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CENTRAL BANK OF MALTA WORKING PAPER



Assessing the impacts of the COVID-19 wage supplement scheme: A microsimulation study

Glenn Abela¹

WP/06/2022

¹ Glenn Abela is a Research Economist in the Modelling Office within the Research Department of the Central Bank of Malta. The author would like to thank Deputy Governor Alexander Demarco, Michael Christl, Aaron G. Grech, Noel Rapa, Ian Borg, William Gatt Fenech, Massimo Giovannini, and Riana Said (Economic Policy Department, Ministry for Finance and Employment) for comments and suggestions, as well as John Farrugia and Juergen Attard for both suggestions and assistance with data. The views expressed are those of the author and do not necessarily reflect the views of the Central Bank of Malta. Any errors are the author's own.

The results presented here are based on EUROMOD version I4.0+. Originally maintained, developed and managed by the Institute for Social and Economic Research (ISER), since 2021 EUROMOD is maintained, developed and managed by the Joint Research Centre (JRC) of the European Commission, in collaboration with EUROSTAT and national teams from the EU countries. The author is indebted to the many people who have contributed to the development of EUROMOD. The results and their interpretation are the author's responsibility.

Correspondence: public relations @centralbankmalta.org.

Abstract

Microsimulation models have been particularly useful when dealing with the economic welfare impact of COVID-19, particularly since such models offer a way to obtain timely and policy-relevant information in the absence of detailed household-level survey data. This study uses EUROMOD, a static tax-benefit microsimulation model calibrated for Malta, to evaluate the microeconomic impact of the wage supplement scheme introduced in Malta in response to the COVID-19 pandemic for the year 2020. Results suggest that the wage supplement scheme had a number of positive effects. First, it dampened average income losses, both across the income distribution and within economic sectors irrespective of the extent to which these were impacted. In particular, the results show that the scheme's impact across the income spectrum was progressive in the sense that it shielded the lowest earners relatively more. Poverty rates are invariably lower under the wage supplement scenario, than under a scenario where the scheme is not enacted, whilst its impacts on income inequality are ambiguous. Importantly, the size of the shock suffered by the worst-hit households declines markedly in the presence of the scheme. Future work can benefit from the availability of household survey data to conduct a more thorough assessment of the impacts this study attempts to measure, and in so doing, serve as a validation tool against which simulation exercises such as this can be compared.

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1 Introduction

The macroeconomic effects stemming from the COVID-19 pandemic are well documented. Rather less so are its micro-level effects and the impacts of policies enacted to mitigate them, particularly at the local level. Thorough analysis of these impacts at the household and/or the individual level is limited, at least in part, by the lack of availability of household-level survey data collected after the outbreak of the pandemic. In such instances, microsimulation modelling offers one way to obtain timely and policyrelevant information. 'Microsimulation' encompasses a variety of techniques which apply policy rules at the level of individual units and consequently enable analysis of related outcomes at a granular level (Figari, Paulus, and Sutherland, 2015). This characteristic makes such techniques ideal for welfare analysis of policy changes, particularly since microsimulation models allow researchers to change relevant policy parameters whilst maintaining other factors constant, avoiding endogeneity problems in the identification of policy effects (Bourguignon and Spadaro, 2006). Microsimulation models have been widely applied in the literature dealing with the economic welfare impact of COVID-19, especially in an effort to estimate the impact of income protection policies adopted by national Governments. In particular, several studies of this sort utilise some version of EUROMOD, a static tax-benefit microsimulation model for the European Union (EU). Developed and maintained by the European Commission's Joint Research Centre (JRC), EUROMOD simulates tax-benefits systems from all EU member states, allowing for transferability of policies and comparison of their effects across countries (Sutherland & Figari, 2013).² It is a static and non-behavioural model, in that it only simulates firstround effects of policy changes and does not endogenously account for changes in the behaviour and/or the structure of the population over time (Sutherland and Figari, 2013; Figari et al., 2015).³

Generally, in static microsimulation models the pandemic is simulated as a shock that abruptly increases unemployment for a given year or assigns previously employed individuals onto furlough or wage compensation schemes. That said, applications in the literature encompass several methods and data sources in order to calibrate the pandemic-related shocks. Some studies use pandemic-related survey data to calibrate shocks to employment resulting from shutdowns, which shocks are then implemented in microsimulation models to examine their associated distributional impacts. Examples include Brewer and Tasseva (2021) and Bronka, Collado, and Richiardi (2020), who study the welfare implications of COVID-19 on households in the UK, Marchal et al. (2021) for Belgium, and Bruckmeier et al. (2021) for Germany. Other studies base their calibration administrative data or legislative documents, in some instances combining these sources with survey data. These include Cantó Sánchez et al. (2022), who study the welfare impacts of the pandemic and government responses for Belgium, Italy, Spain and the

² The model was originally developed and maintained by the Institute for Social and Economic Research (ISER) at the University of Essex, until 2021.

³ Figari et al. (2015) provide a comprehensive review of several microsimulation techniques and their uses for policy analysis.

UK, Figari and Fiorio (2020) for Italy, Christl et al. (2022a) for Germany and Christl et al. (2022b) for Austria.

Studies highlighted so far are concerned with one or at most a few (European) countries each. However, Christl et al. (2021) and Almeida et al. (2021) carry out similar work for all 27 EU member states, both using EUROMOD. Shocks simulated in Christl et al. (2021) are based on available statistics from Eurostat and other national-level bodies regarding transitions to unemployment and to monetary compensation schemes in the wake of the economic shock. Almeida et al. (2021) use a different approach; they use the differences between the macroeconomic forecasts for 2020 included within the European Commission's Autumn 2019 and Spring 2020 economic forecasts, as a proxy for the macroeconomic effects in a scenario including both the effects of COVID-19 and related government policies vis-à-vis a no-COVID baseline, and subsequently also adjust the Spring 2020 forecasts to remove the effects of governments' policy responses and produce a scenario with the effects of COVID-19 but without the effects of discretionary policies. Meanwhile, several authors use microsimulation models to conduct similar work for non-European countries. Examples include Li et al. (2021) for Australia, Avellaneda et al. (2021) for Colombia, Ecuador and Peru, Barnes et al. (2021) for South Africa, Huesca et al. (2021) for Ghana, Mozambique, Tanzania, Uganda, and Zambia.

Comparing findings across these studies requires a significant degree of caution due to the differences in timelines considered, the design of the policies simulated, and methodologies employed to calibrate the shocks and implement them within models. Most studies show that when including pandemicrelated discretionary policies, equivalised disposable income losses for affected individuals tend to be progressive. For instance, Figari & Fiorio (2020) show that disposable income losses for affected individuals range approximately between 6% and 14%, with larger losses for those in higher income quintiles. Beirne et al. (2020) show similar results for Ireland; they estimate average disposable income losses ranging from approximately 2% for households in the bottom equivalised disposable income quintile to around 18% for those in the highest fifth of the distribution. Changes in household equivalised disposable incomes across quintiles are also universally progressive in Cantó Sánchez et al. (2022), although they vary by country. Approximate ranges are 0% to -5% for Belgium, +3% to -10% for Italy, 0% to -6% for Spain, and -1% to -10% for the UK. Conversely, Christl et al. (2022a) find higher disposable income losses among the lowest-earning households, which they attribute to their calibration strategy. Indeed, this study uses a probit model to assign probabilities of being affected by the shock to individual workers, which takes account of a wider range of variables apart from the sector of activity and consequently assigns higher probabilities of being affected by the shock to lower earners. Nevertheless, they estimate that the short-time work scheme and other policy measures enacted in Germany lower household disposable losses by around 6% for the first two deciles, with the cushioning effect falling to around 2% for the top two.

Literature also estimates sizeable poverty and inequality impacts of both the crisis itself and the policies enacted in response. Figari & Fiorio (2020) estimate that poverty rates in the overall population rise from 19% in the baseline to 38.5% without discretionary policies and 27% with policies; for the working population, poverty rates in the baseline are at 12.5%, rising to 68% without pandemic assistance but to around 28% when accounting for pandemic-related compensation schemes. The Gini coefficient increases from 0.31 in the baseline to 0.33 with discretionary policies enacted, increasing to 0.42 in the scenario without policy measures. These results are driven by an increase in unemployment leading to a larger role of "between population groups" inequality. Namely this implies that most of the overall inequality increases are due to a divergence in the disposable incomes of those affected and those not affected by shutdowns. Moreover, these results show that despite not being able to fully shield the population from the outcomes of this crisis, policy interventions were very effective at dampening the inequality increases that would have persisted in a no-policy intervention scenario. Cantó Sánchez et al. (2022) also show significant cross-country heterogeneity in the overall Gini coefficient changes based on disposable income. Results are statistically insignificant except for Italy, where the measure indicates slightly higher income inequality after the shock even in the presence of income protection policies. Poverty rates for all individuals rise by 1-4% across all four countries, but by 5% (Belgium) to 17% (Italy) for individuals affected by the shock. Christl et al (2022a) find that the newly-introduced benefits tend to slightly reduce the Gini coefficient based on disposable income, although it remains marginally above the baseline.

Almeida et al. (2021) and Christl et al. (2021), who estimate changes to incomes, poverty rates and inequality indicators for the EU as a bloc and for all EU member states, provide the only known estimates of these impacts for Malta thus far. Almeida et al. (2021) estimate the average loss of equivalised disposable income in Malta to be around 12% in the COVID-19 scenario with no policy changes, which falls to approximately 2% with policy changes. They also estimate the at-risk-ofpoverty (AROP) rate to increase by approximately 6% (1%) in the COVID-19 scenario without (with) policy intervention, and the Gini coefficient to fall slightly in the no-policy case but to see no significant change under policy interventions. In Christl et al. (2021), market incomes fall by 14.7% in Malta, but disposable incomes (which take taxes and benefits into account) fall by 4.7%. The estimated AROP rate with a fixed poverty line based on disposable income increases by 0.8% after the shock, whilst the Gini coefficient falls from 0.279 to 0.268. However, due to their focus on the European dimension, these studies necessarily lack a detailed calibration for the Maltese scenario and a detailed discussion of results for individual countries. Indeed, in the case of Christl et al. (2021), the calibration for Malta assumes no monetary compensation is given to the self-employed, an assumption which is not in line with the actual implementation of the Wage Supplement scheme in Malta and that is likely to substantially impact results. Meanwhile, results in Almeida et al. (2021) are dependent on assumptions made in the 2020 Spring Forecast round, which include assumptions that economic activity would

recover and restrictions would be lifted in the second half of 2020. Moreover, the latter work transmits the calibrated shocks into EUROMOD through reweighting input data, rather than using labour market transitions on the individual level. This has a number of drawbacks, such as implicitly assuming that the characteristics of the newly unemployed are similar to those unemployed in the original data.

In this light, the present study seeks to evaluate the microeconomic impact of the wage supplement scheme introduced in Malta in response to the pandemic, for the year 2020. Simulations are carried out using a version of EUROMOD for the Maltese economy (Vella, Said, and Apap, 2021). The study involves constructing a baseline scenario calibrated to model a 'no-Covid' 2020 and contrasting the differences vis-à-vis this baseline for two other simulated scenarios: a counterfactual simulation where the economic effects of the pandemic, in terms of employment losses, take hold without the wage supplement scheme being enacted, and an actual simulation of 2020 with the wage supplement scheme in place. The counterfactual and actual scenarios are hereinafter referred to as the 'no support' and the 'wage supplement' scenarios respectively. For the purpose of these simulations, the model is recalibrated using the most recently available data. Moreover, several policies are amended accordingly to simulate the respective scenarios as accurately as possible. This study adds to a sizeable literature which uses microsimulation and nowcasting techniques to make similar assessments for several other EU member states. More specifically, this work adds to the literature making use of EUROMOD's LMA add-on to implement labour market transitions at the individual level, an approach which is potentially more advantageous than reweighting input data in periods of stark economic changes (Christl et al. 2021, Almeida et al. 2021). Lastly, to my knowledge, this study is the first attempt at specifically modelling and appraising in detail the microeconomic effects of Malta's wage supplement scheme, building on the latest-available data to achieve a calibration which is as detailed as possible.

Results suggest that the wage supplement scheme had a number of positive effects. First, the scheme meets the primary aim of dampening average income losses, both across the income distribution and within economic sectors irrespective of the extent to which these were impacted. In particular, the results show that the scheme's impact across the income spectrum was progressive in the sense that it shielded the lowest earners relatively more. Poverty rates are invariably lower under the wage supplement scenario, than under a scenario where the scheme is not enacted, whilst its impacts on income inequality are ambiguous, likely owing to different impacts across the income distribution stemming both from the sectoral heterogeneity of the shock and the design of the scheme. Importantly, the size of the shock suffered by the worst-hit households declines markedly in the presence of the scheme.

The paper proceeds as follows. Section 2 details the simulation design for each scenario and its implementation within EUROMOD. Section 3 presents results in terms of income changes experienced

by households across both the income distribution and across different economic sectors, together with impacts on poverty and income inequality and some sensitivity exercises. Lastly, section 4 concludes.

2 **Simulation Design**

2.1 The baseline scenario

The baseline scenario is intended to simulate microeconomic conditions in 2020 as forecasted to be in the absence of the pandemic and involves adjusting a subset of the so-called 'uprating factors' used by the model.⁴ This is done in two steps. First, where possible, I retrospectively update uprating factors for the years 2017-2019, the years which are relevant to this simulation given the dataset being used. This is done for uprating factors which are derived from macroeconomic data or published aggregates namely the Harmonised Index of Consumer Prices (HICP), the Retail Price Index (RPI), GDP at market prices, and mean annual gross basic salaries – using the latest-available data vintages as of 2 May 2022.⁵ The baseline scenario is subsequently constructed by updating these uprating factors for 2020 using the Central Bank of Malta's latest-available pre-COVID-19 forecasts for 2020.⁶ No changes are made to uprating factors for benefits or indexation rules for pensions, which are updated in line with actual amounts specified in budget speeches and/or legislation.

2.2 The 'No Support' scenario

The counterfactual 'no support' scenario simulates the effects of COVID-19 in a scenario where the wage compensation scheme is not enacted.⁷ Adversely affected individuals in this scenario are therefore only protected by the automatic stabilisers built into the Maltese social security system prior to the pandemic. Using the method described below, a share of workers in each sector is simulated to become unemployed for a determined proportion of the year, losing a corresponding share of earned income and benefiting from statutory unemployment support according to their eligibility. The sectoral detail embedded in EUROMOD is a significant advantage for the purposes of this simulation, in that it allows the researcher to account for the substantial sectoral heterogeneity in the economic impacts of COVID-19, and consequently the asymmetric impacts that the pandemic would have had on the labour market in the absence of the wage supplement scheme.

⁴ EUROMOD uses specifically constructed datasets based on EU-SILC data. The latest-available dataset as at the beginning of this study was based on the 2018 EU-SILC, where income variables correspond to 2017. The model then uses what it refers to as 'uprating factors' to adjust monetary values from their income year values to the 'policy year', in this case 2020. A detailed list of all monetary variables and the associated uprating factors with which these variables are uprated can be found in Vella et al. (2021).

⁵ The annual values for the HICP and the RPI are obtained from Eurostat and from the NSO (as replicated in the Central Bank of Malta's statistical database) respectively. For mean annual gross basic salaries, I average out quarterly figures from Labour Force Survey (LFS) releases published by NSO, taking for each quarter the latest-available release in which figures for that quarter are published. This same process is used to update the GDP figures. ⁶ Forecast data relates to the December 2019 BMPE.

⁷ Both this and the subsequent 'wage supplement' scenario are built within EUROMOD using the same uprating factors as in the baseline scenario for the 2017-2019 period but using actual uprating factors for 2020 as observed in the data.

In order to arrive at an estimate of these sectoral employment shocks I proceed in five stages. First, I obtain sectoral GVA forecasts for 2020 conditioning on the latest available pre-pandemic information, using the sectoral extension to STREAM (Rapa, 2020), and derive initial shocks to GVA as the difference between actual and forecasted sectoral economic activity.⁸ At this primary stage, the calculation is done for 10 sectors as grouped in the NSO's Gross Domestic Product releases.⁹ Forecasts of final demand aggregates used to produce sectoral forecasts correspond to the final sending of the December 2019 BMPE, the same used for calibrating the baseline scenario. These initial shocks are shown in Table 1 below.

The interpretation of these initial shocks to GVA requires two qualifications.¹⁰ First, the disaggregation of final demand forecasts into sectoral GVA forecasts is purely mechanical and utilises factor intensities and past data to decompose aggregate information. It is therefore unable to account for any sector-specific trends in the latest actual data, which would have impacted the sectoral forecasts and consequently the sectoral shocks. Secondly, constructing shocks as the difference between pre-COVID forecast GVA and actual realised GVA is likely to lead to an underestimation of the true effects of COVID-19 and therefore of the effects of the wage supplement scheme. Whilst actual GVA does not include subsidies paid and received in lieu of wages, it can be strongly argued that the wage supplement scheme still indirectly pushes the published GVA figure upwards through positive indirect effects, mainly through supporting consumption. Similarly, actual GVA figures will also internalise indirect effects of additional government schemes (such as utility and rent subsidies, extension in tax payment deadlines, liquidity loans guaranteed by the Malta Development Bank, consumer vouchers), This in turn implies that the initial shocks estimated using the above methodology are being dampened by the positive indirect effects of these discretionary policies.

To correct for these factors, I adjust the sector-specific shocks by incorporating additionally available information. First, I make use of results published by Rapa and Debono (2021) who estimate that the drop in tourism resulting from travel and other relevant restrictions in 2020 led to a decline of 48.4% in GVA for the 'Accommodation and food services activities' category, corresponding to NACE category I and to the 'Hotels and Restaurants' sector in EUROMOD.¹¹ The three NACE sectors G, H, and I (for which an aggregate initial shock of 37.8% is calculated through the exercise described above) are weighted by their GVA at basic prices as published in the 2015 SIOT (NSO, 2021), in order to extract

⁸ This module allows the researcher to disaggregate aggregate-level information into sectoral data, using Symmetric Input-Output data for 2015.

⁹ Sectoral results for the forecasted GVA growth rates are available for either 18 or 40 NACE categories, whilst actual GVA data obtained from NSO is disaggregated into 10 economic sectors. Meanwhile, EUROMOD uses a separate grouping of NACE categories to define 12 economic sectors. The mapping of NACE sectors across these definitions is described in Appendix A, whilst additional detail on the process of obtaining sectoral GVA forecasts is found in Appendix B.

¹⁰ Average employment figures (including self-employed) in 2019 for each NACE category are obtained from Eurostat and reallocated across EUROMOD sectoral definitions. For a few small categories (namely B, D, T, and U) some figures are missing from the dataset; these were interpolated using data for the period 2010-2019.

¹¹ This particular result from Rapa and Debono (2021) is used in view of the fact that the method initially used can only produce a GVA shock figure which is aggregated for NACE categories G, H and I, as seen in Table 1 above, and specifically because this discussion concerns the hardest-hit sector. Other results in Rapa and Debono (2021) are not incorporated into this analysis.

the share of the aggregate shock attributable to sectors G and H after setting the shock to NACE sector I to 48.4%. As detailed in Appendix B, a similar method is used to calculate the applicable shock magnitude for the Transport and Communication sector in EUROMOD, since this combines NACE categories H and J which belong to different categories as specified by the NSO.

Subsequently, having made this initial adjustment to the shocks shown in Table 1, I rescale upwards all sectoral shocks obtained thus far in an attempt to account for the indirect effects of government intervention on GVA. The scaling factor is determined as follows. Attard and Farrugia (2021) estimate that all government expenditure on pandemic-related support measures in 2020 stood at 5.0% of GDP. This expenditure is in turn estimated to have positively contributed 2.8 percentage points (p.p.) to GDP growth in that year, a figure derived using specific multipliers for each category of government expenditure making up the total (Farrugia, Attard, and Borg, 2021). Using some simplifying

Tat	sle	1

Initial estimated percentage shocks to GVA by sector; sectoral categorisation as per NSO releases

NSO	release sector	NACE Categories	Forecast GVA (€m)	Actual GVA (€m)	Shock %
1	Agriculture, forestry and fishing	А	65.74	56.90	-13.5%
2	Mining and quarrying; manufacturing; electricity, gas, steam and air conditioning supply; w ater supply; sew erage, w aste management and remediation activities	B, C, D, E	1266.20	1197.08	-5.5%
3	Construction	F	553.04	540.08	-2.3%
4	Wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; accommodation and food service activities	G, H, I	2663.24	1655.42	-37.8%
5	Information and communication	J	1130.02	1126.09	-0.3%
6	Financial and insurance activities	К	1107.20	1140.33	0.0%*
7	Real estate activities	L	769.62	726.29	-5.6%
8	Professional, scientific and technical activities; administrative and support service activities	M, N	2225.77	2010.45	-9.7%
9	Public administration and defence; compulsory social security; education; human health and social w ork activities	O, P, Q	2215.09	2108.71	-4.8%
10	Arts, entertainment and recreation, repair of household goods and other services	R, S, T, U	1034.07	1067.32	0.0%*
			13030.00	11628.66	-10.8%

*Where actual GVA is higher than forecast, the shock is set to 0%.

assumptions, I assume that this is also the magnitude of the impact of such expenditures on GVA and that the decline in GVA in the absence of all such government initiatives would also have been 2.8 p.p. larger than that observed in the data. This implies that the macroeconomic impact of COVID-19 on GVA as estimated above – a 10.8% drop in aggregate GVA – is re-estimated to be 13.6%, thus amplified by a factor of 1.26. Therefore, all sectoral GVA shocks multiplied by a factor 1.26.

The adjusted GVA shocks are reallocated across the 12 sectors used in EUROMOD (see Appendices A and B) and for the purposes of the simulation, further transformed into sectoral shocks to employment. Rather than applying the percentage shocks to GVA directly to sectoral employment, I account for the labour intensity of output. The process, briefly described here, is fully detailed in Appendix C. Using sectoral GVA in levels and the annual average level of employment in each of the 12 EUROMOD sectors in 2019, I first calculate the average number of employees per € million of GVA by sector. Then, using the rescaled sectoral percentage shocks to GVA and the sectoral forecast 2020 GVA in levels (also derived in Appendix C), I convert the shocks to GVA from percentage to level terms and multiply the result by the employees/€m GVA ratio to obtain the estimated loss of employment in levels per sector. As a last step, this is converted once again into percentage employment losses using the 2019 average number of employees.

In the fourth stage of the process, a further adjustment to the estimated sectoral employment losses is made. The estimated employment shocks described thus far are based on annual GVA losses, and thus correspond to an *annual average* employment loss – that is, they correspond to the percentage of workers that have to be unemployed on average over the year to result in the observed GVA loss.

Table 2

					Rescaled	Employment	Fmployment	
per El	JROMOD	i estimated	percentage shocks	to GVA and	empioymen	l by sector, sectoral	categonsation	as
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				Rescaled	Employment	Employment
		NACE	Initial GVA	GVA	shock (%)	shock (%)
EUR	OMODsector	Categories	shock (%)	shock (%)	(annual average)	(average Q2-Q4)
1	Agriculture and Fishing	А	-13.5%	-16.9%	-18.1%	-24.1%
2	Manufacturing, Mining & Quarrying, Utilities	B, C, D, E	-5.5%	-6.9%	-7.2%	-9.7%
3	Construction	F	-2.3%	-3.0%	-3.1%	-4.2%
4	Wholesale and Retail	G	-34.6%	-43.6%	-46.2%	-61.6%
5	Hotels and Restaurants	I	-48.4%	-60.9%	-64.6%	-86.1%
6	Transport and Communication	H, J	-13.4%	-16.9%	-17.9%	-23.9%
7	Financial intermediation	К	3.0%	3.8%	0.0%	0.0%
8	Real estate and Business	L, M, N	-8.6%	-10.8%	-11.5%	-15.3%
9	Public administration and defence	0	-4.8%	-6.0%	-6.6%	-8.8%
10	Education	Р	-4.8%	-6.0%	-6.6%	-8.8%
11	Health and Social Work	Q	-4.8%	-6.0%	-6.6%	-8.8%
12	Other	R, S, T, U	3.2%	4.0%	0.0%	0.0%

However, for a more accurate representation of the effects of the COVID-19 pandemic, I configure the model such that individuals who become unemployed can only be unemployed for a maximum of 9 months, to simulate the shock to start at the beginning of the second quarter. Therefore, the annual average employment shocks are rescaled to the required average shock over the last three quarters of the year to attain the annual average shock found, assuming no job losses take place in the first quarter. The latter are the shocks actually simulated within the model and are tabulated in Table 2.

Table 3 Proportion of sectoral employment shock realised in each quarter							
Sectors	1	2, 9, 10, 11	3	4, 5, 6, 8			
Quarter							
2020/1	0.0%	0.0%	0.0%	0.0%			
2020/2	30.8%	79.3%	20.3%	38.1%			
2020/3	57.3%	15.0%	23.8%	34.1%			
2020/4	11.9%	5.7%	55.9%	27.8%			

Lastly, the 'trajectory' a particular sectoral shock takes over the course of the year will also impact results, through its effect on *when* individuals lose their job. This can be accounted for within the model by calibrating the re-assignment of

the number of months worked in the year for each affected individual. Such calibration is based on the proportion of the annual shortfall of GVA in each sector attributable to each quarter of the year, under the assumption that the shock's impact starts as from the second quarter. In the interest of conciseness, the full explanation of this process is given in Appendix C. Implicitly assuming that the impact on employment is contemporaneous to that on GVA, I apply the trajectories derived therein to the employment shock, as seen in Table 3. As an example, in Agriculture and Fishing (sector 1), around 31% of workers being simulated to lose their job are assigned to do so during the second quarter, i.e., to be in work for at most 6 months in the entire year. Applying the trajectory does not affect the overall size of the shock; the share of individuals being moved out of employment by the model in each quarter is such that the average share of persons having lost their employment in each sector over the period Q2-Q4 remains consistent with the estimated shocks shown in Table 2.

2.3 The 'Wage Supplement' scenario

The 'wage supplement' scenario intends to simulate the microeconomic effects of COVID-19 in the presence of the wage compensation scheme enacted in response to the pandemic. It is important to note that no other COVID-19-related aid, except the wage supplement scheme, is studied in this exercise.¹²

The Wage Supplement scheme was launched by the Government of Malta in early 2020 and ensured a minimum income to workers employed by businesses affected by the COVID-19 pandemic. The extent of the support offered by Government was sector dependent. To this end, all businesses were categorised under three lists or "Annexes". Each annex collected a number of sectors (categorised by NACE Rev2

¹² The only other pandemic-related benefit that can be simulated with the version of the model used in this study (I4.0+) is the parental benefit, but this is not enabled for this exercise in order to focus on the impact of the wage supplement scheme.

categories) which were judged to be equally exposed to the COVID-19 emergency. Businesses falling under Annex A were judged to be operating in the most critically affected sectors, that is sectors that were for some months forced to close down to business due to COVID-19 mitigation policies. Thus, employees and self-employed in businesses falling under Annex A received €800 per month if they work full-time and €500 per month if part-time throughout the period during which they are on the scheme. Some sectors that fell under Annex A until June 2020 were then moved to Annex C from July to December, under which full-time employees received €600 per month and part-timers €375. Employees of businesses operating under sectors that were only indirectly affected by the COVID-19 emergency were listed under Annex B throughout, thus receiving €160 per month if full-time and €100 if part-time for the entirety of their duration on the scheme.

To construct this scenario, I combine monthly data from Malta Enterprise indicating the number of workers receiving the wage supplement by NACE category between April and December 2020, with data on annual employment by NACE category sourced from Eurostat, and the Annex lists published by Malta Enterprise outlining the level of benefits to which individuals active in specific NACE category are entitled. The monthly average number of wage supplement recipients in each NACE category are then translated into shares of workers receiving the wage supplement in each of the model's 12 sectors using the mapping described in Table I in Appendix A. ¹³ For sectors containing NACE categories which fall solely under either Annex A/C or Annex B, the applicable Annex is obtained from the lists published by Malta Enterprise; otherwise, workers are split between Annex A/C and Annex B using the default ratios provided within the model.^{14, 15, 16}

In order to reflect the fact that employees under the wage supplement scheme could still receive part of their salary from their employers in addition to the minimum aid granted by government support, I assume that employees falling under Annex A/C have worked between 20% and 40% of their normal hours (and thus receive 20%-40% of their normal monthly wages). On the other hand, for employees in Annex B, I assume that they receive between 50% and 70% of their pre-COVID salary in addition to the government supplement. Moreover, for all employees, the total monthly income received from the

¹³ It is known that some NACE codes falling under some of the categories making up the 12 modelled sectors were not included under the Annexes. In the absence of more disaggregated sector data within the model, it is not possible to distinguish between categories at a level which is more detailed than the aggregated NACE sections (A-U). Nevertheless, since the percentages of workers moved to the wage supplement in the simulation are based on actual shares from Malta Enterprise data, such proportions are as accurate as possible at the level of the aggregated sectors in the model. ¹⁴ The default version of the wage compensation scheme module in EUROMOD includes pre-set shares of workers assigned to each

¹⁴ The default version of the wage compensation scheme module in EUROMOD includes pre-set shares of workers assigned to each Annex (A/C or B) of the wage supplement scheme in each sector. Where possible, the pre-loaded shares are revised for the purposes of this study, in light of more recent data being available. However, available data does not indicate how beneficiaries in particular sectors are split between Annexes. In cases where it is known from the Annex lists that a particular EUROMOD sector includes workers from both Annexes, these are split in the same ratio as that of the initial shares found in the model.

¹⁵ Certain detailed conditions related to Annex B cannot be simulated in the model. Namely, the relevant conditions stipulated that full-time (part-time) employees in Annex B based in Gozo would receive \notin 320 (\notin 200), whilst self-employed persons in Annex B sectors who employ at least one employee are also entitled to \notin 320 or \notin 200, increasing to \notin 480 or \notin 300 if the self-employed person is based in Gozo.

¹⁶ Whilst sector 2 encompasses NACE categories B to E, only NACE codes falling under category C (Manufacturing) were listed in the Annex.

wage supplement benefit paid by the state and the top-up paid by the firm cannot exceed the monthly salary the employee has before entering the scheme. However, there is logically no such capping for the self-employed, potentially leading some self-employed individuals to receive a slightly higher level of income when under the wage supplement than otherwise.

The shares of workers assigned to receive the wage supplement in each sector in the simulation are shown in Table 4.

FUR	OMOD sector	NACE Categories	% of workers in Annex A/C	% of workers in Annex B	% of workers on wage supplement
1	Agriculture and Fishing	A	0.0%	0.0%	0.0%
2	Manufacturing, Mining & Quarrying, Utilities	B, C, D, E	0.0%	27.2%	27.2%
3	Construction	F	0.0%	0.0%	0.0%
4	Wholesale and Retail	G	26.7%	13.4%	40.1%
5	Hotels and Restaurants	I	95.1%	0.0%	95.1%
6	Transport and Communication	H, J	15.2%	11.6%	26.9%
7	Financial intermediation	К	0.0%	0.0%	0.0%
8	Real estate and Business	L, M, N	33.0%	1.6%	34.6%
9	Public administration and defence	0	0.0%	0.0%	0.0%
10	Education	Р	8.1%	0.0%	8.1%
11	Health and Social Work	Q	0.0%	0.0%	0.0%
12	Other	R, S, T, U	20.8%	5.9%	26.7%

Table 4

Share of workers receiving wage supplement, by sector

2.4 Simulation design: a summary

Table 5 provides a summary of the average proportion of workers (both employees and self-employed) by sector hit by the shock in each scenario over the period from the second to the fourth quarter of 2020.

It is important to note that this study does not follow most studies in literature (e.g. Bronka et al., 2020) which simulate the same increase in unemployment due to the COVID emergency both in the presence and in the absence of discretionary policy. This is, however, deemed as too simplistic an assumption for the purposes of capturing the effects of the wage supplement scheme. Indeed, the design of the 'no support' scenario of this study allows to internalise the fact that had the wage supplement scheme not been introduced, the number of individuals who would have lost their employment at least temporarily would most likely be larger than the actual beneficiaries of the wage supplement.

Workers losing employment in the 'no support' scenario, whether employed or self-employed, receive statutory unemployment benefits and/or means-tested assistance contingent on their eligibility. As detailed in the EUROMOD 2018-2021 country report (Vella et al. 2021), since the EU-SILC dataset

does not include social security contribution history, this is approximated based on employment in the income year and observed benefit receipts. Meanwhile, wage supplement benefits received depends on the Annex to which the worker is assigned, based on sector-specific conditions which mimic as much as possible the actual Annex to which the majority of workers in a particular sector were assigned during 2020.

		NACE	'No Support'	'Wage supplement'
EUR	OMOD sector	Categories	shock (%)	shock (%)
1	Agriculture and Fishing	А	24.1%	0.0%
2	Manufacturing, Mining & Quarrying, Utilities	B, C, D, E	9.7%	27.2%
3	Construction	F	4.2%	0.0%
4	Wholesale and Retail	G	61.6%	40.1%
5	Hotels and Restaurants	I	86.1%	95.1%
6	Transport and Communication	H, J	23.9%	26.9%
7	Financial intermediation	К	0.0%	0.0%
8	Real estate and Business	L, M, N	15.3%	34.6%
9	Public administration and defence	0	8.8%	0.0%
10	Education	Р	8.8%	8.1%
11	Health and Social Work	Q	8.8%	0.0%
12	Other	R, S, T, U	0.0%	26.7%

Table 5
Average share of workers affected by shock in each scenario, by sector

3 Results

3.1 Income changes across the household income distribution

The first set of results hereunder aims to quantify the impacts on households across the distribution of equivalised household incomes which prevails in the baseline scenario. Figure 1 plots the average percentage changes in incomes by decile in each scenario vis-à-vis the baseline, for households in which at least one member is in work in the baseline (hereinafter referred to as 'working households'). Households which do not contain any economically active members are excluded since they are not directly affected by employment shocks. Figure 1 suggests that households are invariably better off under the 'wage supplement' scenario. Households in the top half of the distribution lose between 10.3% and 12.7% of their pre-shock (equivalised) income under the 'no support' scenario. Losses are limited to between 5.9% and 7.8% under the 'wage supplement' scenario. The wage supplement seems to have a slightly larger impact on households in the bottom half of the distribution; these lose 7.3% to 12.4% of their income in the absence of the wage supplement scheme, but between 3.3% and 5.3% in a scenario where it is enacted. Overall, the impact of the shock under both scenarios plays out in a mostly

Figure 1

Mean % change in equivalised household disposable income, by baseline decile, all working households



progressive manner across the income distribution. This is expected since under both scenarios the benefits received are of a nature, flat-rate thus covering relatively less of income losses the of higher-earning households. The progressivity is however distorted slightly by several other factors at play, mainly stemming

from the sectoral heterogeneity of the shocks.

Analysis based on average changes across the distribution does not provide information on the dispersion of income losses *within* each decile. Figure 2 plots the distribution of percentage changes in equivalised disposable income by decile for working households in both scenarios using box-and-whisker plots. The interquartile ranges generally shift upwards between the two scenarios, consistent with Figure 1. However, a number of additional insights can be gleaned from Figure 2. First, it is immediately clear that in the absence of the wage supplement, some households suffer income losses which are markedly greater than those indicated by average losses shown in Figure 1. In fact, the simulation data shows that 5% of working households suffer losses exceeding 47% under the 'no support' scenario, with some households losing more than half of their pre-shock equivalised income.¹⁷ Second, the dispersion of losses within deciles tends to fall significantly under the 'wage supplement' scenario, shown by the considerable narrowing of the box plots. In other words, apart from dampening losses in general, the wage supplement scheme limits considerably the magnitude of losses suffered by the worst-hit households. The distribution of changes by decile, including the outside values, are much less skewed than in the 'no support' scenario, with the lower tail of the distributions shifting much closer to the medians. The 5th percentile value of the distribution under the 'wage supplement' scenario

¹⁷ Values lying outside the whiskers fall beyond a threshold of 1.5 times the interquartile range away from the nearest quartile value.

Figure 2

Distribution of % changes in household equivalised disposable income vis-à-vis baseline, by income decile, all working households



corresponds to a loss of 18%, which remains sizeable but much lower than the comparable figure under the 'no support' scenario. Meanwhile, less than 0.5% of households face losses exceeding 30% in the presence of the wage supplement.

Figure 3 better visualises the impacts on households actually hit by the shocks, by removing unaffected households from the picture. In so doing, it illustrates more clearly the impact of the wage supplement scheme across the income distribution. Whilst an element of progressivity is retained, across all deciles, the interquartile range of income losses suffered by affected households are shifted upwards, and the lower tails are compressed. Once again, this indicates that the scheme tends to both dampen the losses incurred by households on average and narrow the discrepancy between the losses suffered by the worst-hit households and the rest.

Figure 3



Distribution of % changes in household equivalised disposable income vis-à-vis baseline, by income decile, affected households only

The factors behind the variability of the income losses suffered within and across income deciles naturally reflect the impacts of the simulated shocks across economic sectors. As suggested earlier, sector-specific circumstances determine not only the probability of a particular worker being hit by the economic shock, but also the duration of unemployment (in the 'no support' case), the duration of receipt of the wage supplement and the share of pre-shock earned income received whilst also receiving the wage supplement. In turn, the relative concentration of workers active in particular sectors in different segments of the income distribution will affect how sectoral impacts play out across the income spectrum. For instance (see Figure II in Appendix D), data shows that individuals active in sectors 6 (Transportation and Communications) and 7 (Financial intermediation) are noticeably more likely to be in the top half of the earnings distribution than those active in, say, Agriculture and Fishing (sector 1) or Wholesale and Retail (sector 4). The extent to which these sectors are impacted will necessarily spill over onto the respective parts of the individual and consequently the household income distribution.

To try and disentangle the effects of different drivers behind these results, Figure 4 plots the average share of income lost by household decile, shown in Figure 1 above, against the average percentage of households that are affected by the shock between Q2 and Q4 in each decile. The overall pattern visible in the chart suggests that the average loss of income by decile correlates well with the share of households that are hit by the shock. This is in turn likely to reflect the impacts on employment in sectors correlated with

different parts of the income distribution.

Given these observations, the next section reframes the results obtained from a sectoral perspective. In this case, it is significantly easier to interpret results by looking at the distribution of individuals, rather than households. Moreover, in the interest of clarity and





brevity, sector-specific results are shown only for five key sectors (Manufacturing, Wholesale & Retail, Hotels & Restaurants, Transport & Communications, and Real Estate & Business), grouping the other seven into an aggregate category.¹⁸

¹⁸ The five chosen sectors are those having the highest share of workers receiving the wage supplement, as per data shown in the Simulation Design section. They also make up the five worst-hit sectors in the 'no support' scenario, with the exception of

3.2 Income changes by sector of employment

Figure 5 replicates Figure 4 for individuals employed in the five key sectors chosen and the aggregate



'Others' category. In the 'no support' case, the proportional losses again correlate well with the size of the unemployment shock. The interpretation for the 'wage supplement' scenario is slightly more nuanced. To account for the treatment of each sector under the wage supplement scheme, the figure includes the share of workers transferred to Annex A by sector (that is the sectors

that receive the strongest financial aid). This helps explain what could initially seem to be inconsistencies in the pattern between the proportion of workers receiving the wage supplement and the share of income lost in each sector. For instance, the chart shows that a greater proportion of workers in Wholesale & Retail are transferred onto the wage supplement scheme when compared to Manufacturing; however, most of those in the former group are transferred to Annex A, whilst in Manufacturing, all shocked workers are transferred onto Annex B. This explains why on average, individuals working in Wholesale and Retail lose about 6.6% of their pre-shock incomes in the 'wage supplement' scenario, as opposed to 8.7% amongst those who are active in the Manufacturing sector. This also explains why, for example, the overall share of income lost by individuals active in the 'Hotels and Restaurants' sector is relatively low under the 'wage supplement' scenario when compared to the share of workers affected by the shock.

Reproducing box plots by sector (Figure 6), for affected individuals only, serves to illustrate the variation in the impacts on individuals working within each sector. As with results across deciles, the compression and the upward shift of the interquartile ranges between the two scenarios are visible for all sectoral groupings. The median loss of income among affected individuals in the sectors analysed shifts noticeably upwards, by magnitudes ranging from 6.9 p.p. in Transport & Communications to 12.2 p.p. in Hotels & Restaurants. This confirms the point made earlier, that is, the wage supplement scheme

Manufacturing (sixth), which is less affected than Agriculture and Fishing (fourth). The latter sector is however not analysed separately due to the very few observations in the data being active in this sector.

Figure 6

Distribution of % changes in individual disposable income vis-à-vis baseline, by sector of employment, affected individuals only



seems to have successfully dampened the losses incurred by individuals and narrowed the discrepancy between the losses suffered by the worst-hit sectors and the rest.

3.3 Decomposition of income changes by source

The next step pursued in this exercise is the decomposition of the income changes hitherto presented. This helps to better appraise the cushioning effect of specific transfer payments and/or policy instruments. This analysis is conducted for both scenarios, decomposing effects by income *quintiles* (rather than deciles, to simplify the graphical analysis) and by economic sector, focusing exclusively on affected households and individuals.

Figure 7 shows the decomposition for each baseline income quintile. The average changes for each quintile are normalised by its average baseline income, hence the changes in each income component shown in the graph are to be interpreted as percentages of the group's mean equivalised pre-shock income. The largest contributor to the income changes is unsurprisingly earned income. The average proportion of earnings lost in the 'no support' scenario is similar across income quintiles, ranging from 32% to 38%. Relatively higher unemployment benefits are afforded to lower-earning households, particularly due to means-testing. This is somewhat countered by the progressiveness of the income tax system, which means that higher-earning households automatically recoup increasingly more income that would otherwise have been paid in tax. Nevertheless, higher earners still tend to lose slightly larger shares of their income. This is also the case in the wage supplement scenario; however, some factors play out differently in this case. First, progressively smaller earnings losses are observed across quintiles, but the lower earning losses for higher-income households are offset by the progressively diminishing relative protection given by the wage supplement. In fact, the scheme covers around two-

thirds of the earning loss for the lowest quintile -a share which falls to slightly more than a third for the highest quintile, due to the flat-rate nature of the sums paid out.

These findings put further weight behind the argument that the wage supplement scheme effectively

shielded lower-income households from the effects of the economic shocks stemming from the pandemic. The importance that this is achieved is more so given that these are more likely to be single-earner

households and thus in a position of higher financial vulnerability. Other households with potentially greater financial needs or vulnerabilities. such households with as three or more children and households including single parents, are also more commonly found closer to the bottom of the income distribution in the data. In general, the

Figure 7

Decomposition of average % changes in household equivalised disposable income vis-à-vis baseline, by baseline income quintile, affected households only



Figure 8

Decomposition of average % changes in individual disposable income vis-à-vis baseline, by sector of employment, affected individuals only



scheme enacted will therefore have effectively protected households with pre-existing financial insecurities.

Decomposing results by sector also suggests the scheme markedly improved average outcomes within the most affected sectors. Individuals working in the five highlighted sectors, with the exception of those employed in manufacturing, are estimated to lose approximately 50% of their earnings in the 'no support' scenario. Those in manufacturing lose 62% of their earnings, with the higher losses being

attributable to the timing of the shock to this sector, as explained earlier. Much of the losses are dampened through the lower income taxes and social security contributions paid. Statutory non-meanstested unemployment benefits only cover an average of 3% to 5% of the income lost over an annual period.¹⁹ This results in the average *affected* worker losing 31% (in Hotels & Restaurants) to 40% (in Manufacturing) of their disposable income over the year. The losses are generally much more contained in the wage supplement scenario. In Manufacturing, affected workers lose less of their earnings (due to less stringent assumptions on loss of output and hours worked), and despite relatively low (falling under Annex B) cushioning from the wage supplement scheme, their losses are halved to 19%. The sectors which enjoy the greatest coverage by the wage supplement scheme are the Wholesale and Retail, Hotels and Restaurants, and Real Estate and Business sectors. Workers active in the latter two almost exclusively receive Annex A or C benefits, whilst the proportional losses of workers in Wholesale and Retail are also somewhat dampened by below-average baseline incomes. Conversely, this factor limits the impact of the wage supplement scheme in the case of individuals in Transport and Communications, which have markedly above-average incomes in the baseline. Despite being the least positively affected by the wage supplement scheme, workers in this sector still lose an average of 10% of their baseline incomes less in the wage supplement scenario, when compared to their losses in the no support scenario. In summary, the wage supplement scenario results in average income losses for affected workers which are between 10% and 28% (in Real estate & Business) lower than in the no support scenario.

3.4 Impacts on poverty

Poverty indicators are indispensable components of analyses of welfare impacts. A widely-used poverty indicator is the at-risk-of-poverty (AROP) rate, defined as the proportion of individuals in a population living in households whose equivalised disposable income is below the poverty line. For the purpose of

Table 6
ROP rates across scenarios (%) by individual characteristics

	Baseline	No Support	Wage Supplement
Overall	17.1	21.9	18.5
Children	16.2	23.1	18.5
Working age	11.5	16.7	12.8
Working age & active	5.3	10.4	6.4
Elderly	35.1	37.2	36.0
Elderly living alone	40.9	41.5	41.5
Single parent	11.7	16.7	13.1
HH w ith 3+ children	43.1	51.4	45.9
Poverty line	€ 850.47	€ 850.47	€ 850.47

this study, the poverty line is conventionally defined as 60% of the median equivalised disposable household income. Moreover, when comparing poverty rates across scenarios, I keep the poverty line fixed at the baseline level, that is at the level of €850.47 monthly.

Results show that under a no support scenario, there would have been a widespread increase in the

¹⁹ The relatively low shares of income recouped through unemployment benefits is not only a result of the *level* of unemployment benefits but also of the *duration* of unemployment. The average affected individual is modelled to lose their employment for 4 months; the maximum is 7.

risk of poverty for all household categories The overall poverty rate in the 'no support' scenario rises by close to 5 percentage points, with stronger increases registered in the number of children living at risk of poverty which climb by 6.9 p.p. to 23%. The proportion of working-age people and active working-age people at risk of poverty also rises by around 5 p.p., whilst the poverty rate amongst the elderly and elderly living alone only increases slightly, driven by the low activity rate amongst these cohorts. Individuals living in households with 3 children or more would have seen significant increases in the risk of poverty in the scenario without wage supplement. The wage supplement scheme has considerably reduced the risk of poverty for almost all categories with the exception of households composed of elderly living alone, who by construction did not receive direct aid through this particular aid scheme. The most significant improvements in the AROP rates due to the wage supplement scheme are found in households with 3 children or more, in the single parents and working age cohorts. On average, the wage supplement scheme is estimated to have reduced poverty rates by more than 3 percentage points.

3.5 Sensitivity analysis

The exercises explained in this section intend to test for the sensitivity of results presented to some key assumptions which are necessary in the modelling process. First, I re-generate the results of the 'no support' scenario under different assumptions on the trajectory of the shock over the year. The trajectory assumed for the results presented in the preceding sections is laid out in Table 3. In this sensitivity exercise, I re-run the model assuming two alternative shock trajectories, which are applied to all sectors, both intended to simulate a scenario where the impact on employment kicks in earlier. The first of these assumes that 75% of the required lay-offs occur in the second quarter, with the remaining 25% taking place in the third quarter, whilst the second alternative trajectory assumes 50% of the shock is realised

Figure 9





realised in quarter 3. These are therefore assumed to lead to longer unemployment spells for workers in all sectors bar Manufacturing, Public administration, Education, and Health and Social Work. On the other hand, this effect is countered by the fact that fewer

in quarter 2 and 50%

Figure 10

Mean % change in individual disposable income, by baseline decile, all working individuals - No Support and trajectory sensitivity scenarios



individuals lose their job over the course of the year in order to achieve the same average annual unemployment increase.

The results for these two sensitivity scenarios are shown in figures 9 and 10, contrasted against the original 'no support'

results. The baseline and the 'wage supplement' results are also displayed for reference; however, it is important to note that no adjustments have been made to these two scenarios. Figure 9 shows the average household equivalised disposable income losses across the baseline household income distribution for 'no support' and the two sensitivity scenarios. Figure 10 meanwhile shows income losses by sector at the individual level. Differences across the income distribution are minimal, and with no particular pattern. In the Hotels and Restaurants, Transport and Communications and Real estate and Business sectors, a slight increase in income losses incurred under the first sensitivity scenario is visible, which is expected given the noticeable difference to the original trajectory of the unemployment shocks. The largest difference, found in the case of the Real Estate and Business sector, is nevertheless

Table 7

AROP rates across sœnarios (%) by individual characteristics, including trajectory sensitivity scenarios in 'no support' case

	Baseline	No Support	Trajectory sensitivity (75/25/0)	Trajectory sensitivity (50/50/0)	Wage Supplement
Overall	17.1	21.9	21.7	21.4	18.5
Working age & active	5.3	10.4	10.4	10.1	6.4
Poverty line	€ 850.47	€ 850.47	€ 850.47	€ 850.47	€ 850.47

a minimal 1.4 p.p.. Changes in the poverty rates under a no support scenario (Table 7) are also small in magnitude.

The second sensitivity exercise concerns the 'wage supplement' scenario. Figure 6 suggests that in general, relatively higher losses are suffered by affected workers in sectors where most of those who are moved onto the wage supplement scheme receive Annex B benefits. This is the case mainly for the Manufacturing and the Transport and Communications sector (see right-hand-side panel of Figure 6).

Figure 11

0 -5 -10 -15 -20 -25 -30 -35 Manuf. Others Annex B* W'sale & Hotels & Transport Real Retail Rest & estate & Comm's Business Wage Supplement Topup sensitivity No Support

Mean % change in individual disposable income, by baseline decile, all working

individuals - Wage Supplement and top up sensitivity scenario

Although one has to aware of the be potential confounding effects of other factors such as the relatively high baseline wages Transport in the sector - this could suggest that Annex B benefits were relatively less effective at cushioning workers

from the impacts of



the economic shock. However, it is crucial to note once again the caveats that apply to the simulation of Annex B benefits. Namely, some additional benefit entitlements under this category (e.g., to workers based in Gozo) cannot be simulated, and the share of wages workers receive together with Annex B benefits is kept as originally assumed in the model, at 50 to 70% of the pre-COVID salary. In this simulation exercise, these shares are revised upwards implying that Annex B employees are allowed to receive between 70% and 90% of their original salary together with wage supplement aid. Indeed, sectors falling under Annex B, could still operate by law, implying that most probably, employees employed in such sectors would have been receiving a wage supplement together with a significant proportion of their original wage.

As is visible in Figure 11, this change in simulation design significantly affects results for sectors falling under Annex B. Most notably, the average income loss faced by workers in Manufacturing is reduced by a third, from 8.7% to 5.8%. For these individuals, losses are more than halved from 18% to 7.3%

Table 8

AROP	rates	across	scenarios	(%)	by	individual	characteristics,	including
topup	s ens iti	vity s cer	nario in 'wa	ges	upp	lement'cas	e	

	Baseline	No Support	Wage Supplement	WS topup sensitivity
Overall	17.1	21.9	18.5	18.1
Working age & active	5.3	10.4	6.4	6.0
Annex B	7.5	15.9	12.4	6.7
Poverty line	€ 850.47	€ 850.47	€ 850.47	€ 850.47

when the top-up shares are augmented. In terms of poverty and income inequality, no substantial impacts are observed on aggregate, yet poverty rates for Annex B workers specifically also decline by close to half their original value, as seen in Table 8.

In summary, results shown are more sensitive to assumptions in the 'wage supplement' scenario. Whilst changing the trajectory of unemployment over the year has negligible impacts on results in the 'no support' scenario, results for Annex B workers under the 'wage supplement' scenario seem to be rather dependent on the assumed share of wages being received by workers in parallel with the wage compensation. This is plausible due to the relatively low benefit amounts in this category compared to average wages. Therefore, the results presented in this study may not be sufficient to conclude that the lower benefit levels associated with Annex B led to a smaller degree of protection to affected workers. To this end, data on actual hours worked or the share of wages received by workers by annex may be helpful to get to more robust conclusions about this aspect of the scheme.

4 Conclusion

This study makes use of three distinct scenarios simulated through EUROMOD to appraise the microeconomic impacts of the COVID-19 pandemic, with and without a wage compensation scheme being in place, in terms of impacts on income, poverty and income inequality at the household and individual levels.

The results presented suggest that the introduction of a wage compensation scheme in response to the anticipated economic fallout of the COVID-19 pandemic and restrictions enacted to curb its spread had a number of positive effects. First, the scheme meets the primary aim of dampening average income losses, both across the income distribution and within economic sectors irrespective of the extent to which these were impacted. In particular, the results suggest that the scheme's impact across the income spectrum was progressive in the sense that it shielded the lowest earners relatively more, an outcome which is important from an equity and financial security perspective. Whilst poverty rates measured against a pre-shock standard generally remain higher than in the baseline, they are invariably lower under the wage supplement scenario, suggesting that the scheme was at least partially effective in shielding people from poverty. It could also be argued that the scheme served to limit the dispersion of losses. Even though the scheme's impact on income inequality indicators is somewhat ambiguous, it is important to note that the size of the shock suffered by the worst-hit households declines markedly between the two scenarios simulated.

This study therefore serves to provide an initial assessment of the microeconomic impacts of the said wage compensation scheme. Having said this, a number of caveats highlighted in the Simulation Design section as well as caveats inherent to the model itself (see Vella et al., 2021) are to be kept in mind when appraising the results of this study. Future work can benefit from the availability of household survey data to conduct a more thorough assessment of the impacts this study attempts to measure, and in so doing, serve as a validation tool against which simulation exercises such as this can be compared.

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Appendices

Appendix A – Mapping between sectoral definitions

The below table illustrates the different sectoral definitions used at several stages of this study. Colours are included solely for easier distinction between definitions. The Input-Output model used in the process of forecasting GVA for 2020 abstracting from the effects of COVID-19 (see Appendix B) defines 18 sectors as seen in the first row of Table I. Meanwhile, both 2019 GVA figures used as the base for such forecast and the 2020 actual GVA figures used to calibrate the shock in the 'no support' scenario (see Appendix C) are available grouped into 10 sectors as seen in the second row. EUROMOD, on the other hand, uses sectoral definitions which split NACE categories into 12 sectors, as seen in the third row. Whilst in most cases the definitions differ on whether or not two or three subsequent categories are grouped, more significant differences exist in definitions including NACE categories B to F and G to J. These require the use of reweighting at various points in the study.

Table I

Mapping between s	ectoral definitions
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18 sectors (I-O module)	А	С	D	Е	В	F	G	Ι	Н	J	Κ	L	М	Ν	0	Ρ	Q	R	S	Т	U
10 sectors (NSO)	Α	С	D	Е	В	F	G	Ι	Н	J	Κ	L	М	Ν	0	Ρ	Q	R	S	Т	U
12 sectors (EUROMOD)	Α	С	D	Е	В	F	G	Ι	Н	J	Κ	L	М	Ν	0	Ρ	Q	R	S	Т	U

Appendix B – Estimation of forecast 2020 GVA

The initial step towards estimating a sectoral forecast GVA for 2020 abstracting from the effects of COVID-19 is to feed forecast GDP component growth rates from the December 2019 BMPE into an internally developed Input-Output model. From the model outputs, GVA growth rates for 18 sectors are obtained.

Table II

Estimation of 202	0 forecast	sectoral	growth	rates	and (GVA
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			Sector				Sector		
Sect	or in Input-Output	NACE	growth rate (%)	Sect relea	or in NSO GDP ases	NACE	growth rate (%)	2019 GVA (€m)	2020 GVA (€m)
1	Agriculture, fishing, forestry	А	6.7	1	Agriculture, fishing, forestry	А	6.7	61.6	65.7
2	Mining, quarrying, construction	B, F	6.4	2	Mining, quarrying, ; manufacturing; electricity, gas,	B, C, D, E	5.3	1202.6	1266.2
3	Manufacturing	С	5.0	3	Construction	F	6.4	519.7	553.0
4	Electricity, gas, 	D, E	6.4	4	Wholesale & retail trade; transportation & storage,; accommodation & food	G, H, I	6.0	2513.5	2663.2
5	Wholesale & retail trade,	G	6.1	5	Information and communication	J	6.1	1065.4	1130.0
6	Transportation & storage	Н	5.3	6	insurance activities	К	4.9	1055.2	1107.2
7	Accomodation, food travel	I	6.5	7	Real estate activities	L	6.5	722.9	769.6
8	Information and communication	J	6.1	8	Professional,; administrative	M, N	5.6	2106.9	2225.8
9	Financial and insurance activities	К	4.9	9	Public administration; education; health & social work Arts; other	0, P, Q	8.6	2039.0	2215.1
10	Real estate activities	L	6.5	10	household production; extraterritorial organisations	R, S, T, U	4.9	985.8	1034.1
11	Professional, scientific Admin and	М	5.4		-				
	support services	Ν	6.0						
12 13	 Public administration	0	9.0						
14	Education	Р	8.2						
15	Health and social work …	Q	8.7						
16	Arts, entertainment …	R	4.8						
17	Other service activities	S	6.4						
18	Households & extraterritorial	T, U	6.5						

These are reworked into growth rates for 10 sectors for which GVA data from NSO is available. Due to some differences in grouping of NACE categories, as can be verified from Table I in Appendix A, a process of decomposition and/or re-aggregation of the obtained growth rates is needed for some categories. During such, each category is weighted by its GVA at basic prices (reproduced in Table III below) available from the 2015 SIOT, on which the model is based. Lastly, the obtained growth rates are then applied to 2019 GVA to obtain forecast GVA for 2020 in the absence of the pandemic. The last step is to reapportion the forecast GVA across the 12 sectoral definitions in EUROMOD, a process illustrated in Table IV. Once again, where necessary, GVA of different NACE categories is weighted by their GVA at basic prices from the 2015 SIOT.

Та	ble	III
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$\sim 1/4$	at basia	nrinon	h.		ootogony	from	2015	CIOT
GVA	al Dasic	prices	Dy	NAGE	calegory,	IIOIII	2015	301

		NACE	2015 SIOT GVA at
Sect	or in 2015 SIOT classification	Categories	basic prices (€m)
1	Agriculture, fishing, forestry	А	92.3
2	Mining, quarrying,; manufacturing; electricity, gas,	B, C, D, E	908.5
	of which: Manufacturing	С	744.6
3	Construction	F	320.5
4	Wholesale & retail trade	G	975.3
5	Transportation & storage	н	504.6
6	Accomodation & food services	I	448.6
7	Information and communication	J	557.5
8	Financial and insurance activities	К	740.7
9	Real estate activities	L	512.6
10	Professional, scientific	Μ	629.5
11	Administrative & support services	Ν	485.4
12	Public administration & defence	0	496.7
13	Education	Р	489.1
14	Health and social work	Q	527.9
15	Arts, entertainment & recreation	R	1100.0
16	Other service activities	S	90.5
17	Household production	Т	9.3
18	Activities of extra-territorial	U	0.0

Table IV Reallocating 2020 forecast GVA from NSO to EUROMOD sectoral definition (NACE categories; forecast GVA in €m)

10 sectors (NSO definition)	A 65.7	B C D E 1266.2	F 553.0	G	l 2663.2	Н	J 1130.0	K 1107.2	L 769.6	M N 2225.8	0	P 2215.1	Q	R S T U 1034.1
Decomposition using shares in Table IV	A 65.7	ВСDЕ 1266.2	F 553.0	G 1346.9	l 619.5	H 696.8	J 1130.0	K 1107.2	L 769.6	M N 2225.8	O 726.9	P 715.7	Q 772.5	R S T U 1034.1
12 sectors (EUROMOD definition)	A 65.7	B C D E 1266.2	F 553.0	G 1346.9	l 619.5	H 182	J 26.8	K 1107.2	L 29	M N 995.4	O 726.9	P 715.7	Q 772.5	R S T U 1034.1

Appendix C – Calibration of shock for 'no support' scenario

Calibrating the shock in the 'no support' scenario involves combining the rescaled GVA shocks (see Table 1 and the first part of Table 2 in the text) with sectoral employment data to convert the GVA shocks into employment impacts. More precisely, the GVA shocks are converted back into level terms for each of the model's 12 sectors (Table V), which are then multiplied by the ratio of employees per €million GVA for each of the 12 sectors (derived in Table VI). The number of employed individuals (including self-employed) by NACE category are obtained from Eurostat. For a few small categories (namely B, D, T, and U) some figures are missing from the dataset; these were interpolated by splitting

Table V

Conversion of GVA shock by EUROMOD sector to level terms

Sector	1	2	3	4	5	6	7	8	9	10	11	12
2020 forecast GVA	65.7	1266.2	553.0	1346.9	619.5	1826.9	1107.2	2995.4	726.9	715.7	772.5	1034.1
GVA shock in %	-16.9%	-6.9%	-3.0%	-43.6%	-60.9%	-16.9%	0.0%	-10.8%	-6.0%	-6.0%	-6.0%	0.0%
GVA shock in €m	-11.1	-87.0	-16.3	-587.5	-377.6	-308.9	0.0	-324.1	-44.0	-43.3	-46.7	0.0

Table VI

Calculation of employees/GVA ratio using 2019 figures

Sector	1	2	3	4	5	6	7	8	9	10	11	12
2019 employment (levels)	2300	30812	17100	35600	18800	22900	11800	26500	16200	22500	24000	20788
2019 GVA (€m)	61.6	1202.6	519.7	1271.2	584.7	1723.1	1055.2	2829.8	669.1	658.8	711.1	985.8
Employees/GVA ratio	37.3	25.6	32.9	28.0	32.2	13.3	11.2	9.4	24.2	34.2	33.8	21.1

across them, for each year, the gap between the total number of employed individuals and the sum of individuals working in all categories for which the figure is available. The discrepancy is allocated between the missing figures in proportion to their average number of employees in years where data is available, using data from the period 2010-2019.

These two results are combined with the average employment shock over the year, converted into level terms using 2019 employment, to obtain the percentage employment shocks corresponding to the GVA shocks observed through the process previously described. This step is illustrated in Table VII. As explained in the text, these employment shocks are still in the nature of annual averages and are thus multiplied by a factor of 1.333 to obtain the required shock percentages over three quarters, assuming no impacts in the first quarter of the year.

Table VII

Derivation of employment shock in percentage terms by EUROMOD sector

Sector	1	2	3	4	5	6	7	8	9	10	11	12
GVA shock in €m	-11.1	-87.0	-16.3	-587.5	-377.6	-308.9	0.0	-324.1	-44.0	-43.3	-46.7	0.0
Employment/€m GVA	37.3	25.6	32.9	28.0	32.2	13.3	11.2	9.4	24.2	34.2	33.8	21.1
Avg. employment shock (levels)	-415.8	-2230.0	-537.1	-16454.8	-12140.8	-4105.7	0.0	-3034.8	-1064.3	-1478.2	-1576.8	0.0
2019 employment	2300.0	30812.0	17100.0	35600.0	18800.0	22900.0	11800.0	26500.0	16200.0	22500.0	24000.0	20788.0
Employment shock in %	-18.1%	-7.2%	-3.1%	-46.2%	-64.6%	-17.9%	0.0%	-11.5%	-6.6%	-6.6%	-6.6%	0.0%

The last step required involves calibrating the shock trajectory over the year. This calibration is derived by assessing, for each of the 12 sectors in the model, the difference between the forecast and the actual output in each quarter of 2020. To do this, I derive average quarterly GVA in 2017-2019 for the 12 EUROMOD sectors and the average share of annual GVA attributable to each quarter for each sector over the same period. These shares are in turn used to estimate a quarterly profile for the forecast 2020 GVA. Combining this quarterly forecast GVA to the actual quarterly GVA, one can obtain how much of the annual drop in GVA compared to the baseline is attributable to each quarter of the year. The result is as seen in Table VIII:

Table VIII

2020 Quarterly GVA drop vis-a-vis. forecast: Quarterly share of annual drop

Sector	1	2	3	4	5	6	7	8	9	10	11	12
Drop in €m	8.6	64.2	5.0	510.5	234.8	227.3	0.0	192.2	15.7	15.5	16.7	0.0
2020-Q1	-12.0%	-11.1%	-74.6%	6.1%	6.1%	-1.8%	0.0%	-6.1%	8.7%	8.7%	8.7%	0.0%
2020-Q2	34.6%	84.8%	35.4%	34.7%	34.7%	39.5%	0.0%	40.8%	73.9%	73.9%	73.9%	0.0%
2020-Q3	64.2%	13.9%	41.6%	33.7%	33.7%	34.5%	0.0%	35.1%	15.0%	15.0%	15.0%	0.0%
2020-Q4	13.3%	12.5%	97.6%	25.6%	25.6%	27.8%	0.0%	30.2%	2.3%	2.3%	2.3%	0.0%

Since COVID-19 first hit in March, two things must be noted. First, some sectors actually register GVA figures which surpass forecasts in the first quarter, thus dampening the annual loss in GVA. Second, but on a related note, it is both sufficiently accurate and also convenient from a modelling perspective to simulate shocks to start from the second quarter onwards. Therefore, two further steps are taken to calibrate the path of the shock to employment over the year in the simulation. First, the entirety of the shock is reapportioned onto the last three quarters of the year, in proportion to each quarter's contribution as a share of the part of the GVA shock attributable to the last three quarters. Thus, for instance, in sector 4 (wholesale and retail), the last three quarters collectively account for 93.9% of the total discrepancy between actual and forecast GVA over the year. Of this 93.9%, 34.7% is attributable to the second quarter, or 36.9% of the subtotal. Repeating this for all sectors results in shock trajectories as below:

Table IX

2020 Quarterly GVA drop trajectory

Sector	1	2	3	4	5	6	7	8	9	10	11	12
2020-Q1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
2020-Q2	30.8%	76.3%	20.3%	36.9%	36.9%	38.8%	0.0%	38.4%	81.0%	81.0%	81.0%	0.0%
2020-Q3	57.3%	12.5%	23.8%	35.9%	35.9%	33.9%	0.0%	33.1%	16.5%	16.5%	16.5%	0.0%
2020-Q4	11.9%	11.2%	55.9%	27.2%	27.2%	27.3%	0.0%	28.5%	2.6%	2.6%	2.6%	0.0%

To simplify the configuration of these trajectories in the model, similar trajectories are grouped together and averaged out, weighted by their sectors' respective GVA levels. The following figure graphs the paths from Table IX, excluding sectors 7 and 12 for which the shock is set to zero. First, since sectors 9 to 11 are decomposed from an aggregate GVA estimate, they necessarily have the same trajectory over the year (dark green line). The shock to sector 2 (light green) also plays out in a similar manner, thus the trajectories of sectors 2, 9, 10 and 11 are grouped together. Most of the shock to these sectors' output results to have been suffered in the second quarter. Similarly, the shocks to sectors 4, 5, 6, and 8, graphed in varying shades of orange, also have nearly identical paths, where once again sectors 4 and 5 were decomposed from an aggregate and thus have fully identical trajectories. Contrary to the previous cluster, the impact to these sectors plays out in a more stable manner over the year. This is congruent with the level of restrictions affecting these sectors and the levels of assistance received by those active in these sectors through the wage supplement over different parts of the year. In fact, whilst most workers and firms in sectors 4, 5, 6 and 8 (respectively Wholesale and Retail, Hotels and Restaurants, Transport and Communication, and Real Estate and Business) who were given the wage supplement were in Annexes A and C, receiving higher benefits, this is not the case for those in Manufacturing, Public Administration, Education or Health. Sectors 1 (Agriculture) and 3 (Construction) are not grouped with any other sectors since the impacts on their output have profiles which are not similar to any other sector. The shocks of grouped sectors are averaged out weighted by their forecast 2020 GVA. The final trajectories to be applied to the employment shock in the model are found in Table 3 in the text.



Appendix D – Income distribution across sectors

Figure II below shows how workers active in each of the model's 12 sectors are spread across the distribution of individual earned income. Earnings are used rather than monthly salaries since the duration of employment and thus the number of months during which an individual earns income in the baseline scenario affects results. The figure also includes self-employed workers. This chart suggests that individuals in sectors 6 (Transport and Communications) and 7 (Financial intermediation) tend to earn the highest incomes, followed by sectors 9 to 11 (Public administration and Defence, Education, and Health and Social Work respectively). On the other hand, the sectors with the highest proportion of workers in the bottom quintile are the 'Others' sector (sector 12, NACE R-U) and sectors 3-5 (Construction, Wholesale and Retail, and Hotels and Restaurants respectively). In all of these sectors, more than 30% of workers are in the bottom quintile of the distribution.



Figure II Distribution of workers across individual earned income distribution, by sector

■Dec. 1 ■Dec. 2 ■Dec. 3 ■Dec. 4 ■Dec. 5 ■Dec. 6 ■Dec. 7 ■Dec. 8 ■Dec. 9 ■Dec. 10