and 2 are not exactly the same because of approximation error. Values between column 2 and 3 deviate due to the different methods but also due to the different industry classifications used which is also affected by not translating positive GDP shocks into positive income shocks. Negative shocks are higher for a larger share of sectors with the industry classification used in the transition method than with the random allocation method.

Table 12 shows mean disposable and original income across quartiles for both methods. The slightly larger GDP shocks for the industry classification used in the transition method for most sectors carries over to larger decreased in original and disposable incomes.

Table 11: Comparison between GDP shock and income shock after imputation method by industry

Industry	GDP shock, positive values at zero (%)	Change in total income, random allocation method (%)	Change in total income, transition method (%)
All sectors	**-6.60**	**-7.07**	**-11.95**
Agriculture	**-2.52**	**-0.87**	**-2.65**
Agriculture	-0.25	-0.24	
Forestry	-6.10	-5.82	
Fishing	-15.99	-15.85	
Mining, Energy, Utilities	**-5.77**	**-8.47**	**-6.08**
Mining and Quarrying	-14.21	-14.14	
Energy[1]	0.00	0.00	
Manufacturing	**-6.92**	**-6.68**	**-7.05**
Construction	**-8.17**	**-8.02**	**-8.43**
Services	**-6.88**	**-9.07**	**-6.94**
Accommodation and Food Service Activities	-25.41	-25.02	
Administrative and Support Services	-14.29	-14.23	
Transportation	-7.20	-7.05	
Other Service Activities	-4.99	-4.79	
Real Estate Activities	-2.47	-2.47	
Activities of Households as Employers[1]	0.00	0.00	
Human Health and Social Work Activities[1]	0.00	0.00	
Public Administration[1]	**0.00**	**0.00**	**0.00**
Education and Science	**-37.89**	**-37.36**	**-38.08**
Professional, Scientific and Technical Activities	-53.12	-51.34	
Education	-28.81	-27.21	
Wholesale and Retail Trade	**-1.95**	**-1.90**	**-2.12**
IT, Tech and Finance[1]	**0.00**	**-0.92**	**0.00**
Information and Communication[1]	0.00	0.00	
Financial and Insurance Activities	-1.17	-1.15	

Note: total income refers to income from employment, self-employment, and agricultural income (variables yem, yse and yag). (1) In these sectors, either detailed or aggregated, there was no income reduction based on the sectoral GDP shock. Note also that in the random allocation method, GDP shocks are matched for the detailed industries (second level with the exception of manufacturing, construction, public administration and trade), while in the transition method, GDP shocks are matched for the aggregated industries.

Source: authors' elaboration using national GDP data (quarterly GDP at constant 2016/17 prices up to Q4/2020, Uganda Bureau of Statistics, National Accounts, March 2021), the Uganda National Household Survey (UNHS), 2016–2017, and World Bank High-Frequency Phone Surveys in Uganda, 2020.

Table 12: Changes (%) in mean disposable income and original income for the whole population and across quartiles, comparing the random allocation method and the transition method

	Random allocation method (%)	Transition method (%)
Original income, mean	**-5.82**	**-7.43**
Quartile 1	-0.26	-1.28
Quartile 2	-0.74	-2.05
Quartile 3	-2.31	-4.13
Quartile 4	-7.10	-8.05
Disposable income, mean	**-5.28**	**-6.86**
Quartile 1	-0.25	-1.34
Quartile 2	-0.72	-2.12
Quartile 3	-2.24	-4.23
Quartile 4	-6.50	-8.68

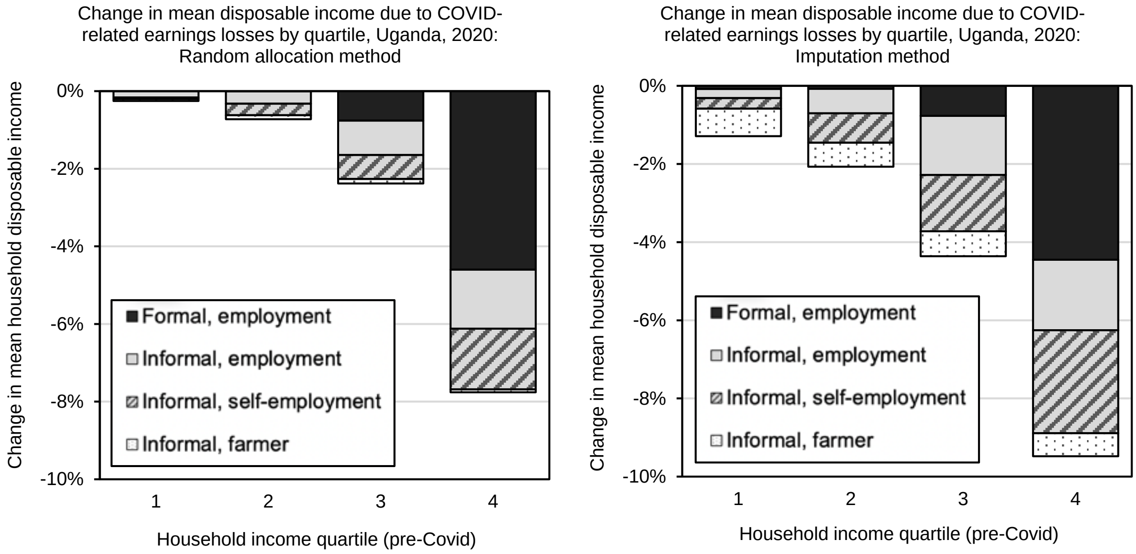
Note: mean drops in disposable income across quartiles match with the decomposition figures. Mean drops in original income are in turn calculated using pre-crisis original income as the comparison instead of pre-crisis disposable income (as in the decomposition calculations). Original income includes income from employment, self-employment and agriculture. It further includes other though less important income sources that are untouched by the imputation methods (such as pensions), as these income components are relevant to the calculation of disposable income.

Source: authors' elaboration using the Uganda National Household Survey (UNHS), 2016–2017, and World Bank High-Frequency Phone Surveys in Uganda, 2020.

Figure 4 shows how earnings losses due to COVID-19 carry over to disposable incomes across the distribution of disposable income and distinguishing between employment type. It thus also captures any offsetting effects of the tax-benefit system which buffers in this case the earnings shocks of those in the formal sector through reduced personal income tax and social security contributions.

By definition, the random allocation method (left panel in Figure 4) leads to earnings contributing to declines in disposable incomes in proportion to the shares of different employment types in a given industry. The regression-based method (right panel in Figure 4) in turn allows for earnings shocks to vary based on individual characteristics as derived from the WBPS, which also leads to a more fine-grained picture regarding the types of workers who ultimately lose disposable income. With the regression-based method the average contribution of earnings to losses in disposable income barely changes for those in formal employment. However, the contribution becomes greater for those in the informal sector across the income distribution. This applies particularly to those in the upper-half of the income distribution and especially to informal farmers and informal self-employed.

Figure 4: Change in mean disposable income only due to earnings losses from COVID-19 by income quartile and employment type using the random allocation method (left) and imputation method (right)



Note: the figures show decomposition outcomes derived using the random allocation method (left) and the imputation method (right). The figures decompose the earnings losses resulting across COVID-19 across mean losses for different employment types. In both figures, effects are shown separately for different income quartiles, derived from disposable household incomes in the pre-COVID scenario. All changes in earnings are based on per capita earnings at the household level.

Source: authors' elaboration using UGAMOD, the tax-benefit microsimulation model for Uganda, as well as data from the Uganda National Household Survey, UNHS 2016–17, and the World Bank High-Frequency Phone Survey in Uganda 2020.

Table 13 below shows how these changes feed through to poverty and inequality measures as presented in Lastunen et al. (2021). The direction and size of effects do not diverge drastically for poverty. However, the impact on inequality, albeit small, changes direction and points to a slight decrease in inequality using the regression-based approach relating to the relatively larger decrease in disposable incomes at the top of the distribution.

Table 13: Impact of COVID-19 on poverty and inequality: Random allocation method vs. imputation method for Uganda

		No COVID scenario	COVID scenario	Total change (pp.)	Total change (%)
		(A)	(B)	(C)	(D)
Random allocation method	FGT(0)	71.40	72.80	+1.40***	+2.0
	FGT(1)	48.66	49.91	+1.25***	+2.6
	Gini coefficient	66.52	66.54	+0.02	+0.0
Regression-based method	FGT(0)	71.40	72.91	+1.51***	+2.1
	FGT(1)	48.66	49.78	+1.12***	+2.3
	Gini coefficient	66.52	65.92	-0.60***	-0.9

Note: the table presents estimates of the impact of the COVID-19 pandemic on measures of poverty and inequality in Uganda in 2020, applying either the random allocation method or the imputation method to allocate earnings shocks due to COVID-19. Columns (A) and (B) show the poverty rate, poverty gap and Gini coefficient in the scenarios without and with shocks from COVID-19. Outcomes are derived based on harmonized equivalence scales and a standard international poverty line (disposable income under $1.9 per day). Column (C) shows the overall impact of the crisis in percentage points (B–A). Statistical significance is based on bootstrapped standard errors after 200 replications. Significance levels indicated as * p < 0.1, ** p < 0.05, *** p < 0.01.

Source: authors' elaboration using UGAMOD, the tax-benefit microsimulation model for Uganda, the Uganda National Household Survey, UNHS 2016–2017, and World Bank High-Frequency Phone Surveys in Uganda, 2020.

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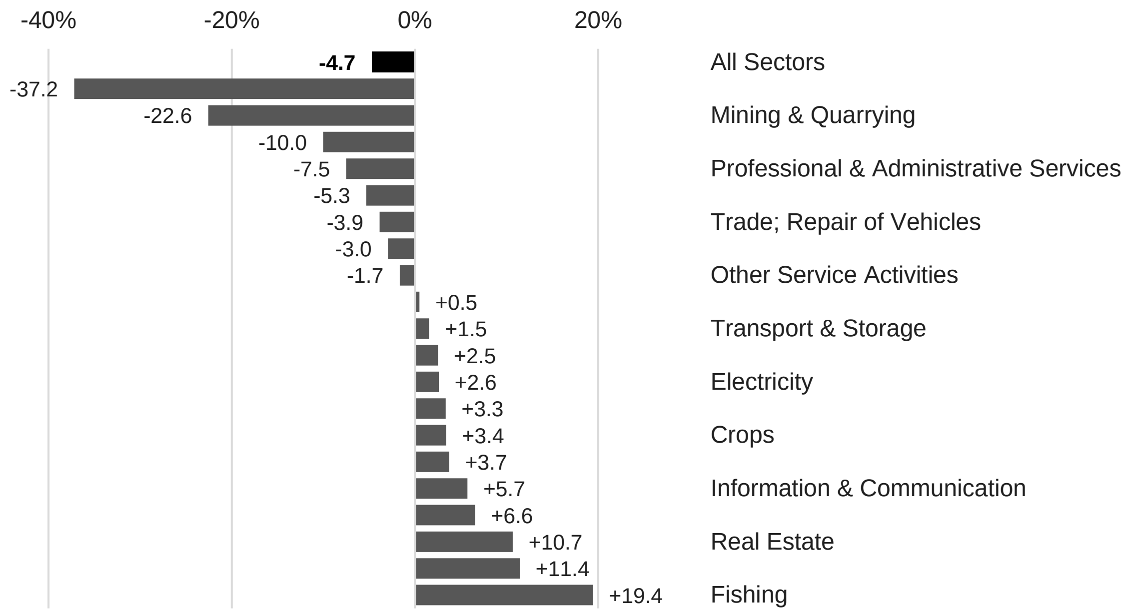
Appendix: GDP shocks for other countries

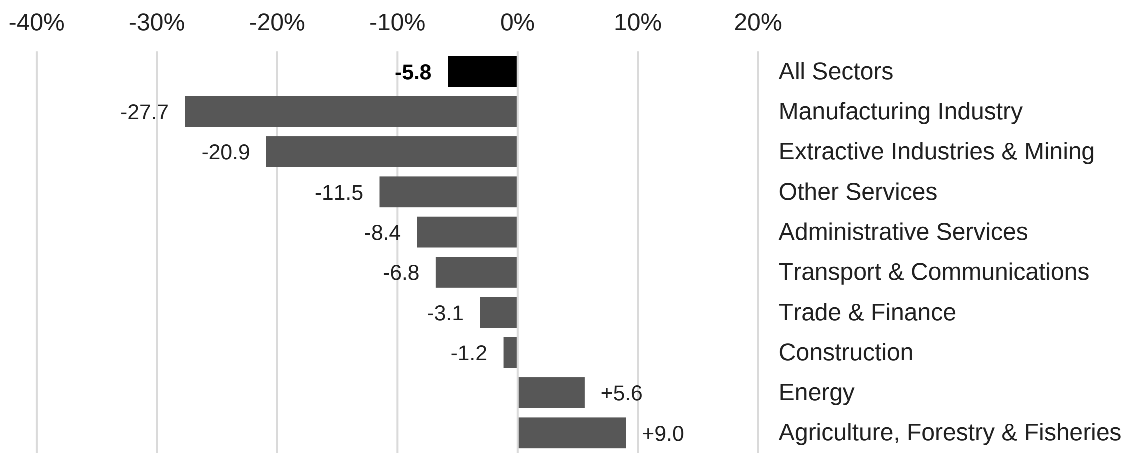
As discussed in Section 4, the shocks are derived as deviations in 2020 real GDP from their 2017–19 linear trend. See Section 3 for the data sources.

Figure A1: Industry-level GDP shocks in 2020, Ghana



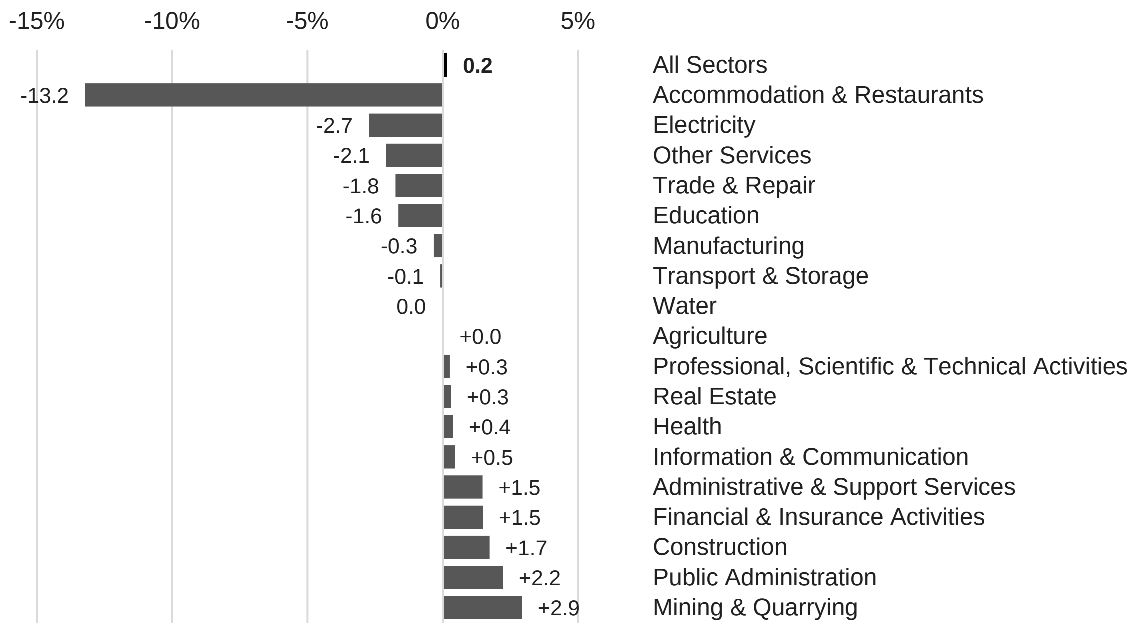
Source: authors' elaboration based on national GDP data (GDP at constant 2013 prices by economic activity, Ghana Statistical Service, May 2021).

Figure A2: Industry-level GDP shocks in 2020, Mozambique



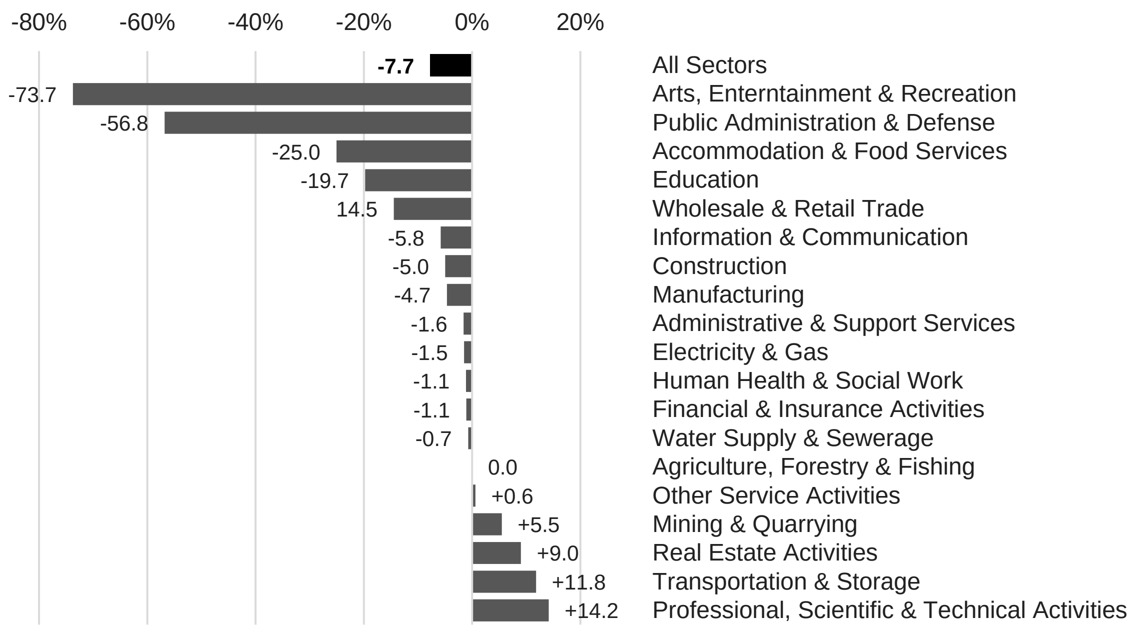
Source: authors' elaboration based on national GDP data (quarterly GDP at constant 2014 prices by industry, National Institute of Statistics, Mozambique, Publication of National Accounts IV for Q4/2020, February 2021).

Figure A3: Industry-level GDP shocks in 2020, Tanzania



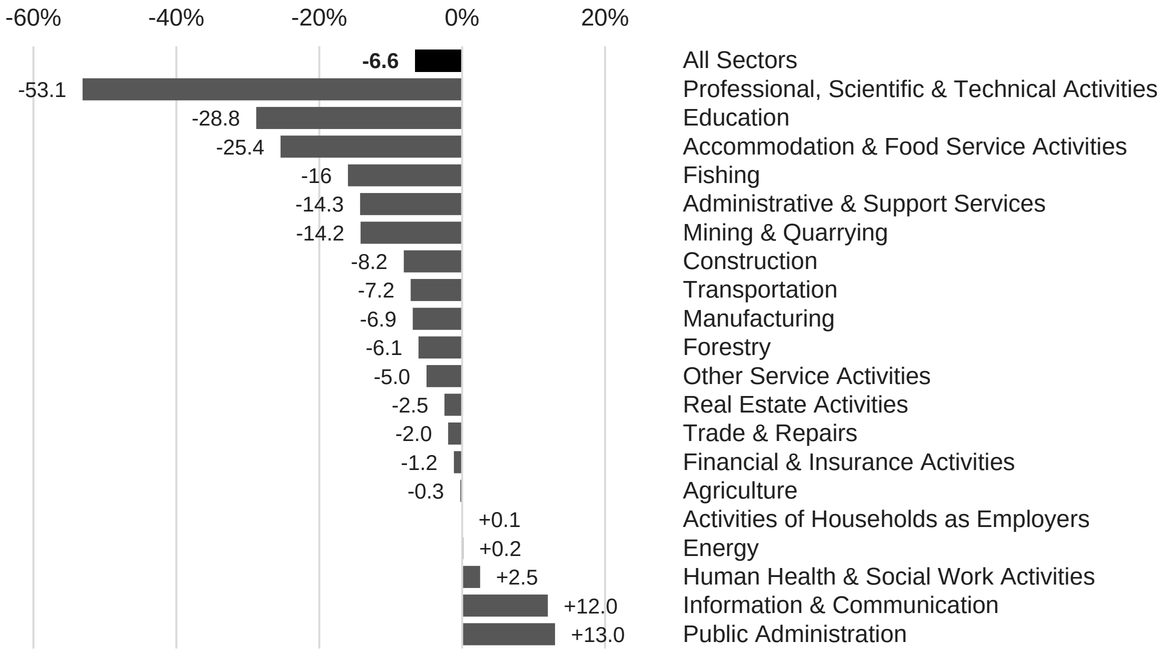
Source: authors' elaboration based on national GDP data (GDP at 2015 prices by economic activity; 2020 Q4 predicted based on 2017–19 Q4 GDPs; Tanzania National Bureau of Statistics, December 2020).

Figure A4: Industry-level GDP shocks in 2020, Zambia



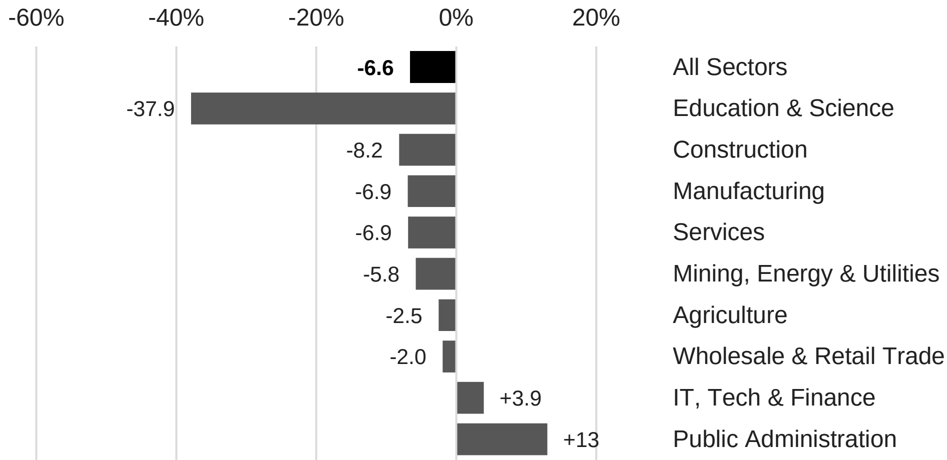
Source: authors' elaboration based on national GDP data (quarterly gross value added by industry at constant 2010 prices, Zambia Statistics Agency, Monthly Bulletins up to Volume 217, April 2021).

Figure A5: Industry-level GDP shocks in 2020, Uganda (random allocation method)



Source: authors' elaboration based on national GDP data (quarterly GDP at constant 2016/17 prices up to Q4/2020, Uganda Bureau of Statistics, National Accounts, March 2021).

Figure A6: Industry-level GDP shocks in 2020, Uganda (imputation method)



Source: authors' elaboration based on national GDP data (quarterly GDP at constant 2016/17 prices up to Q4/2020, Uganda Bureau of Statistics, National Accounts, March 2021).