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Simulating business failures through the liquidity and solvency channels:

A framework with applications to COVID-19

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Simulating business failures through the liquidity and solvency channels: a framework with applications to COVID-19

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Abstract:

We develop a microsimulation model that can identify Small and Medium Enterprises (SMEs) as financially distressed due to their inability to meet short term losses with cash (liquidity distress) or to meet their debt repayments (solvency distress). We estimate that – on these metrics – around one-in-six Irish SMEs may have been financially distressed at the end of 2020, or 14 per cent when weighted by debt balances. The model can be used for policy assessment: we calibrate the model to fiscal support implemented in Ireland during the first three quarters of 2020 and estimate that it reduced the share of distressed SME debt by two-fifths. On targeting, we show that a hypothetical scheme selecting firms with the smallest losses first could reduce distress rates from 19 to 7 per cent – albeit we do not suggest this is the welfare-optimising approach. On policy design, we show that debt-based support schemes reduce distress rates by less than grants, and this is driven by the greater role played by solvency over liquidity concerns in a debt-based support regime.

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Non-Technical Summary

Small and medium enterprises (SMEs) play a key role in the Irish economy, accounting for two thirds of private sector employment. During the COVID-19 crisis, large cohorts of the SME population have been severely affected by public health measures imposed by the government to contain the spread of the virus. To mitigate the adverse economic impact of the pandemic shock, the Irish government has implemented a range of policy supports, aiming to inject liquidity directly to SMEs during the lockdown period, supporting the payment of wages and other outgoings. Given the rapid development of the crisis and difficulty of gathering timely data on small businesses, it is important to develop a modelling approach to fill the gap between data that arrives with lags and real-time policy questions.

This paper showcases a simulation-based model that can assist real-time policy-making. We present an application of this model to the COVID-19 crisis in Ireland. We use the model to gauge the impact of the pandemic on the financial distress (FD) rate of SMEs and to provide timely assessments of the effectiveness of government policy support. The model uses firm-level data from the pre-crisis period, combined with a range of survey data sources and macroeconomic projections to map the economic effect of the pandemic in 2020 and 2021 onto a representative sample of SME balance sheets from 2018-19.

Our simulation model reveals that, firstly, policy support packages that are calibrated to match the size (€7.5bn of non-payroll support) and mix (between debt, grants, and wage subsidies) introduced in Ireland up to September 2020 reduce the FD rate from 19 to 16 per cent, and have larger effects in reducing the debt-weighted FD rate from 26 to 14 per cent. While important, these effects still leave firms with financial distress, and suggest that despite the commitments of the exchequer to support business, forbearance and restructuring policies will be crucial in ensuring the system can absorb the shock over the medium term.

Secondly, our results also highlight the importance of policy targeting, which can have significantly greater effectiveness in reducing FD, per euro spent: a hypothetical scheme that has perfect information on firm losses can, by selecting first those SMEs closest to avoiding financial distress, reduce the FD rate from 19 to 7 per cent for an outlay of €7.5bn, compared to the reduction from 19 to 16 per cent when calibrating 2020 policy. This hypothetical targeting regime is not modelled as a policy recommendation, but rather to give a useful benchmark against which to compare the size of policy effects estimated in our model. The illustration makes clear that, where achievable, targeting support towards firms with smaller losses can lead to substantial reductions in FD rates. In practice, policymakers face a much wider set of decision-making criteria, including regional, sectoral, and long-term considerations.

Our final analysis examines debt-related financial distress up to 2021 H1. In these simulations, we consider both the liquidity-based measure of financial distress used in the aforementioned modelling of the 2020 situation, and indicators related to debt servicing and leverage. We find that the level of financial distress would be higher in 2021 H1 under a system of debt-based versus grant-based support, and that the increased distress rate under a debt-based regime is driven by the higher rate of firms falling into difficulty due to leverage or interest payment difficulties. This result highlights the risks that come with debt-based supports, even when the credit risk facing lenders is partly guaranteed by the exchequer.

1. Introduction

The COVID-19 pandemic has had an extraordinary effect on the finances of businesses globally, with companies in sectors relying on customer physical presence experiencing common and dramatic falls in revenue across the globe. Another common trend internationally has been the relatively muted level of business closure and insolvency at the time of writing. This delay owes to traditional lags between revenue shocks and business closure, but more importantly, due to active policy decisions by monetary, fiscal, macroprudential and microprudential authorities, all of which have acted to either directly support business balance sheets, facilitate governments and banks in channelling support to the real economy, or provide forbearance to those unable to meet their outgoings.

Due to this delay in observing insolvencies, and to data publication lags, a detailed understanding of the degree of financial distress across the SME population is not available, and can only be proxied by measures such as the take-up rate on bank loan moratoria, or survey data on requests for other creditor forbearance. For this reason, simulation models are required to understand the way the shock is likely to be transmitting to the real economy, and the likely trajectory for financial distress and ultimately insolvencies. Such models can allow us to understand how financial distress depends on a range of factors including sector exposure to the pandemic, ex-ante financial health, and the extent of available support and forbearance. Further, simulation models can allow counterfactual policy calibrations and macroeconomic scenarios to be imposed, providing the audience with an understanding of the sensitivity of financial distress to such forces.

In this paper we introduce a simulation model for the Irish Small and Medium Enterprise (SME) sector which can address all of these topics. We focus on the SME sector both due to its importance in the real economy,[2] but also the specific nature of SME financial distress, which cannot be alleviated by access to international financial markets or pandemic-specific central banking policy measures that can support corporate borrowers such as the ECB's Pandemic Emergency Purchase Programme (PEPP) or the US Federal Reserve's Primary and Secondary Market Corporate Credit Facilities. Rather, SME financial distress, in the absence of outside private investment, must be alleviated either through fiscal support, local creditor forbearance, or when these avenues fail, liquidation. Given that insolvent liquidations are not observable until they have passed through the court system, which even in normal times will lag economic shocks, simulation models that can be deployed to approximate financial distress rates in close to real time are particularly important. We use our firm-level data to define financial distress along two dimensions: firstly, if cash cannot cover three months of operating losses; secondly, if cash cannot cover three months of interest payments on debt, while the SME is simultaneously in negative equity.[3]

The microsimulation framework we present works with SME balance sheet and P&L information to assess SMEs' financial distress, and can be used for a wide range of purposes. We highlight one particular application in this paper, namely to assess the role of a range of fiscal support packages during the COVID-19 pandemic, that directly inject liquidity into a subset of SMEs in alleviating financial distress rates. The design of the model and representativeness of

[2] In Ireland, small businesses encompass 249,690 micro firms (1-9 employees), 17,713 small businesses (10 - 49 employees), and 3,154 median business enterprises (50 - 249 workers), together accounting for 68% of total Irish employment and 39% of gross value added.

[3] In the paper we show the sensitivity of financial distress estimates to a variety of choices for these threshold points.

the underlying firm-level data allows scaled versions of announced policy supports to be modelled as reaching a certain share of the overall SME population, and for the supports to then reduce the financial distress rate as a direct function of the level of shortfalls on business balance sheets, and design features of schemes such as eligibility criteria and maximum amounts per applicant.

To allow our estimates of financial distress to reflect the heterogeneity in the link between SMEs' experience of the pandemic and ex-ante financial health, we utilize three distinct data sources. Firstly, we use a representative survey of Irish SMEs in 2018 and 2019 which captures profit and loss and balance sheet information, allowing us to measure ex-ante cash holdings, leverage and profitability; secondly, a series of firm-level surveys (the "Business Impact of COVID-19 surveys", BICS) carried out monthly during the initial phase of the pandemic by Ireland's Central Statistics Office (CSO) allows us to measure changes in revenue, wage costs and non-wage costs between April and September 2020 at the sector level; thirdly, we use Central Bank of Ireland *Quarterly Bulletin* economic forecasts to construct sector-specific paths for revenues beyond September 2020. In this way our analysis uses richer data that more directly captures heterogeneity in the effects of the pandemic than recent papers estimating SME failure rates such as Gourinchas et al. (2020), who impose country-level shocks to revenue based on GDP forecasts onto cross-country SME balance sheet data.

Our granular data allow a rich description of the pre-pandemic financial health of Irish SMEs. In general the sector was profitable, with our estimated profit margin being positive for 68.5 per cent of firms, and an average profit margin of 21.2 per cent.[4] Indebtedness was low, with only 42 per cent of firms reporting positive bank debt balances, while among those firms with operational losses, 10 per cent did not have cash buffers sufficient to cover them.[5]

From this starting point, we then simulate the effect of the COVID-19 shock in 2020 Q2 and Q3 using survey responses from the CSO's BICS. We model how they evolve over the subsequent 12 months up to 2021 H1 absent any fiscal policy supports using macroeconomic forecasts from the Central Bank of Ireland. This no-policy counterfactual analysis serves as a benchmark for discussing the role of different policy measures introduced by the government in lowering financial distress rates. We find firstly that the COVID-19 shock has had substantial effects. Over the model horizon, the FD rate would reach 24 per cent (and 30 per cent of SME debt balances) owing solely to macroeconomic developments.[6] At the sectoral level, there is

[4] To mitigate risks coming from reporting error and misinterpretation of survey questions around business expenditure, we adjust the reported profit margins in the survey data so that sectoral level average profit margins match "Gross Operating Surplus" data reported at sector level by the Irish Central Statistics Office *Industry, Construction and Services* statistics, for which the most recently available data related to 2017.

[5] McCann and McQuinn (2017) and the Central Bank's *SME Market Reports* have previously shown that there has been a steady downward trend in SME indebtedness in the decade following the previous financial crisis. On liquidity, we show, in line with other studies globally, that Irish SMEs' liquidity coverage suggested there were vulnerabilities to exogenous shocks among cohorts of the population: the share of SMEs with cash balances insufficient to cover either 3 or 6 months of reported pre-pandemic operational losses was 8.7 and 12.6 per cent, respectively

[6] General equilibrium effects of policy support measures, such as the effect of wage subsidy and enhanced welfare schemes on consumption, are embedded into the macroeconomic projections used. However, the specific effects at the firm level of pandemic-related SME support policies, and their role in improving SME solvency and liquidity by directly injecting liquidity onto distressed balance sheets, are not captured through these macroeconomic channels and must therefore be imposed in the micro-simulation we propose in this research.

unsurprisingly substantial variation, with the FD rate in the Accommodation and Food sector reaching above 40 per cent, with the least affected sectors having initial FD rates around 20 per cent, and falling over the scenario horizon.

In a series of simulations, we use our model to disentangle individual policy effects and investigate the features of policy design that are associated with greater success in lowering financial distress rates.[7] The first key insight is that policy support packages that are calibrated to match the size (€7.5bn of non-payroll supports) and mix (between debt, grants, and wage subsidies) introduced in Ireland up to September 2020 reduce the FD rate at end-2020 from 19 to 16 per cent, and have larger effects in reducing the debt-weighted FD rate from 26 to 14 per cent. While important, these effects still leave a large amount of firms in financial distress, and suggest that despite the exceptional commitments of the exchequer to support business, forbearance and restructuring policies will be crucial in ensuring the system can absorb the shock over the medium term.

In this vein, our results echo the narrative of Greenwood et al. (2020) that legal and institutional features related to company closure and restructuring should be at the forefront of policymakers' minds as they plan for the next phase of the crisis response – even with substantial direct supports implemented, there will unavoidably be firms entering insolvency proceedings.

Secondly, our results on policy targeting suggest that policy supports can have significantly greater effectiveness in reducing FD, per euro spent, if they can target the firms with the smallest losses in euro terms, i.e. each euro spent is targeted to bring as many marginal cases out of financial distress as possible. While these findings may appear obvious, they act as a very useful benchmark with which to compare the effects of announced policies. The scale of the difference is substantial: announced policy supports lower FD rates from 19 to 16 per cent in our baseline model, while our hypothetical loss-based system, when allocating €7.5bn in direct grants, lowers FD from 19 to 7 per cent.

This suggests that, due to a need for rapid introduction and wide eligibility criteria, along with difficulties in the practical implementation of targeting and the wider range of considerations of policy makers, fiscal supports implemented in Ireland in 2020 achieved significantly lower reductions in financial distress than a hypothetical scheme whose sole aim is the reduction of financial distress. It is important to note that this outcome is not necessarily the one that would maximise welfare. The topic of welfare-maximising policy design of fiscal supports is beyond the scope of this study and would require a general equilibrium setting. Such a discussion requires serious treatment of trade-offs related to targeting versus speed of provision of funds, as well as regional and sectoral issues that have implications for long-term scarring from an under-provision of support. Lambert et al. (2020) provide a detailed summary of the public policy debate around policy support and design during the pandemic.

Our framework is flexible enough to allow a contribution to the debate on the implications of debt-based versus grant-based supports.[8] The debate has focussed on the informational and operational advantages of banks in implementing debt-based policy support, along with incentive alignment from partial guarantees, which must be weighed against the direct,

[7] Lambert et al. (2020) discuss the wider mandate of government policy, which goes beyond solely the minimization of financial distress rates, and may include longer-term considerations around regional and sectoral patterns.

[8] See for example Honohan (2020) and Boot et al. (2020).

unconditional nature of grant-based support, which is likely to reach more firms due to a lack of demand-side frictions (see McQuinn, McGeever and Myers (2020) for a more detailed discussion). We project financial distress rates to mid-2021, firstly allowing bank loan payment moratoria to expire at end-2020, implying that bank debt is due for six months in the model, and secondly by allocating the full €7.5bn of governmental non-payroll support through either loans or grants. We find firstly the level of financial distress is higher by 2021 H1 for debt-based versus grant-based support when running both alongside the Central Bank's baseline macroeconomic scenario (14 versus 11 per cent). Secondly we show that the composition of FD rates is quite different: our solvency criteria are responsible for one quarter of financial distress cases in the economy with grant supports, versus 47 per cent in the economy with debt-based supports. The result highlights the longer-term risks that come with debt-based supports, even when the credit risk facing lenders is guaranteed by the exchequer.

While our model is calibrated to Irish data and policy implementation, it is relevant to an international audience. The COVID-19 pandemic has generated a remarkably similar shock across the global economy, with survey results from a range of countries showing a similar range of effects on business revenues across sectors. Further, debates about the appropriate mix of debt and grant support, the risk of debt overhang, and the effectiveness of such policy in mitigating financial distress, have been occurring across the globe as a response to the pandemic. Our findings on the relative success of various policy packages is therefore of a general interest.

Our analysis builds on a rapidly evolving literature on the economic impacts of COVID-19. Both Greenwood et al. (2020) and Gourinchas et al. (2020) have used a combination of macro projections, surveys and balance sheet data to project firm failure or distress rates resulting from the pandemic. Bartik et al. (2020) have shown survey evidence on the effect of the pandemic on businesses in the USA, while others have studied in detail the "credit line" channel, through which large draw-downs of existing available credit facilities were an important part of the corporate response to the liquidity shock (Chodorow-Reich et al., 2020, Greenwald et al., 2020).

Martinez-Cirillo et al. (2020) have carried out a similar study using the same data as ours, focussing solely on the revenue gap for Irish SMEs resulting from the pandemic. In particular, our approach is very similar in spirit to Gourinchas et al. (2020), with our study having the advantage of sector-specific survey results on experiences during the pandemic to map to ex-ante granular balance sheet data. Further, our treatment of policy design matches the specifics of that implemented by the Irish government in 2020, treating the effect of debt-based supports differentially, as such supports increase leverage over the medium term.

Separately, several recent papers have used micro data to assess the effectiveness of government supports for small businesses with respect to short and medium-run survival and employment outcomes (e.g., Chetty, Friedman, Hendren and Stepner (2020), Bartlett III and Morse 2020, Granja, Makridis, Yannelis, and Zwick 2020). These papers have identified a number of important results consistent with our findings. For example, when analysing the Payroll Protection Program (PPP) and Pandemic Unemployment Insurance (PUI) for small businesses survival, Granja, et al. (2020) conclude that significant heterogeneity across banks in terms of disbursing PPP funds, which does not only reflect differences in underlying loan demand. The top-4 banks alone account for 36% of total pre-policy small business loans, but disbursed less than 3% of all PPP loans. Consequently, areas that were significantly more exposed to low-PPP banks received much lower loan allocations. Chetty, et al. (2020) also find

that PPP loans have also had little impact on employment at small businesses, because firms that apply for PPP loans don't intend to lay off workers on the first place. These results, including ours, all point to the same insight that, for a policy to be effective, it should be designed in a way to target the most affected firms and give targeted amount the money to reflect the loss caused by the pandemic.

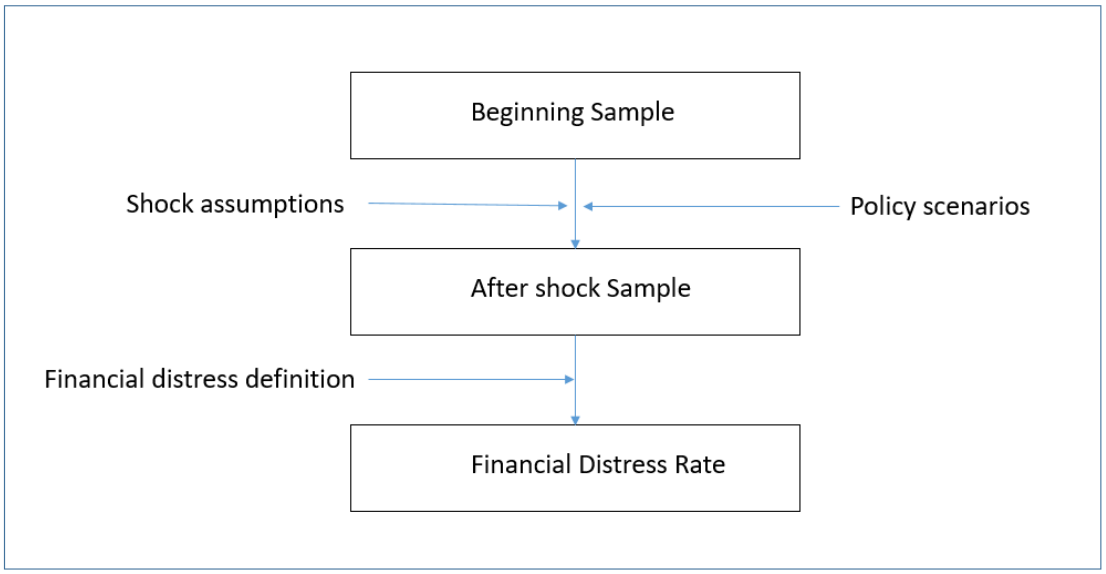
The rest of the paper is organized as follows. In Section 2 we present our framework for determining financial distress of small businesses. We describe our data in Section 3 and provide summary statistics of key variables. Our initial simulation results are reported in Section 4. Section 5 evaluate the policy outcomes with respect to the design of small business assistance programs. Section 6 discusses the longer-run consequences of debt support. Section 7 concludes.

2. A simulation-based Model for Financial Distress

The first objective of the microsimulation model is to estimate the impact of the COVID-19 crisis on financial distress (FD) of SMEs. The model can then be used to conduct policy counterfactuals.

The starting point of our simulation modelling is based on a sample of SMEs surveyed before the COVID-19 crisis.[9] The data contain information about revenue, costs and key variables of balance sheets of SMEs in Ireland. As shown in Figure (1), to simulate the financial position of SMEs during the pandemic, we make assumptions on how the COVID shock impacted on revenue and costs based on a number of sources. These are a combination of monthly surveys carried out from March to August to approximate sectoral shocks to revenue and costs in Q2 and Q3, followed by macroeconomic projections for 2020Q4 and 2021Q1. We also design different policy scenarios according to what is implemented by the government during the crisis. We will discuss those assumptions in detail in turn below. After simulating the SME sector in the COVID crisis, we calculate the aggregate rate of financial distress based on the definition of FD.

Figure 1: Overview of modelling approach



[9] We describe our data in Section 3.

2.1 Assumptions on COVID impacts

We simulate the effect of the pandemic across the distribution of SMEs for three points in time - 2020Q2, 2020H2 and 2021H1. These key periods during the COVID-19 crisis are supposed to capture the impacts at the immediate impact, short-run and medium-run. We must rely on simulation because we are mapping sector-level average real-time survey responses on experiences during the pandemic to firm-level ex-ante financial information.

In the micro-simulation exercise, we calibrate three key variables – turnover, personnel costs and non-personnel costs. We use the Business Impact of COVID-19 Survey (BICS)[10] carried out by the Irish Central Statistics Office (CSO) to gauge the impact of public health restrictions on the revenue and costs of SMEs in 2020 Q2 and Q3. Surveys were published covering periods of roughly one month finishing on the following dates: 19 April, 3 May, 31 May, 28 June, 26 July, 23 August. The survey was carried out at the firm level, by telephone, and does not come with the typical CSO guarantee of representativeness. Nonetheless, it represents a powerful source of information to assess the real-time experiences of SMEs across sectors during the pandemic, while researchers must wait for additional granular data on actual pandemic experiences at the firm level to be collated. The evolution of turnover and non-personnel costs as reported in the surveys is reported in Figure 2.

Figure 2: turnover and non-personnel cost experiences during the pandemic

Figure 2a: share of firms reporting turnover declines of more than one half relative to pre-pandemic levels.

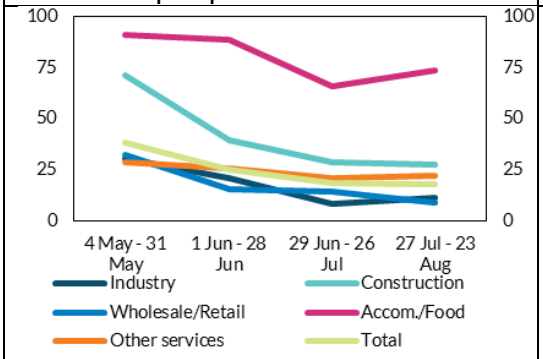
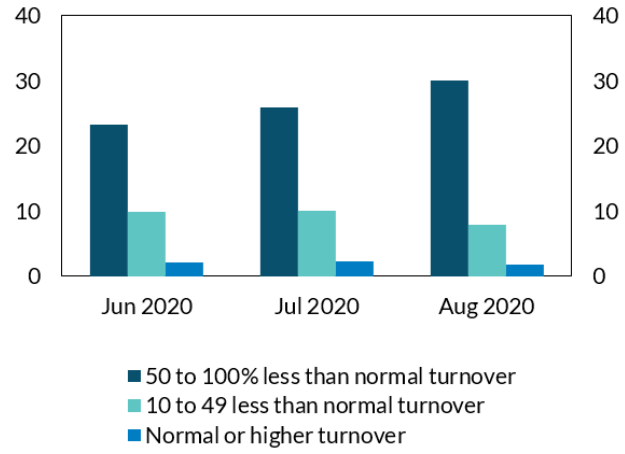


Figure 2b: extent of non-personnel cost reduction, as a function of reported falls in revenue



Source: CSO Business Impact of COVID-19 Survey, authors' calculation. Surveys may not be fully representative of the population of Irish SMEs and are provided on a best-efforts basis by the CSO to depict the revenue and cost situation facing these firms

We use the survey information from the first four waves to construct the joint distribution of changes in turnover and non-personnel costs for each firm in the CDS starting data in 2020 Q2 (See Table A2). For personnel costs, we apply a flat reduction of 20 per cent to all SMEs in the no-policy scenario calibration. We then run a Monte Carlo simulation of the COVID-19 shock in 2020 Q2, based on our sample of SME firms in 2018/19. During the simulation, each firm in a given sector has the sector-level average response for changes in turnover and non-personnel costs applied. More specifically, as shown in Table A2, each sector has three possible levels of

[10] For more details of BICS, please visit: https://www.cso.ie/en/methods/tn/businessimpactofcovid-19survey/

non-personnel cost reduction, and six possible levels of turnover changes specified in the BICS. These give 18 possible outcomes for each SME's turnover and non-personnel costs. Table A2 summarises probabilities of all 18 possible outcomes depending on sectors. We then draw a random whole number between 1 and 18 for each firm based on the probability distribution for a given sector, with each whole number pointed to a fixed combination of changes in turnover and non-personnel costs. By applying this procedure to all five sectors defined in the survey, we simulate the new levels of turnover and non-personnel costs of every SME in the data under the COVID-19 shock in 2020 Q2, and then we use those simulated levels of turnover and costs to generate the new levels of key outcome variables for each firm in 2020 Q2.

For the simulations beyond 2020 Q2, we then use the survey responses from the July and August waves to proxy the Q3 revenue and cost experience of SMEs, carrying out the same Monte Carlo simulation approach. To get to year-end 2020, and on to 2021H1, we use quarterly macroeconomic projections with sectoral variation under a baseline and adverse scenario as published by the Central Bank of Ireland's *Quarterly Bulletin 2020 Q3.* We use projected growth rates in sectoral employment levels to map proportional sectoral revenue growth in each scenario.[11] During 2020Q4 and 2021H1, SME costs are projected to remain at 2020Q3 levels.

Table 1: Summary of key assumptions and policy scenarios used in simulations

Period	Growth assumptions for revenue and costs	Policies in operation
2020 Q2	Table A2	TWSS, Payment breaks
2020 H2	Table A3	EWSS, Payment breaks, Grants, State loans and credit guarantees, Tax warehousing.
2021 H1	Table A3	All policies remain, except for payment breaks
Note: TWSS and EWSS are wage subsidy schemes ; tax warehousing involves the suspension of tax liabilities until a future date at zero interest; payment breaks were implemented in line with EBA Guidelines on payment moratoria and were in place for up to six months during 2020. *See Lambert et al. (2020) for a detailed description of all schemes implemented up to September 2020 in Ireland.*		

2.2 Definition of Financial Distress

Financial distress is an abstract concept that is not directly observable in the data. We follow the literature to use indicator variables to capture this concept. Building on Martinez-Cillero, Lawless, O'Toole (2020), we estimate the short-term liquidity gap of SMEs due to revenue shortfalls, and relate it to the cash buffers on SME balance sheets. We also take into account debt-related variables, such as the leverage ratio and the interest coverage ratio. The key indicators are defined as follows:

1. Liquidity coverage ratio: number of months in which a firm's cash reserve covers its operational losses. As flow variables in our data are measured on an annual basis, we divide them by 12 to get monthly quantities.

$$LC = 12 * \frac{Cash}{Opernational\ Loss}$$

[11] We use quarterly sectoral employment growth rate projections to map to sectoral revenue growth rates because employment is the only variable that is forecast with sectoral heterogeneity by the Central Bank of Ireland's forecasting team.

2. Leverage ratio:

$$LV = \frac{Debt}{Total\ Assets}$$

3. Interest coverage ratio: number of months in which firm's cash flow and cash reserve can cover its interest expenses

$$IC = 12 * \frac{Operational\ surplus + Cash}{Interest\ expense}$$

A firm is classified as being in financial distress under one of two conditions:

$$(1)\ LC < \underline{LC}$$
$$(2)\ IC < \underline{IC}\ and\ LV > \overline{LV}$$

Our financial distress framework covers both a short-run liquidity shortfall (1) and a debt servicing distress (2). We refer throughout the paper to the former as "liquidity distress" and the latter as "solvency distress". In the short-run as of 2020 H2, we focus on criterion (1) above as the key indicator for financial distress. We define a firm to be in financial distress when its cash holding can cover less than three months of operational loss ($\underline{LC} = 3$). Given there is no standard regulatory definition of financial distress, we have chosen the three month threshold to match the spirit of regulatory banking definitions of loan default.[12] However, in robustness tests, we stress the threshold value of all key indicators of FD to show the extent of level differences resulting from these choices.[13] We do not consider the solvency distress criterion (2) during our 2020 H2 simulations in order to match the policy environment as closely as possible : in the initial phase of the pandemic, interest coverage was not a relevant burden for SMEs in Europe owing to standardized payment moratoria in place in accordance with EBA guidelines published in April.

Given that the Irish payment moratoria lasted for a maximum of six months, we switch on criterion (2) when assessing FD during 2021 H1. In particular, in our baseline simulation we define a firm in financial distress, when the leverage ratio is greater than one ($\overline{LV} = 1$) and the interest coverage ratio is less than three months ($\underline{IC}$=3). The first condition indicates that a firm has negative equity. In this case, it is difficult for those firms to continue borrowing from banks, as they cannot provide collateral. The second condition captures the debt servicing difficulties faced by distressed firms. When both conditions are met, the firm has both a debt servicing problem and binding borrowing constraint.

One important contribution of our methodology is to allow for debt-like and grant-like supports to have differing effects on the FD rate, owing to the leverage and interest-increasing effects of the former once payment moratoria are switched off in the model. Unlike debt-based supports, grant-like instruments immediately improve the liquidity coverage and interest cover ratios without increasing the leverage ratio over the longer term. Our final set of simulations will quantify the importance of these distinctions.

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[12] Conversations with examinership and insolvency practitioners in Ireland suggest that, while no hard rule exists, three months is a reasonable parametrization for the *LC* criterion.
[13] Results are shown in Table A1.

2.3 Limitations

Our modelling approach is subject to several limitations. First of all, our simulation is partial equilibrium in nature. Given that wider general equilibrium effects of policy supports on firms' capacity to hire and spend, and their knock-on effects in the wider economy, our estimates can be interpreted as a capturing the "first-round" effects of COVID-19.

The second caveat is that we ignore all endogenous adjustments in factor inputs and prices at the firm-level. Our simulation only takes the minimum set of accounting entries into account, while leaving all optimal adjustments at the firm's level out of scope. Gourinchas et al. (2020), by contrast, adopt a simple theoretical model in which firms optimize profits by choosing inputs given demand and prices of their output. This approach resolves the behaviour bias, but introduces many "deep parameters" regarding the production function and the technology shock process, which are difficult to calibrate, thereby introducing additional sources of model uncertainty.

Third, regarding the measure of financial distress, the choice of thresholds for our *LC*, *IC*, *LV* benchmarks do not have formal regulatory basis, given that financial distress is an economic rather than a legal concept. Given the importance of these thresholds in assigning firms in a binary "yes/no" financial distress state, we conduct robustness tests on parameter threshold uncertainty in Table A1. Lastly, while we model a rich sectoral environment, we do not incorporate input-output linkages that could amplify some of the results (see McCann and Myers (2020) for a discussion of such linkages in Ireland during the pandemic). While allowing for the network effect would be an interesting exercise for the future research, we believe they are unlikely to weaken our main findings, particularly in the short run.

3. Data and Summary Statistics

We begin by documenting the initial conditions of SME sectors before the COVID-19 shock. For this purpose, we use data from the Credit Demand Survey (CDS) to gauge the profitability and financial conditions of SMEs before the crisis.[14] The CDS is a biannual small and medium-sized enterprise survey, conducted by the Irish Department of Finance and aims to monitor the credit demand and financing needs of SMEs. The latest two waves available before the pandemic cover the period April 2018 to March 2019. After initial data cleaning and removing outliers, 1787 firms across all sectors are left in our dataset. In Table 2, we report summary statistics of key economic indicators that we use later as starting points for our micro-simulation.

[14] The CDS sample was selected at random from a database of all SMEs across Ireland supplied by Bill Moss, which covers approximately 115,000 SME records in Ireland. The starting sample of SMEs was randomly extracted from this database, across each SME size category and NACE sectoral group, ensuring that respondents included a reasonable spread of micro, small and medium sized SMEs and a proportional representation of the 16 key business sectors. Based on a total database of 130,000 SMEs in Ireland, the total sample of 1,501 companies has a possible sample error of just +/- 2.6% (at a 95% significance level), while the sub-samples of micro, small and medium companies (each with approximately 500 interviews) has a possible sample error of just +/- 4.4%. More details are available here.

Table 2: summary statistics for 2018/19

Sector	No.	Profit Margin*	LC < 3+	Indebt	leverage	LV >1	IC < 3
Wholesale, Retail Trade, Transport & Comm.	634	16%	11%	42%	0.64	4%	6%
Manufacturing	230	25%	5%	46%	0.64	4%	6%
Construction	187	19%	10%	36%	0.55	4%	4%
Business & Admin. Services	529	25%	7%	39%	0.63	5%	10%
Hotels & Restaurants	207	24%	9%	55%	1.39	13%	13%
Summary	**1787**	**21%**	**9%**	**43%**	**0.77**	**6%**	**8%**

*Notes *: due to some uncertainty around the reporting of expenditures in the CDS, we adjust the annual costs of firms in the data to arrive at profit margins that are on average consistent with sector-level data reported by the CSO's enterprise statistics*

Note +: LC criterion is only applicable to firms with operational losses in the starting point data. All firms with an operating profit receive an NA.

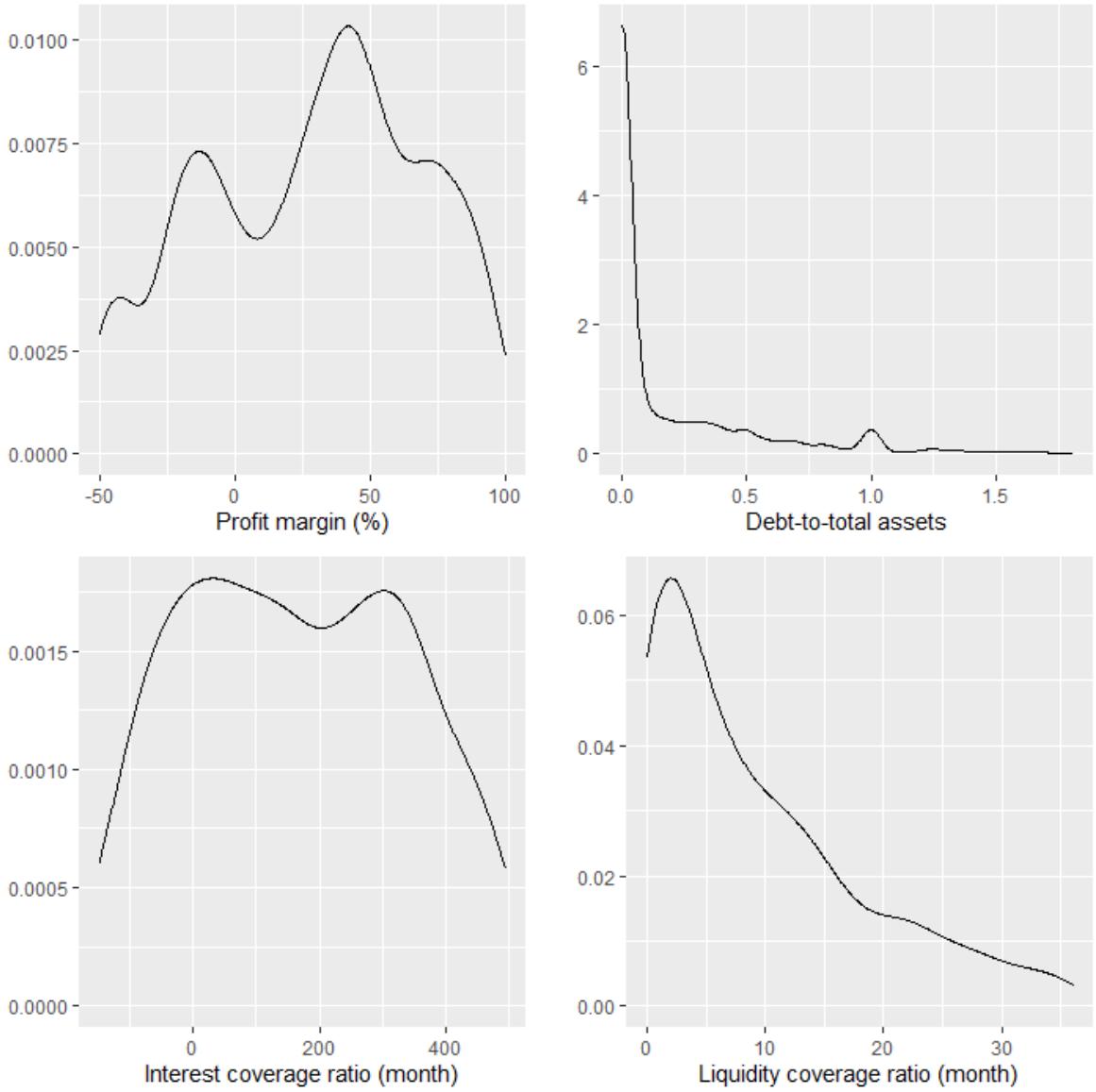
Before the pandemic, SME sectors were generally profitable and liquidity shortage was not pronounced. 8.6% of firms (among those making losses) did not have enough liquid assets to cover more than three-month operational losses. On indebtedness, 43% of SMEs reported having outstanding bank debt, with leverage ratios is generally below 0.7 except for Hotels & Restaurants. Only 6% of firms had negative equity. Our *IC* criterion suggested that in 2018/19, among firms with debt, 7.7 per cent did not have cash to meet three months' interest payments.

Figure 3 reports distributions of key variables used in our simulation. Panel (A) shows the majority of firms making positive profit margins, with the majority in the range 10 to 50 per cent. However, negative margins face close to one third of firms, with some having margins below -25 per cent.

The bifurcated nature of indebtedness is apparent in Panel (B), with over half of firms having zero debt. Among those with debt, the leverage (debt to asset ratio) distribution is skewed to the left, with ratios below one half more common than not, and a small right tail of 6 per cent of firms in negative equity.

Panel (C) highlights the relatively uniform distribution of the ICR, with similar numbers of firms spread between ICRs of zero to ten years. The left-skewed nature of the LCR, with many firms having less than one year's worth of operational losses as cash, is borne out in panel (D).

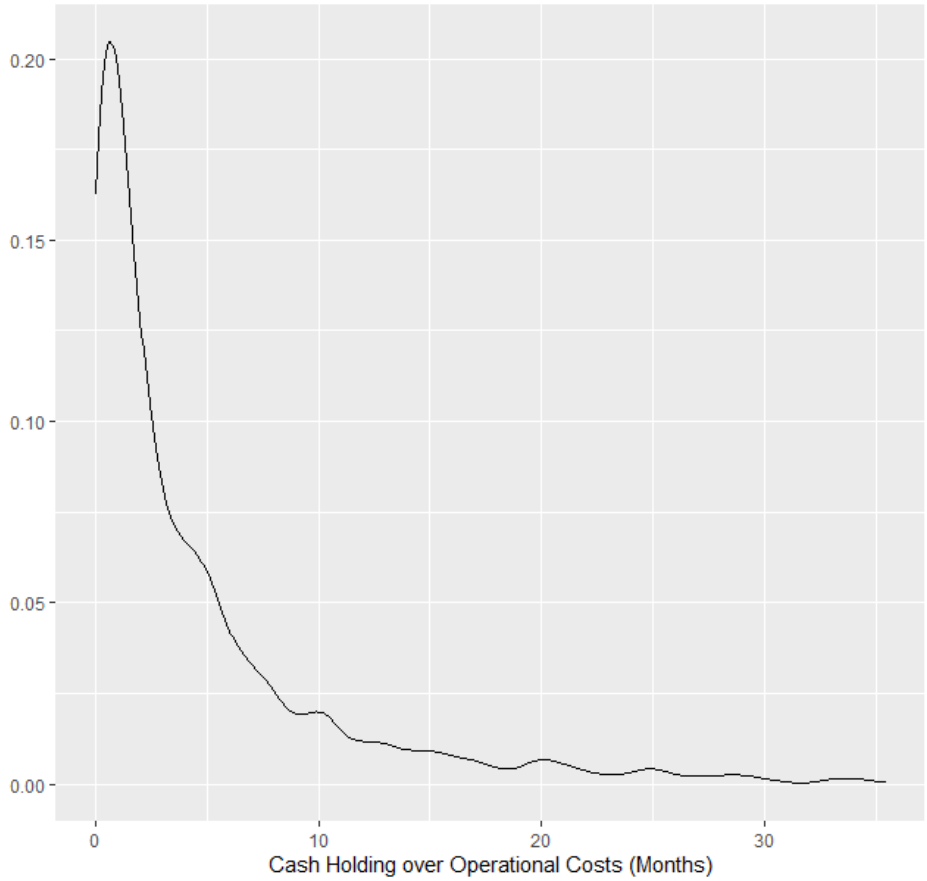
Figure 3: distributions of key variables



Notes: all distributions reported using the 2018-2019 data and represent the distribution of starting values for our simulation. Panel (A) reports adjusted profit margins. Panel (B) reports debt to total assets. Panel (c) reports ICR as the ratio of operational surplus to monthly interest expenses on debt, and are only reported for those firms carrying debt (42 per cent of the sample); values can be negative where firms were making operational losses pre-pandemic. Liquidity coverage ratios are calculated as cash relative to operational losses, meaning that only firms making a loss pre-pandemic are included in the graph in Panel (D).

Given that our measure of the LCR is reported only for those making an operational loss pre-pandemic, we also report a second liquidity metric in Figure 4: the ratio of cash to operational expenses. The graph highlights clearly that liquidity buffers of less than six months' worth of total operational expenses were prevalent across the system.

Figure 4: ratio of cash to operational expenses



Notes: reported 2018-2019 data, all firms.

4 Simulation Results for COVID-19 Crisis

We begin by running simulations based solely on sectoral shocks mapped from the BICS for 2020Q2 and 2020Q3, and *Quarterly* Bulletin forecasts from 2020Q4 to the end of 2021H1. N o policy supports are introduced onto SME balance sheets in these simulations. The results are reported in Table 2. Column 1 shows that, before any projections are applied, the starting point FD rates were 8.9 per cent, and 7.3 per cent when weighting firms by debt balances. In Column (2) we report the immediate effect of the pandemic in 2020Q2: 24 per cent of firms, or 30 per cent when weighted by debt balances, are estimated to have been in financial distress by June 2020.

Our projections beyond the immediate lockdown phase begin in Column 4. In columns 4 and 6 we show that the FD rate falls to 18.6 or 20.7 per cent during the second half of the year in the model, depending on the scenario. These reductions are caused by the relative improvement in the economy, even in the adverse scenario, when compared to 2020Q2. Using the 2021 H1 projections, the baseline and adverse FD ratios are projected to fall to 17.2 and 18 per cent in the base and adverse scenarios as a result of a gradually improving macroeconomy.

In all cases, during the pandemic simulations, debt-weighted FD rates are higher than those using a simple count of the number of enterprises. This is primarily due to the sectoral composition of the shock, with high-debt sectors like hotels, restaurants and retail having experienced worse-than-average effects of the pandemic.

Table 3: simulations for 2020 without any policy supports

	2018/19	2020 Q2	Baseline		Adverse	
	Starting point		2020H2	2021 H1	2020 H2	2021 H1
FD (%)	8.89	23.9 (22.3 – 24.5)	18.6 (17.6 – 19.9)	17.2 (16.1 – 18.4)	20.7 (20.0 – 22.3)	18.0 (17.4 – 19.7)
Debt-weighted FD (%)	7.34	30.1 (24.1 – 35.3)	25.9 (21.2 – 31.6)	24.3 (19.2 – 29.8)	28.9 (23.9 – 33.4)	24.8 (20.4 – 31.0)

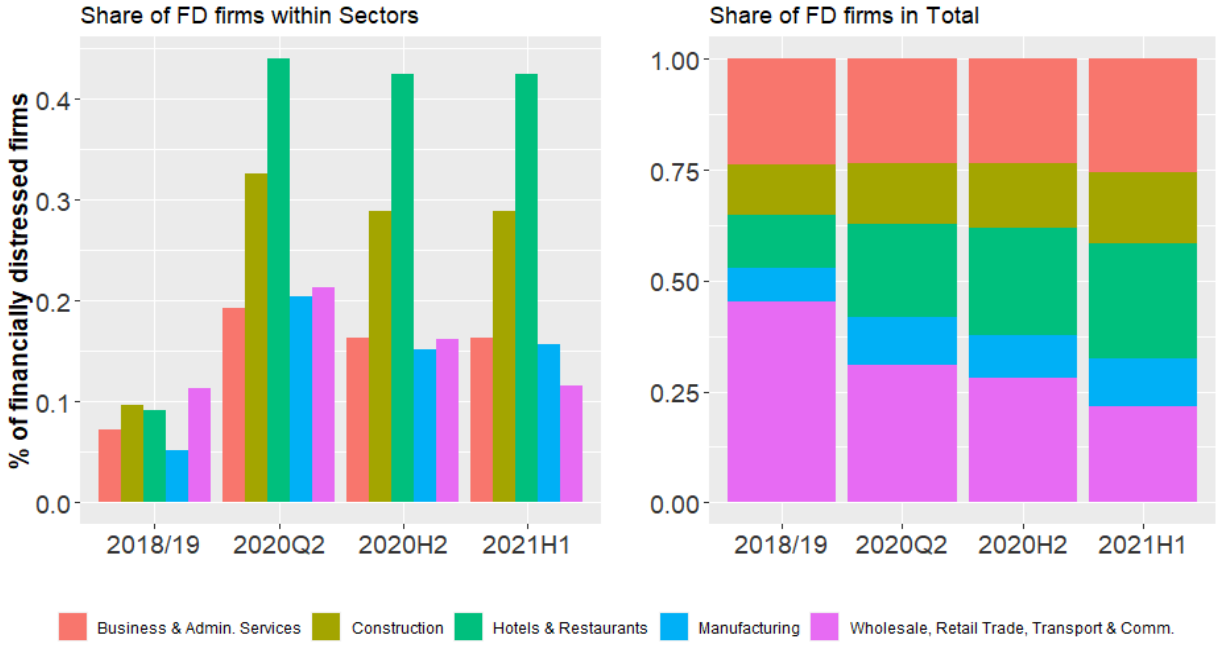
Sector level heterogeneity is shown in Figure 5. In proportional terms, hotels, restaurants and construction firms stand out for their FD rates, while Business and Administrative services sectors are less affected. Looking at the share of each sector in all firms in distress, a different picture emerges: due to their weaker macroeconomic relevance, even though over 40 per cent of hotels and restaurants are in distress, they only account for around 20 per cent of 2020Q2 distress cases. However, our sectoral heterogeneity in the modelling approach means that, as the scenario elongates and other sectors of the economy are projected to recover, the importance of hotels and restaurants in total distress levels rises to closer to 30 per cent.

4.1 Robustness and modelling uncertainties

Table A1 reports results on how our simulated FD rate is sensitive to three main sources of modelling uncertainties – macroeconomic uncertainty, sectoral COVID impact uncertainty and parameter uncertainty. To account for macro uncertainty, we present FD estimates based both on baseline and adverse scenario of the central bank's macro forecast. The range of variation is about 2% across these scenarios. For sectoral COVID impact uncertainty, the Monte Carlo simulations show the 90% confident interval of the FD rate. The largest uncertainty comes from the choice of FD threshold parameters. As results shown, the most binding parameter is the liquidity coverage constraint (LC). When it increases from 3 months to 6 months, the FD rate shifts from 18.1% to 24.5%. That means many SMEs are located at the range where their cash holdings could only cover their operational losses between 3 and 6 months. On the other hand, simulated FD rates are not very sensitive to the interest coverage constraint and the leverage ratio constraint.

Overall, we find that modelling uncertainties do have a material impact on the level of the FD rate, therefore we have to be modest when taking any single point estimate of the FD rate into policy consideration. Importantly, our main policy conclusions are rather based on the difference of FD rates under certain policy scenarios, implying that level differences based on calibrations of *LC*, *IC*, and *LV* pose less of a concern, once a consistent set of threshold parameters is inputted to all scenarios. For our purposes for the rest of the paper, the results are reported for *LC*, *IC*, and *LV* levels of 3, 3 and 1, respectively.

Figure 5: Sectoral impact of COVID-19 shock



4.2 Using the model to inform policy debates: debt, grants and targeting

In this section, we simulate the financial distress rate in 2020 H2 under different policy supports. We begin by mimicking as closely as possible the exact size and eligibility parameters of the range of support schemes implemented in Ireland up to September 2020, and impose them on our SME balance sheets in the simulation. We then compare them with the no-policy counterfactual simulations to evaluate the effect of various support types on the distress rate. In Table A4, we list the policy supports implemented/ proposed by the government up to September 2020. We group support measures into four broad categories and model them differently in our simulations. A detailed discussion of the range of support schemes, and a link to the recent economic and financial debates on the merits of various scheme types, is included in Lambert et al. (2020).[15]

First, we model wage supports, such as the Employment Wage Subsidy Scheme (EWSS) and its predecessor the Temporary Wage Subsidy Scheme (TWSS), by allowing firms that have suffered more than 25% of turnover decline from the pre-pandemic level to reduce their personnel costs by 58%. In total, these schemes are projected to have provided over €5bn of support over 2020 and 2021. The rate of reduction in personnel costs is calibrated based on the BICS responses of the Hotel and restaurants sector, which had almost full take-up of TWSS support between March and June in 2020. The BICS shows that the average reduction of personnel costs in Hotel and restaurants sector was 58% during 2020Q2, with this figure applied.[16]

[15] To sum up the firm level nominal amounts into aggregate euro volumes so that the magnitude of policy support schemes can be accurately imposed on the simulation, we follow Martinez-Cillero, Lawless and O'Toole (2020), which is based on numbers of active SMEs in the CSO sectoral business demography data. Further details regarding the aggregation procedure are provided in the reference paper, Page 19.

[16] Other sectors have variable levels of take-up rates of the wage support, therefore the average reduction of personnel costs in those sectors reflect both the effect of policy and the usage rate.

Second, we group grant supports together at €2.3bn. Following the design of the "Restart Grant", we assume all firms that experience a turnover reduction of greater than 25% of pre-pandemic levels obtain a one-off €25,000 grant.

Third, there have been around €3.3bn in debt instruments (either direct loans or loan guarantees) proposed. We model them so that firms with more than a 25% drop in turnover can take loans that are equal to 25% of the pre-crisis revenue. Unlike grants, the new debt is be added to the existing debt of the firm, therefore affecting the *IC* and *LV* criteria for financial distress.

Last, we also model the tax warehousing of €1.9 billion as a separate category. These are debt-like in nature, given that liabilities have been deferred but will eventually fall due. However, the nature of obligations for future repayment is less certain than in the case of a bank loan, and eligibility criteria differ, informing our judgment to treat this support as a separate category. For simplicity, we assume all firms can get their VAT tax back equivalent to 23% of their pre-pandemic revenue, but the money will be added to the existing debt. The key difference between tax policy modelled here and the debt support is that the latter is more targeted to firms suffering actual losses during the crisis, while tax supports can be used by every company that applies for it. Further, the size of support provided by a VAT relief can be very large, at 23 per cent of previous turnover.

In addition to the actual policy supports that had been implemented by the government by September 2020, we also design a "Targeted Grant", whose size is calculated based on the actual losses that firms suffer during the pandemic, with the firms with smallest losses being supported first, so that the overall scheme can alleviate as much financial distress as possible per euro spent. We implement this scheme as a €7.5bn programme that replaces all of the 2020 non-payroll supports (whether guaranteed loans, grants, or tax warehousing) with an unconditional cash grant. We will show with our micro-simulations that this loss-targeted policy leads to significantly lower FD rates than the actual 2020 policies discussed above, sometimes bringing FD rates to half the rates arising in our 2020 policy modelling.

We impose the schemes on the model in a number of ways. In all cases, we assume that all schemes are eventually fully used, i.e. take-up of schemes is 100 per cent. To the extent that some schemes do not ultimately have full utilization of available funds, measures of effectiveness will be reduced. Figure 6 reports results from an exercise where FD rates are reported iteratively as more of the announced policy support is implemented in the model. We first implement a scenario where wage costs are reduced in line with reported falls in wage costs in the BICS, but where this only applies to firms experiencing revenue declines beyond 25 per cent. This exercise suggests that the wage bill reductions alone can reduce FD rates from 19 to 16.5 per cent at year-end 2020. Next, grants, credit and tax supports are added. In each case, the estimates suggest that additional reductions in the FD rate are not large based on currently-announced policy.

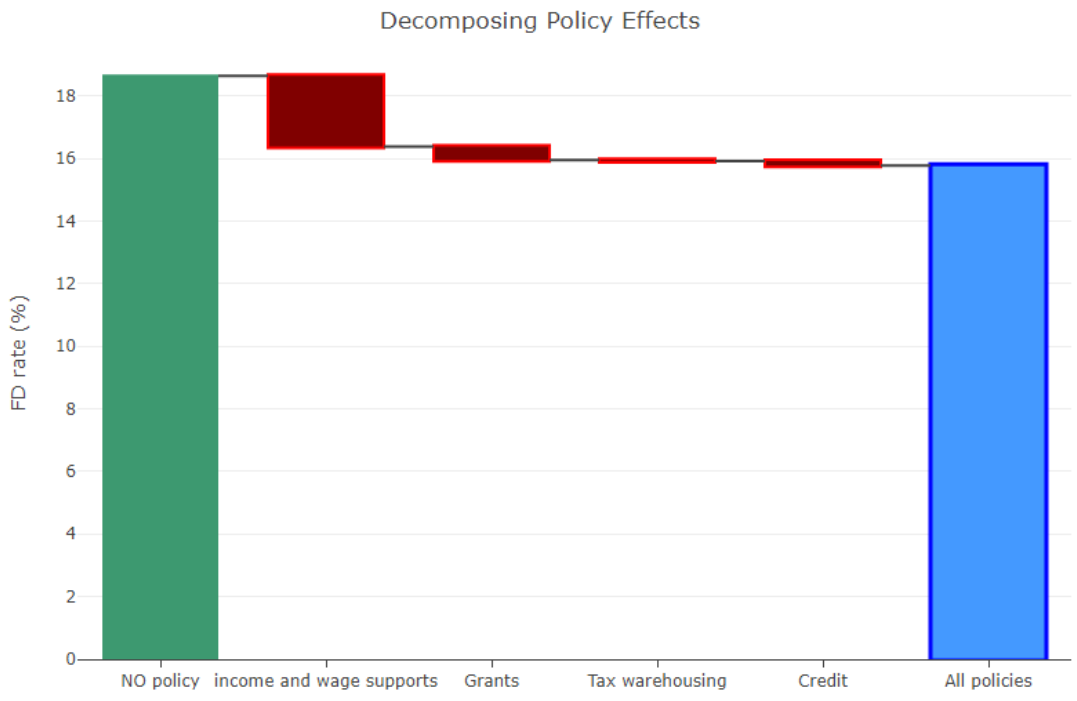
The FD rates that result after policy is implemented in the model might be considered to be high, given the unprecedented nature of the direct fiscal support provided. One explanation is that, given the design of most schemes, all firms that surpass particular thresholds for the effect of COVID-19 on revenues are eligible in many cases. This means that many firms who do not require policy support to avoid FD are just as entitled to receive funding as those in deeper levels of distress, highlighting the practical difficulties in targeting support at those needing it most. Larger firms will also in many cases account for larger volumes of total support, where maximum

allowable amounts are relatively large, meaning that funding will not necessarily be available to alleviate FD for all enterprises experiencing FD.

The objective of policy must be recalled when observing these results. While the model only assesses the effects of policy on FD, the current policy package in place in Ireland does not have as its sole objective the lowering of FD rates. Funds received by recipient firms will alleviate pressure through many channels, supporting employment and investment even in cases where funds were not required to move recipients out of financial distress.

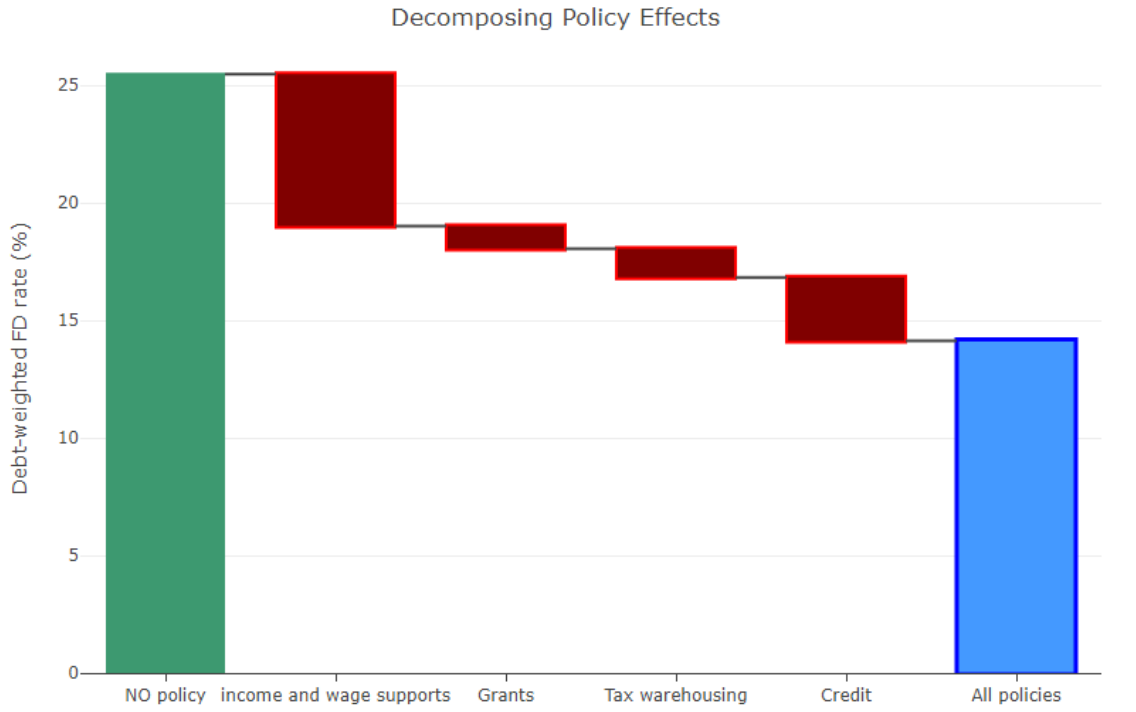
Taking a financial stability standpoint, we focus on debt balances in Figure 7. When looking only at firms with bank debt and weighting FD rates by debt volumes, the current policy support mix can reduce FD rates from 25.9 to 14.3 per cent, a reduction of two-fifths. These estimates suggest that, while a sizable cohort of smaller firms are likely to remain financially distressed even with policy supports in place, the current package will have non-negligible financial stability benefits among firms with debt. Why are there larger effects on a debt-weighted basis? Firstly, the distribution of firms with debt relative to firms in the wider economy is different, with debt balances being more concentrated in the Hotels and Restaurants, and Wholesale and Retail sectors, which account for large shares of FD in 2020. Further, debt balances will be larger among SMEs with larger levels of turnover typically, implying that these firms are likely to avail of larger shares of currently-designed policy supports. Given that larger SMEs with bigger debt balances are also likely to have bigger supplier networks and wider linkages, this suggests the aggregate economic benefits are larger than patterns solely based on Figure 6.

Figure 6: Share of firms in financial distress under combination of policies



Notes: Moving to the right, additional policy actions are included cumulatively. The blue bar is a model run where all reported policy actions are included together.

Figure 7: Debt-weighted financial distress under combination of policies



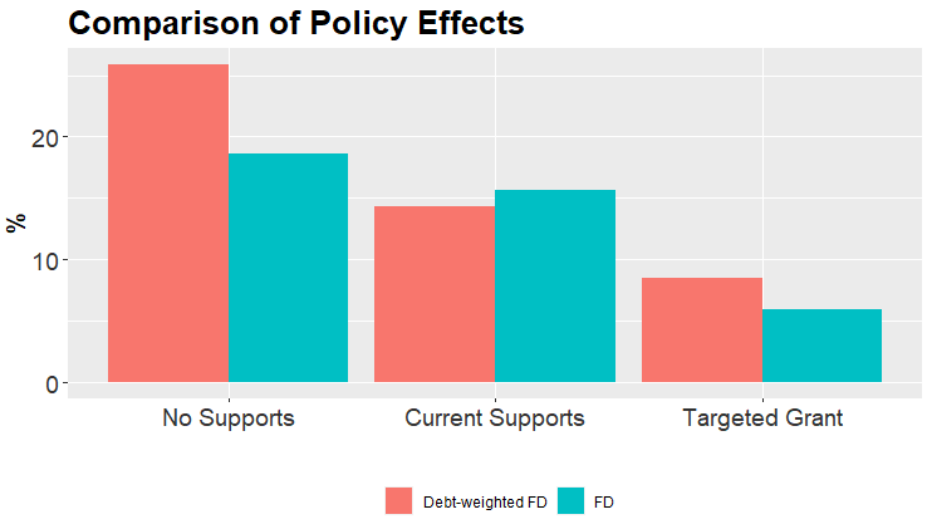
Notes: Moving to the right, additional policy actions are included cumulatively. The blue bar is a model run where all reported policy actions are included together.
Notes: This exercise relates only to firms with debt balances above zero in the 2018-19 data

Finally in Figure 8, we explore the merits of targeting. As an illustrative device, a hypothetical system of "Targeted Grants" is implemented in the model, whereby firms with losses are the only recipients of public funds, with the firms with the smallest losses receiving grants first, and funds sequentially allocated to less and less profitable firms, so that the scheme can "save" as many firms from financial distress as possible. The graph compares the FD rate, with and without debt-weighting, for three scenarios: no policies, current announced policy, and a scenario where the targeted grant replaces the €7.5bn of announced non-payroll support. This scheme is shown to lower FD rates to 5.9 per cent, and 8.5 per cent on a debt-weighted basis, which represents more than a halving of FD rates relative to the current policy package and slightly less than a halving of debt-weighted FD. In practice, policy design will not and should not operate as per the system in Figure 8, due to a wide range of regional, sectoral and longer-term considerations that go beyond a targeting of FD-minimization as the sole objective. Nonetheless, the results of Figure 8 allow a comparison of currently-designed schemes to a useful benchmark system.

A key finding in this section is that even targeted schemes for non-payroll support totalling €7.5bn would not eliminate financial distress among Irish SMEs, nor should the full elimination of FD be the aim of any policy support scheme. From a policy perspective, the identification of FD does not imply that a company will be liquidated; rather, many of the firms modelled as being in FD may be viable over the medium term but our estimates suggest that to arrive there, current financial supports will not be enough. For the most-affected firms, additional forbearance, restructuring or protection will be required, as outlined in Greenwood et al. (2020). In order to ensure that viable firms in FD have the chance to trade out of difficulty under renewed financial terms, policymakers must focus immediately on ensuring that mechanisms in

place are fit-for-purpose and will be able to operate at the required scale and speed once the current period of forbearance begins to unwind.

Figure 8: Comparing a targeted grant system with current supports



Source: Model-based estimates from McCann and Yao (2020)
Y-axis: percentage of firms (or debt balances) in financial distress
Note: "Targeted Grants" replicate payroll supports modelling from the "Current Supports" scenario, but replace the grant, credit and tax components with a €7.5bn grant that provides support to firms, with those closest to exiting financial distress receiving support first
Note: by construction, the debt-weighted exercise relates only to firms with debt balances above zero in the 2018-19 data

In Table 4, we report the key simulation results with regard to FD and debt-weighted FD rate looking at each component of schemes implemented by the Irish government in 2020 in isolation. Given that schemes have differing eligibility criteria and differing total sizes, we propose indices of "policy efficacy" measured by the reduction in the number of firms in FD under each policy relative to the no-policy cases divided by billions euros spent on the policy support. We also weight the indices by either employment or turnover of affected firms. The employment-weighting gives the index a wider economic perspective, while turnover-weighting is arguably more relevant for the government's tax revenue focus. We report them in the last two rows of Table 4.

We find that all policy schemes individually achieve better outcomes compared to the no-policy scenario. The ranking doesn't depend on the weighting schemes, with tax warehousing having higher efficacy metrics than the other schemes. The reason that tax warehousing involves greater efficacy than a simple grant system relates to the design of the schemes in the Irish context: our simulation allows all firms with a 25 per cent drop in turnover access a grant of a maximum of €25,000, whereas all firms with a turnover loss can warehouse their VAT payments equivalent to 23 per cent of turnover under our simulation of the tax warehouse. In isolation, the targeted grant scheme cannot alleviate distress for firms with shortfalls larger than €25,000, whereas the design of the tax warehouse allows a wider group of firms to avoid financial distress.

Table 4: simulation results for 2020 with announced policy support schemes implemented separately

	No Policy	Wage (2.35 bn)	Grant (2.3 bn)	Debt (3.3 bn)	Tax (1.9 bn)
FD	18.6%	16.5 %	15.9 %	16.3 %	16.5 %
FD (Debt-weighted)	25.9%	19.1 %	19.0 %	17.2 %	17.7 %
Policy Efficacy (employment weighted)	n/a	641	766	524	911
Policy Efficacy (turnover weighted)	n/a	129	153	106	184

Notes: each scheme implemented in isolation in each case. Financial distress rates at end-2020 reported. Baseline macroeconomic scenario for 2020Q4 used in all cases.

We also report the same set of results for all policies together, with €7.5 billion euros of supports in total, in Table 5. The first column shows that all policies implemented so far bring the FD rate down from 18.6% to 15.6%, and the debt-weighted FD rate down from 25.9% to 14.3%. If all liquidity supports are implemented according to the targeted grant scheme, the improvements will be much higher. Balanced against this, grant-based schemes have a much greater up-front cost to the exchequer than debt-based schemes, which can limit the scope for implementation in practice, particularly on a wide scale.

Table 5: simulation results with hypothetical €7.5 billion policy support package provided along different scheme types

	2020 H2			
	Announced Policies (7.5 bn)	All Grant (7.5 bn)	All Credit (7.5 bn)	Targeted Grant (7.5 bn)
FD	15.6 %	14.5 %	16.4 %	5.9 %
FD (Debt-weighted)	14.3 %	18.9 %	14.1 %	8.5 %

4.3 Incorporating the effects of debt over a longer horizon

In this section, we report longer-run simulation results up to 2021 H1. We assume in this period loan moratoria (referred to as "payment breaks" locally) expire and, as a result, we use all three financial distress indicators introduced in Section 2 to capture debt-related solvency risks in the SME sectors, rather than solely relying on criterion (1) ("liquidity distress") as is the case in Section 5 where results are based only on the experience in 2020.

Table 6 reports FD rates and its breakdowns into financial distresses associated with liquidity and solvency risks, respectively. We simulate three parallel SME economies for 2021 H1 with different policy histories. While two economies have grant supports (both targeted and untargeted), another one has only debt supports in 2020 H2. The FD results shown in the table are for 2021 H1 under the same recovery scenario. We assume that in 2021 H1 all policy supports except for wage subsidies are removed. In all cases, the policy implementation of loans or grants in 2020H2 is assumed to total €7.5bn, will full uptake of allocated funds.

Table 6: Financial distress rates at 2021H1 under varying regimes

	Grant	**Targeted Grant**	**Debt**
FD	11.4 %	6.9 %	14.4 %
FD (Solvency risks)	2.8 %	2.4 %	6.8%
FD (liquidity risks)	8.6 %	4.5 %	7.6%

Notes: Policy supports are implemented in 2020H2 and 2021H1 in all simulations. In previous sections, debt-based distress criteria were not implemented during 2020 to match the reality of loan moratoria being in place. If a firm is in both liquidity and solvency distress, it is categorised as "solvency distressed".

Our main findings are: the three economies with different policy support histories perform quite differently over this horizon. While the grant-based economy has FD rates fall to 11.4 per cent, approaching the levels seen pre-COVID-19, the debt-supported economy experiences higher FD rates at 14.4 per cent. This is due to the incorporation of the leverage and interest criteria (2) and (3) in our FD modelling: as debt-based supports are provided in 2020H2, they weigh on SME recovery in the following six months. Compared to the grant and debt-based economies, the targeted grant system brings FD rates to 6.9 per cent, below pre-pandemic levels, echoing findings of previous sections. In the targeted grant system, the ratio of firms facing liquidity distress to solvency distress is roughly two to one.

The final two rows of Table 6 are instructive as to the mechanisms at play. We define firms as having suffered distress due to liquidity if only criterion (1) is breached, whereas a firm that suffers distress either due to our insolvency criteria only, or to a combination of solvency and liquidity, is defined as having experienced solvency distress. When comparing both untargeted grant and debt policies, the composition of FD rates is quite different. The economy with grant supports has a much lower FD rate associated with solvency risks (2.8 from a total 11.4 per cent) than the one with debt supports (6.8 from a total of 14.4 per cent). Through this exposition we have pinpointed the risks coming from debt overhang that are associated with policies weighted towards debt supports. These additional risks can inform researchers and policymakers in debates regarding the longer-term effects of debt versus grant supports and economic recovery (for example, Honohan, 2020).

5. Conclusion

In this paper, we present a micro-simulation framework which can apply sectoral shocks, macroeconomic forecasts and firm-level policy support injections onto a distribution of business balance sheets. We apply this framework to the case of SMEs in Ireland during the COVID-19 pandemic. Exploiting representative surveys which include P&L and balance sheet data for Irish SMEs in 2018 and 2019, we use an indicator system to define a firm's financial distress and simulate this distress across a representative sample of SMEs over the pandemic period.

We show initially that the effects of the pandemic on the SME population in Ireland are estimated to be stark, with close to one-in-five SMEs modelled as being in financial distress as a result of the economic shock (excluding the role of fiscal policy support) by end-2020. We show that government supports act to alleviate the effect of the shock, lowering the financial distress rate from 19 to 16 per cent (with larger reductions when looking at debt balances in distress).

The flexibility of the simulation framework is extremely useful when evaluating fiscal policies during COVID-19. The granular nature of the data allow us to map precise eligibility thresholds and overall policy package sizes onto our representative data set, and assess the reduction in financial distress rates achieved by various policy packages, both observed and hypothetical.

Our simulation results highlight the importance of details of policy support design. The tax warehousing scheme implemented by the Irish government in 2020 is shown to be of greater efficacy in alleviating financial distress than the wage support, grant or debt-based schemes also introduced during the pandemic, due to the eligibility criteria and support sizes that surround each.

We design a hypothetical scheme that aims to achieve the greatest possible reduction in financial distress rates per euro spent, by targeting funding towards SMEs with the smallest shortfalls. Quantitatively, while the announced schemes are modelled to reduce distress rates from 19 to 16 per cent, the hypothetical targeted package reduces distress rates further to 7 per cent. This hypothetical scheme is used as a benchmark for an equivalent €7.5bn outlay, rather than as a policy recommendation in itself; in practice, policy does not have as its sole aim the reduction of financial distress rates, with a range of wider regional, sectoral and social aims under consideration.

In the last part of the paper, we also discuss the longer-lasting effects of policy design stretching into 2021, focussing on the relative roles of liquidity and solvency criteria under debt-based and grant-based regimes. Our modelling approach allows us to pinpoint the higher levels of longer-term distress as well as the disproportionate role of insolvency over illiquidity criteria in driving higher financial distress rates when policy support is provided through loans rather than grants.

Future research will be able to readily deploy the workhorse model presented in this paper to databases that contain information at the firm level on experiences during the pandemic, at which point researchers will no longer need to rely on mapping shocks from aggregate data onto pre-pandemic granular starting point data, as is necessary at the time this research was carried out.

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Appendix:

Table A1: Robustness tests for Financial Distress

Parameters	**2021 H1 (baseline)**	**2021 H1 (adverse)**
LC=3 IC=3 LV=1	18.1 (17.0 – 19.3)	19.9 (18.9 – 20.9)
LC=6 IC=3 LV=1	24.5 (23.3 – 25.7)	26.9 (25.8 – 28.2)
LC=6 IC=6 LV=1	24.5 (23.2 – 25.7)	27.0 (25.8 – 28.3)
LC=3 IC=3 LV=1.5	18.0 (16.9 – 19.0)	19.8 (18.6 – 20.7)
LC=6 IC=3 LV=1.5	24.4 (23.1 – 25.6)	26.7 (25.6 – 28.2)

Note: all results reported are 5%, 50% and 95% percentiles of 1000-run Monte Carlo simulations. In simulating the outcome in 2021 H1, we use the baseline policy scenario where there is no policy supports provided in 2020.

Table A2: Joint distribution of changes in turnover and non-personnel costs due to COVID-19

INDUSTRY (B,C,D,E)

		Non-personnel costs		
		-75	-25	0
Turnover	-87.5	2.03	3.61	7.36
	-75	2.33	4.16	8.46
	-37	0.24	5.45	17.50
	-17	0.18	4.01	12.86
	0	0.49	2.35	21.87
	1.1	0.00	0.28	6.81

CONSTRUCTION (F)

		Non-personnel costs		
		-75	-25	0
Turnover	-87.5	5.51	9.83	20.02
	-75	3.12	5.56	11.33
	-37	0.22	5.01	16.09
	-17	0.11	2.37	7.59
	0	0.17	0.79	7.35
	1.1	0.00	0.19	4.73

WHOLESALE AND RETAIL (G)

		Non-personnel costs		
		-75	-25	0
	-87.5	2.09	3.73	7.60

Turnover	-75	1.99	3.55	7.24
	-37	0.21	4.81	15.42
	-17	0.14	3.18	10.20
	0	0.45	2.14	19.93
	1.1	0.00	0.68	16.63

ACCOMMODATION AND FOOD

		Non-personnel costs		
		-75	-25	0
Turnover	-87.5	10.94	19.50	39.72
	-75	3.15	5.61	11.43
	-37	0.06	1.39	4.45
	-17	0.04	0.88	2.83
	0	0.00	0.00	0.00
	1.1	0.00	0.00	0.00

ALL OTHER SERVICES (H,J,K,L,M,N,R,S)

		Non-personnel costs		
		-75	-25	0
Turnover	-87.5	3.04	5.42	11.04
	-75	1.45	2.59	5.27
	-37	0.17	3.92	12.57
	-17	0.19	4.17	13.39
	0	0.64	3.04	28.32
	1.1	0.00	0.19	4.60

Table A3: Sectoral growth in 2020 H2 and 2021 H1

Wholesale, Retail Trade, Transport & Comm.	0.21	0.09	0.05	0.02
Manufacturing	0.20	-0.02	0.10	0.06
Construction	0.25	0.02	0.14	0.10
Business & Admin. Services	0.16	-0.01	0.05	0.06
Hotels & Restaurants	0.19	0.01	0.09	0.06

numbers in the table are the growth rate relative to the end of pervious period. Baseline and adverse growths of 2020Q4 are based on quarterly macroeconomic projections published by the Central Bank of Ireland's *Quarterly Bulletin 2020 Q3*. 2020H2 numbers are based on a combination of BICS survey responses for 2020Q3 and these Q4 projections. Baseline and adverse growths of 2021H1 are based on sectoral employment forecasts for 2021Q1 and 2021Q2 also retrieved from the *Quarterly Bulletin 2020 Q3*.

Table A4: List of Policy Supports proposed by the government by September 2020

Policy Supports for SMEs	Value	Type
Covid-19 Credit Guarantee Scheme	€2 billion	Debt
TWSS (value to date)	€2.736 billion	Wage
Employment Wage Subsidy Scheme	€2.35 billion	Wage
Restart Grant (original)	€250 million	Grant
Restart Grant Plus	€300 million	Grant
COVID-19 Working Capital Scheme	€450 million	Debt
Future Growth loan scheme (original)	€300 million	Debt
Future Growth loan scheme (July expansion)	€500 million	Debt
Microfinance Ireland Covid-19 Business loan (original)	€20 million	Debt
Microfinance Ireland Covid-19 Business loan (July stimulus)	€55 million	Debt
The Businesses Continuity Voucher	€25.7 million	Grant
Trading Online Voucher Scheme	€19.8 million	Grant
Online Retail Scheme (original)	€6.5 million	Grant
Online Retail Scheme (Expansion)	€5.5 million	Grant
COVID-19 Business Financial Planning Grant	€5.5 million	Grant
Sustaining Enterprise Fund	€180 million	Grant
Enterprise Support Grant	€12 million	Grant
Commercial Rates Waiver (July Stimulus)	€600 million	Grant
Tax warehousing (debt warehoused to date as of 10 Aug 2020)	€1.9 billion	Tax
LEAN Business Continuity Offer	€585,000	Grant
Temporary VAT reduction, tourism tax credit, corporate tax loss relief, legislative basis for warehousing of tax liabilities	€900 million	Grant

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