Real-time financial stability assessment with an application to the Covid-19 crisis*

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Abstract

The sudden and severe economic consequences of the Covid-19 pandemic have underlined the need for real-time financial stability assessments by banks and their supervisors, which are hampered by sluggish accounting-based provisioning. Using a Merton contingent claims framework, we develop a novel market-based approach to financial stability assessments – and apply it to assess euro area banks' vulnerability to the Covid-19 crisis in real time. Although market-based indicators have improved considerably after an initial sharp downturn in March 2020, they still provide warning signals for a range of (sub)sectors. During the market low point, implied losses on corporate loans amounted to 12-38% of banks' capital. We uncover a substantial role for monetary policy (lower discount rates) in the subsequent stock market recovery.

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1. Introduction

Besides the human toll, measures to fight the spread of the Covid-19 virus have had a severe impact on the global economy as well as its future outlook. The pandemic has led to both large supply shocks, for example due to factory and business shutdowns including interruptions in supply chains, and large demand shocks, for example due to unemployment and reduced spending on non-essential products and services. During the first months of 2020, the STOXX Europe 600 (a leading European stock market index) has lost no less than 33% of its value by its low point on March 18. The global economy shrank by 4.2% in 2020, which constituted a larger negative economic shock than the 2008-2009 "Great Recession" (OECD, 2020). Between March 2020 and July 2021, however, unprecedented support packages kept the economy afloat and led global stock markets, including the leading European indices, to recover to or even exceed their pre-pandemic levels.

Throughout the pandemic, an important question to financial supervisory authorities has been whether banks were adequately capitalized to absorb any losses on loans and other assets that were affected by the economic downturn. Preventing a banking crisis after a financial markets crisis is imperative, since it is well-known that recessions involving banking crises last longer and are significantly more profound than other recessions (e.g., Dell'Ariccia et al., 2008; Claessens et al., 2009; Reinhart and Rogoff, 2009). To determine provisions for banks is not an easy task, and one for which both supervisors and banks typically resort to accounting rules that use historical data to estimate future losses. However, this could severely underestimate the potential impact of Covid-19 on the banking sector, which is an event without a precedent in modern history. Furthermore, accounting-based loan loss provisions suffer from delayed recognition and hence may not adequately reflect current market valuations (Laeven and Majnioni, 2003; Benston and Wall, 2005). The Covid-19 crisis has thus reinforced the need for more real-time and forward-looking approaches to assess potential future losses, in order to ensure adequate loan-loss provisioning and thereby safeguard the stability and soundness of the financial system.

In this paper, we develop an innovative approach to financial stability assessments (or bank stress testing) that uses real-time stock market data to estimate potential loan losses at a detailed industry level. In particular, we assess the effect of different scenarios, and at different points in time, on the magnitude of expected losses for banks.[1] One challenge to do this is that the market value, and the expectation on potential future losses, cannot be directly observed for most loans and needs to be inferred from observable asset prices, such as equities. To that end, we build upon the option valuation techniques developed by Black and Scholes (1973) and Merton (1974). Specifically, we use Merton's (1974) insight that the equity of a firm is the equivalent of a call option on the value of the firm's assets, while the debt of the firm is the equivalent of a risk-free bond and a short put option on the assets. Merton's model shows how, as a result, a negative asset valuation shock (such as the one caused by Covid-19) affects the value of both equity and debt in a non-linear way.

In the second part of the paper, we apply our novel approach to financial stability assessments to evaluate the impact of the Covid-19 crisis on the expected loan losses of Euro area banks from March of 2020 till July 2021 in real time. We are able to obtain changes in the estimated probability of default (PD) of 1,752 publicly listed firms in the euro area. To account for potential bias in our estimates due to our focus on listed firms, we use a set of OLS regression models to predict changes in the PD due to the Covid-19 shock also for non-listed firms. We do this based on structural characteristics of firms that are observable for both listed and non-listed firms. We find that leverage and the liquidity ratio are significant predictors, while not finding evidence for size as a relevant factor. We then estimate changes in the PD for

[1] Using scenarios and looking both at base cases and worst cases is common practice in financial sector supervision and when analysing bank solvency (Ong, 2014).

a random sample of 50,000 non-listed firms in the euro area that have a non-zero amount of bank lending. When aggregating to the sector level, we weigh our findings based on the amount of bank lending to reflect the relative importance of each firm to euro area banks' loan portfolio.

After estimating changes in the PD of firms in different industries, we proceed by performing a stylized stress test of the banking sector in the euro area. To this end, we obtain data on aggregated industry-level loan exposure (1-digit NACE) of euro area banks from the European Central Bank (ECB) data warehouse. We then estimate expected losses per unit of exposure by combining our estimated changed in PD with both a lower and an upper bound loss given default (LGD). Calculations for the PD are performed at the firm level.

For the stress test, we aggregate firm-level results to the one-digit industry classification to link our estimates on expected losses to the ECB loan exposure data. Subsequently, we apply our stress factors to the aggregated corporate debt portfolio of euro area banks under four different scenario parameters. These four sets of parameters reflect the uncertainty in the change in yearly equity volatility (which can only be observed ex post) as well as uncertainty in the potential change in the LGD as a result of the Covid-19 crisis.

We furthermore investigate a counterfactual scenario in which discount-rates would have remained constant between March 2020 and July 2021. To do so, we decompose stock price developments into effects stemming from shorter- and longer-term earnings forecasts (i.e., cash flow effects) and other effects related to the prevailing cost of capital (i.e., discount-rate effects). We then perform our stress test while holding the cost of capital constant from the start of the Covid-19 pandemic, providing an indication of the effects of monetary policy and the associated lowering of long-term interest rates.

Results indicate that the expected losses in the corporate debt portfolio during the low point of the markets, in March 2020, ranged between 7% and 22% of the book value of the loans (or up to more than €1 trillion in absolute values), depending on the scenario. As a fraction of available capital and reserves, the estimated losses ranged between 12% and 38% across the four scenarios. These estimates have improved over time as governments enacted unprecedented support packages and more information on Covid-19 became available. In July 2021, estimated losses on corporate loans were between 1% and 15% of available capital and reserves. However, we find that the stock market recovery between March 2020 and July 2021 is partly attributable to a lower cost of capital, in line with the easing of monetary policy and a lower long-term risk-free interest rate (as proxied by the 10-year German government bond yield). This observation is important for financial stability assessments, since even if stock prices have recovered due to a decrease in the discount rate, banks may still face substantial loan losses when firms cannot fulfil their obligations due to deteriorated profitability (cash flow news rather than discount rate news in the terminology of the return decomposition of Campbell and Shiller, 1988). In a counterfactual scenario, in which we keep the discount rate constant from the start of the pandemic, we find that estimated losses in July 2021 are substantially larger, between 4% and 21% of available capital and reserves. This represents more than a doubling of expected losses in two out of the four scenarios. Our results for are likely conservative due to our exclusive focus on the corporate credit portfolio, while losses may also be incurred on other asset classes, such as household and government debt.

Our findings are relevant for regulators, banks, other financial market participants, and their supervisors. Although we find that estimated expected losses have diminished substantially after the initial stock market crash, our analysis shows that there are a number of industries and subsectors that still pose increased risks of loan losses to banks. Furthermore, our approach provides a real-time assessment of potential losses in bank's corporate loan portfolios after a major economic shock and could be applied to any type of stock market shock. This can be of specific interest to estimate effects of future shocks are asymmetric across industries or firms. In July 2021, the industries that were still at a substantially elevated default risk compared to the pre-pandemic baseline include accommodation and food services, mining and quarrying, professional, scientific and technical activities, real estate activities, and education.[2] We further find that, in the euro area, the stock price bounceback can be explained by a combination of partially recovered earnings forecasts and declining discount rates. The fact that earnings forecasts alone have in most cases not yet recovered to pre-pandemic levels is highly relevant to euro area banks, since short-term earnings are an important indicator of the ability of firms to meet their periodic loan instalments – especially when government support packages are phased out.

Our paper contributes to the literature by providing a stylized but forward-looking model to estimate expected loan losses on bank's corporate credit portfolios. Since our model relies on observed (real-time) stock market responses rather than accounting data, our analysis provides an early warning indicator of potential accounting losses to follow. As part of this modelling, we use a large sample of euro area firms and perform most of our calculations at firm level – including both listed and non-listed firms. This is in contrast to more common "representative firm" approaches (Kalemli-Ozcan et al., 2015). A firm-level analysis enables us to incorporate cross-firm and cross-industry heterogeneity which is important to account for the non-linear effects of shocks on the probability of default (PD) and market value of debt. We furthermore calibrate and apply our model in the context of the Covid-19 shock and decompose stock market shocks into cash flow and discount-rate effects, to investigate the importance of monetary policy and discount rates on estimated losses for euro area banks.

[2] Our analysis also sheds light on the industries whose default probabilities were elevated the most during the beginning of the Covid-19 crisis in March and April 2020, which includes financial and insurance activities, administrative and support service activities, accommodation and food service activities, construction, manufacturing, and transportation.

2. The Covid-19 shock and recovery in the euro area

In this section, we provide descriptive statistics on stock market developments in the euro area. We do this by constructing a broad index of listed firms based on all firms in the Bureau van Dijk Orbis database for which an ISIN identifier code is available. For those firms, we obtain total assets from the Orbis database and daily stock prices (return index) from Thomson Reuters Datastream. We then construct an index by weighing daily stock returns by total assets, to account for the importance of each firm to the euro area economy. In total, we cover 2,057 listed firms in the euro area. We then proceed by decomposing our index into 1-digit and 2-digit NACE industry codes to track their stock price over time. We also calculate pre-shock and post-shock indicators for the volatility of equity. Both the stock price developments and equity volatility variables are used to calibrate our structural model in section 4.

Figure 1 shows the development of the asset weighted average stock price of firms in our sample between November 2019 and July 2021. From January 1st to March 18, 2020 the average stock price declined with 38%, representing the worst three-month loss since the financial crisis. Since then, the average stock price has steadily increased over time. On April 20, 2022, after both the Europe and the US had announced their initial stimulus packages, stock prices on average recovered to a decline of 29%. Since then, stock prices have increased further to fully recover on February 15, 2021 (compared to January 1, 2020) and to further increase with 14% by July 1st, 2021. Compared to two other leading euro area indices (the STOXX Europe 600 and the STOXX Europe 50) our broader index has experienced a higher initial shock (minus 38% compared to minus 33% and minus 37%, respectively), however recovering to similar levels compared to the STOXX indices during December 2020.

We further disaggregate our index sample to a sectoral level. Table 1 reports the difference in average stock price per industry between January 1st, 2020 and March 18, 2020, April 20, 2020 and July 1st, 2021, respectively. Changes in stock price between January 1st, 2020 and March 18, 2020 ranged between -53% for mining and quarrying and -19% for professional, scientific and technical activities. The worst affected industries during this initial shock after mining and quarrying were administrative and support services (-53%), accommodation and food service activities (-49%) and financial and insurance activities (-43%). Between January 1st, 2020 and April 20, 2020 stock price changes ranged between -45% for administrative and support service activities and -14% for human health and social work activities. By July 1st, 2021 most industries recovered to the January 1st, 2020 level. Three main exceptions are accommodation and food services (-23%), administrative and support service activities (-13%), and mining and quarrying (-11%).[3]

Table 1 also reports observed equity volatilities. For the standard deviation of equity, we estimate the pre-shock value of the parameter based on the yearly standard deviation of the stock return over the last 20 years. We also look at daily equity volatility, based on a three-month period before the Covid-19 shock (November 1st, 2019 to February 1st, 2020) and the period after the initial shock (April 20th, 2020 to July 1st, 2021). To obtain annualized volatilities we multiply the standard deviation of daily stock price changes by the square root of the amount of business days in a year: 252. On average, the annualized daily equity volatility has increased from 19% to 30% (a factor 1.6) between these two periods, with the highest changes observed for mining and quarrying (2.2), accommodation and food service activities (2.1) and administrative and support service activities (2.1). Overall, we observe an increase in equity volatility across all industries – indicating that there has been a structural change in the volatility of equity that has persisted after the initial Covid-19 shock from April 20th 2020, onwards.

[3] At a 2-digit sectoral level the industries that still have the largest subdued stock valuations on July 1st, 2021 compared to January 1st, 2020 are: creative, arts and entertainment activities (-44%); air transport (-34%); mining support service activities (-31%); food and beverage service activities (-29%); gambling and betting activities (-24%); rental and leasing activities (-23%); travel agency, tour operator and other reservations service activities (-21%); security and investigation activities (-21%); accommodation (-21%); office administrative, office support and other business support activities (-15%).

3. Financial vulnerability model

In this section, we set out our methodology to estimate market-based expected losses to banks their credit portfolios as a result of the Covid-19 crisis at different points in time. We start with a general definition for expected loss (*EL*) with time horizon *t*:

$$EL(t) = PD(t) * LGD * EAD \tag{1}$$

In this formula, *PD* is the probability of default, *LGD* the loss given default (i.e., one minus the recovery rate), and *EAD* the exposure at default. Note that, in this representation, the value of *LGD* and *EAD* are constant over the time horizon *t.* Hence the additional expected loss (ΔEL) as a result of a shock in the probability of default (ΔPD) can be expressed as:

$$\Delta EL(t) = \Delta PD(t) * LGD * EAD$$

with (2)

$$\Delta PD = PD_{post-shock} - PD_{pre-shock}$$

$$\Delta EL = EL_{post-shock} - EL_{pre-shock}$$

In general, however, *LGD* and *EAD* are not necessarily constant. In particular, several authors observe that the *LGD* increase during economic downturns (e.g., Miu and Ozdemir, 2006; Jacobs, 2011). We can write a more general expression for additional expected loss as when assuming that *LGD* changes after the shock compared to its pre-shock value:

$$\Delta EL(t) = \Delta PD(t) * LGD_{post-shock} * EAD + PD_{pre-shock} * \Delta LGD * EAD$$

with (3)

$$\Delta LGD = LGD_{post-shock} - LGD_{pre-shock}$$

Both the credit exposure data and the firm-level data that we use allow a breakdown into *n* industries according to the NACE industry classification. We thus estimate total expected losses in banks' credit portfolio by summing expected losses over *n* industries *j*:

$$\Delta EL_{credit\,portfolio}(t) = \sum_{j=1}^{n} EL_j(t) \tag{4}$$

Finally, we assume a constant *EAD*, which seems reasonable given that most bankruptcies due to Covid-19 would likely materialise in the short-run (i.e., within one to two years). This assumption may lead to a slight overestimation, given that there can be some (monthly) repayments of the loan before bankruptcy.[4]

To estimate ΔPD, we employ the Merton (1974) structural credit risk model to determine the change in the probability of default of individual firms (*i*) that is implied by the observed changes in the value of that firms' stock. Merton's critical insight is that equity can be viewed as a residual claim on assets after the debt has been repaid. This implicates that holders of equity hold a de facto put option on the assets of the firm, limiting their losses in the case when the assets of the firm are less valuable than the outstanding debt. The stock price thus conveys information about investors' expectation of a firm defaulting. We refer to Reinders et al. (2020) for a more detailed discussion. Following the notation in Dar and Qadir (2019), the market-implied probability of default can be expressed as:

$$PD_i = N\left(\frac{\ln\left(\frac{L}{V}\right) - \left(r + \frac{\sigma_V{}^2}{2}\right)t}{\sigma_V\sqrt{t}}\right), \tag{5}$$

[4] We argue, however, that this effect will be small given that many banks have allowed their corporate customers to postpone repayments and this would be especially so for firms in financial trouble.

where *N(·)* is the standard normal density function, with *PD* being a function of asset value *V*, contracted repayment *L* (i.e., the face value of debt), time to maturity *t*, the standard deviation of asset value σ_V, and the risk-free interest rate *r*. Except for the risk-free interest rate, all parameters are firm-specific (we drop the subscript *i* for simplicity).

The problem with equation (5) is that it is not possible to observe asset value (*V*) directly. We thus follow a standard approach in the financial literature to estimate asset value by using the Black-Scholes call option formula (Black and Scholes, 1973):

$$E = VN(d_1) - Le^{-r(t)}N(d_2) \tag{6}$$

with

$$d_1 = \frac{\ln(\frac{V}{L}) + (r + \frac{\sigma_V{}^2}{2})(t)}{\sigma_V \sqrt{T}}$$

$$d_2 = \frac{\ln(\frac{V}{L}) + (r - \frac{\sigma_V{}^2}{2})(t)}{\sigma_V \sqrt{t}}.$$

In which *E* is the value of the equity of the firm. Furthermore, under the assumption that asset values follow a geometric Brownian motion, the volatility of the firm's equity is given by:

$$\sigma_E = \frac{V}{E} N(d_1)\sigma_V, \tag{7}$$

where σ_E is the standard deviation of equity value. Since both *E* and σ_E can be observed from the stock market, we can solve equations (6) and (7) simultaneously to obtain *V* and σ_V. We then can perform the *PD* calculation twice, before and after the shock, to obtain ΔPD_i. Finally, since our exposure data is at the industry (*j*) level, we aggregate the estimated *PD* shocks for each firm to an industry aggregate shock, by taking the weighted sum:

$$\Delta PD_j = \sum_{i=1}^{m} \Delta PD_{i,j} * \omega_i \qquad (8)$$

For our analysis, we use the total bank loans as the weighting factor ω_i, which is the closest indicator in our firm-level data of the amount of bank debt that a firm has on its balance sheet (and hence the contribution of its valuation shock to banks their expected losses).

4. Data and calibration for application to the Covid-19 crisis

This section describes the data sources and calibration for the three main variables in the vulnerability model for our application to assessing euro area bank loan losses over the course of the Covid-19 crisis. We calculate the implied probability of default (PD) for a sample of listed firms in the euro area, which we use to estimate the PD for firms in a large and representative sample of both listed and non-listed firms in the euro area. We then proceed to calibrating the necessary loss given default (LGD) and exposure data. Since there is no suitable publicly available LGD data at firm level, we obtain lower and upper bound estimates which we will use to inform different parameters in our stress test in section 5.

4.1 Market-based estimation of increased default probabilities (PD)

To calculate PDs for the listed firms in our sample, we need all the parameters that are present in the Merton model (equations 6 and 7). These include equity value, yearly equity volatility, leverage, time to maturity, and the risk-free interest rate. Since we are looking at differences in PDs, the percentage difference in equity value before and after the shock suffices and it is not needed to obtain its absolute value. We hence use the firm level data for changes in the return index (RI) and pre-shock long term equity volatility as reported in Table 1. Since the post-shock value of the standard deviation of equity is not known yet, we introduce two scenarios in our analysis. One scenario assumes that equity volatility remains constant before and after the shock and constitutes a lower bound. A second scenario assumes that equity volatility structurally increases as a result of the Covid-19 shock, in line with the change in daily equity volatility before and after the shock (last column in Table 1) which we deem to be a plausible upper bound. For each firm, we also obtain leverage (debt as a fraction of total assets), total assets, and total bank loans. We only keep those firms in the sample that have no missing values for any of those variables. This leads to a total of 1,732 listed firms in our sample. Furthermore, we use an average duration of loans for euro area banks is three years across all firms.[5] We also use a flat risk-free interest rate of zero per cent during those three years in line with current market conditions.

Table 2 reports the increase (decrease in parentheses) of the probability of default (in percentage points) that is implied by the Merton (1974) model as put forward in section 2.2. Results are obtained for three points in time on March 18, 2020 (March), April 20, 2020 (April), and July 1, 2021 (July) compared to the January 1, 2020 baseline. We find that the average market-implied changes in probabilities of default of the whole sample range between 0.01 (constant volatility assumption in July 2021) to 0.41 (increased volatility in March 2020). Sectors that have the highest market-implied changes in probability of default in March 2020 include accommodation and food service activities (NACE I), arts, entertainment and recreation (NACE R), other service activities (NACE S), and education (NACE P).

We proceed by regressing changes in probability of default on four variables including size (total assets in billion USD), profitability (return on assets) and financial structure (leverage and liquidity ratios), in line with variables found to be relevant predictors of corporate default (e.g., Altman and Sabato, 2007; Traczynski, 2017). We perform our regression for

[5] The ECB reports that the weighted-average maturity at origination of loans to corporates for euro area banks is 6.6 in 2018. Assuming constant origination practices, we conservatively take the remaining maturity to be three years (rounded down from 3.3).
https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.creditunderwriting202006~d2a9e3329c.en.pdf

changes in probabilities of default observed at different points in time on March 18, 2020 (March), April 20, 2020 (April), and July 1, 2021 (July) compared to January 1, 2020 and for different equity volatilities (constant and increased). Results provided in Table 3 indicate that both the leverage ratio and the liquidity ratio are relevant predictors of changes in probability of default compared to the pre-Covid baseline. We find, however, no evidence of the importance of firm size and profitability (where especially firm size could be a potential concern since non-listed firms tend to be smaller than listed firms). We include industry fixed effects to account for substantial differences in shocks across economic sectors. Based on the reduced-form models in Table 3, we estimate changes in PD for a random sample of 50,000 firms from the Bureau van Dijk Orbis database. The random sample is drawn from the full set of 3,564,023 active firms in the euro area that have a non-zero value for "bank loans" and non-missing values for industry classification, leverage ratio, and liquidity ratio. This approach ensures that we have an as representative sample of both listed and non-listed firms in the euro area.

4.2 Upper and lower bound loss given default (LGD)

Similar to the post-shock standard deviation of equity, the post-shock loss given default (*LGD*) is not known yet. To account for this uncertainty, we use two further scenarios consisting of a lower bound and upper bound estimate of the *LGD*. For the lower bound, we assume that the *LGD* remains constant over time, using equation (2) to obtain an estimate for expected losses. For the upper bound, we assume that the average *LGD* during our three-year time horizon increases by 15 percentage points.[6] Since this scenario has a non-zero change in the *LGD* as a result of the shock, we obtain our expected loss estimate through equation (3). This requires a

[6] This is in line with the EBA guidelines for downturn LGD estimation (EBA/GL/2019/03) when observed or estimated impact is not available. Banks are in that case required to use a final downturn LGD that is higher than the long-run average LGD plus 15 percentage points.

long-term average probability of default for corporate loans in the euro area, which we set to two per cent in line with data reported in Castrén et al. (2009).

To set the lower bound *LGD* for our stress test model, we base ourselves on data from Moody's Ultimate Recovery Database between 1987 and 2009 in Jacobs (2011). For 514 defaulted loans over that period, the paper reports a discounted *LGD* of 49.3%.[7] This estimate is supported by industry-level estimates of *LGD* in the Italian banking system in Accornero et al. (2017). They find that, for corporate loans, *LGD* estimates average around 50 per cent across industries between 2002 and 2014. Moreover, they find that *LGD* estimates are rather homogeneous across industries, ranging between 40% and 58% for the relevant industries in our analysis.[8] We thus (conservatively) use a lower bound *LGD* of 45% across all industries.[9]

4.3 Exposure data (EAD)

For the exposure at default (*EAD*), we use end-2019 (pre-shock) loan exposure data obtained from the European Central Bank (ECB) data warehouse. This dataset provides the aggregated exposure of euro area banks to industries (according to the NACE-1 industry classification) in their loan portfolios. Table 1 shows these exposures for the NACE-1 industries. Total corporate loan exposures for all euro area banks are €4.46 trillion. Some industries are reported in groups. The largest group exposure is for Real estate activities (L), Professional, scientific and technical activities (M), and Administrative and support service activities (N) and amounts to €1.68 trillion. This is followed by Manufacturing © with loans totalling €0.63 trillion in exposure and Wholesale and retail trade; repair of motor vehicles and motorcycles (G) totalling €0.57 trillion.

[7] Discounted LGD is defined as the ultimate dollar loss given default on the defaulted debt instrument. It equals one minus the total recovery at the emergence from bankruptcy or time of final settlement divided by the outstanding amount at default.

[8] This is with the exception of oil and gas, for which Accornero et al. (2017) estimate a LGD of 68%. However, this industry is not included in our analysis at the same level of granularity but part of the larger category Mining and quarrying (B). The Mining and quarrying (B) category makes up only 0.5% of the total loan portfolio of euro area banks and hence is not highly relevant for the overall outcome of our stress test.

[9] We use 45% instead of 50% given that the Italian economy was hit harder by the crisis period after 2008 than most other euro area economies.

5. Results of the financial stability assessment during the Covid-19 crisis

Tables 4 and 5 present our main results. Table 4 reports the estimated market-implied changes in probabilities of default (*ΔPD*) per industry, based on our representative random sample of 50,000 listed and non-listed firms in the euro area. The table shows shocks for March 18, 2020 ("March"), April 20, 2020 ("April") and July 1, 2021 ("July") compared to the January 1, 2020 baseline. We also how outcomes for two scenarios: a future state of the world in which economies regain their stability and hence experience similar equity volatility as before the shock ("constant volatility") and a future state of the world in which uncertainty prevails and the volatility of equity increases substantially ("increased volatility").

At the stock market low point on March 18, 2020 and assuming constant volatility, we find the highest percentage point (ppt) increases in the market-implied probability of defaults for education (28 ppt), public administration and defence (20 ppt), mining and quarrying (20 ptt), professional, scientific and technical activities (18 ptt), accommodation and food service activities (17 ppt), administrative and support service activities (17 ppt), wholesale and retail trade (17 ppt), and construction (17 ppt). In the period after March 18, 2020 the estimated increases in PD improve substantially. Especially education decreases from 0.28 ppt in March 2020 to 0.13 in April 2020 and 0.03 in July 2021. Industries that are still estimated to have substantially increased probabilities of default in July 2021 include accommodation and food service activities (9 ppt) mining and quarrying (8 ppt).

A similar pattern arises when assuming an increased volatility of equity and looking at the stock market low point on March 18, 2020, however with higher differences in estimated PDs across all sectors and time periods. Industries that are the most severely impacted are mining and quarrying (66 ppt), public administration and defence (59 ppt), administrative and support service activities (55 ppt), construction (50 ppt), accommodation and food service activities (49 ppt), and transportation and storage (46 ppt). Similar to the constant volatility outcomes, the impact of the Covid-19 shock on implied probabilities of default decreases between March 18, 2020 and April 20, 2020. Industries that are still estimated to have substantially increased probabilities of default in July 2021 include accommodation and food service activities (36 ppt), mining and quarrying (35 ppt), and administrative and support service activities (29 ppt). The latter includes travel agencies and rental and leasing activities.

Table 5 presents the results of our stress test. This table combines the shocks in default probabilities with our exposure data to obtain an estimate for the increase in expected losses for euro area banks. The first column presents the market value losses for euro area bank's corporate loan portfolios based on the stock price response as of March 18, 2020 under four different scenarios which are the intersection between the two assumptions on equity volatility (constant or double) and on the LGD (0.45 or 0.6). The second and third columns present the market value losses based on the stock price response as of April 20, 2020 and July 1, 2021, respectively, for the same four scenarios.

The results in Table 4 suggest that banks could experience substantial additional losses on their corporate credit portfolios as a result of the Covid-19 crisis. Based on initial shock to stock markets observed on March 18, 2020, these losses range from 7.1% to 21.9% of the book value of the corporate loan portfolio, depending on the scenario. In the most optimistic scenario, in which equity volatility returns to its pre-crisis level for the next three years and loss given default (LGD) is similar to before the crisis, implied market value losses on corporate loans are 7.1% of current book value. In more pessimistic scenarios, in which the LGD increases to 60% or equity volatility doubles, these losses are 9.6% and 16.3%, respectively. In the most severe scenario, in which the LGD increases to 60% and equity volatility doubles, losses amount to 21.9% of the book value of the corporate loan portfolio. For the four scenarios, the losses as a fraction of available capital and reserves range between 12.3% (most optimistic) and 38.2% (most severe), which indicates that the loan losses for euro area banks as a result of Covid-19 were potentially very large. Comparing absolute loss values leads to the observation that market developments between March 18 and April 20 (which includes stimulus packages in Europe and the US) may have avoided between €114 billion (most optimistic) and €177 billion (most pessimistic) in market value credit losses for euro area banks.

Looking at the recovery of the economic situation until July 1, 2021, we find that expected losses on corporate loans have declined substantially. Depending on the scenario, losses then ranged between 0.7% and 9.1% of total corporate loan exposures or 1.2% and 15.9% of total capital and reserves. In the most optimistic scenario, assuming the same equity volatility and LGD as before the Covid-19 shock, we find that expected losses in July 2021 have declined by more than ten-fold (10.2 times) compared to the market low point in March 2020. This is driven by an improvement in stock market conditions, which reflects both improvements in the outlook for business as well as financial conditions. We look at the drivers of stock market improvements in the next section.

5. Counterfactual results with constant discount rates

To understand the drivers of the stock market recovery between April 2020 and July 2021, we decompose stock prices into cash flow (CF) and discount (DR) effects, in line with the approach taken by Chen, Da, and Zhao (2013), which was inspired by the Campbell-Shiller (1988) return decomposition framework. Doing so allows us to construct a counterfactual scenario in which we can look at the impact of CF effects in isolation – disregarding DR effects. CF effects are especially important to banks, as firms' earnings determine their short-term ability to repay loans. It also allows us to estimate what potential losses would have looked like in the absence of changes in the discount rate.[10]

We start with a standard net-present value formula that relates the price of a stock *P* at time *t* to the expected future dividends for the years *k* ahead using a discount rate *q*:

$$P_t = \sum_{k=1}^{\infty} \frac{E_t(D_{t+k})}{(1+q_t)^k} \tag{1}$$

We follow Pástor, Sinha and Swaminathan (2008) by adjusting the net present value formula to a finite horizon sum with a terminal value that is equal to the value of the perpetuity of the expected dividend in year $t+T+1$ and by rewriting the expected dividends in year *k* as the forecasted earnings (FE) in year *k* multiplied by the plowback rate $(1-b_{t+k})$ in that same year, with b_{t+k} being the dividend pay-out ratio:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k}(1-b_{t+k})}{(1+q_t)^k} + \frac{FE_{t+T+1}}{q_t(1+q_t)^T} \tag{2}$$

To carry out this decomposition for the euro area, we obtain analyst forecast data on a quarterly basis from the IBES database. Specifically, we use five forecasts for the earnings per share (EPS): one for the current year and one each for the following four years. We furthermore obtain, from the same database, historical earnings per share and annual dividends (to estimate the dividend pay-out ratio) and stock prices and stocks outstanding per firm. For forecasted earnings farther than five years into the future, we follow Chen et al. (2013) in assuming that the firm specific long-term growth forecast converges to the long-term analyst industry growth

[10] We argue that most of the discount rate changes observed during the March 2020 to July 2021 period can be explained by a lower long-term risk-free rate as proxied by the German 10-year government bond. The yield on those bonds has on average decreased almost to the same extent as the decrease that we find for the implied cost of capital (ICC). See Figure 2, panels C and D.

forecast at $t=T=15$. Using estimates for the forecasted earnings and dividend pay-out ratio over time, while directly observing the stock price, the implied cost of capital (ICC) is obtained by numerically solving equation (2) for q_t. The ICC can be interpreted as the firm-level discount rate used by investors that is implied by firm-level earnings forecasts and stock market valuations. Forecast data are not available for all firms in our ORBIS sample, hence we base our analysis on a smaller group of firms for which all required data is available. This leaves us with 151 firms. Details on the calculation of the ICC can be found in Appendix I.

Results are provided in Figure 2. We find that, for the IBES sample, the total market capitalization experiences a sharp drop in March 2020 and thereafter recovers to close to its pre-shock level in March 2021 (Panel A). This is in line with the development in the overall Orbis sample (Figure 1). The recovery to pre-shock levels is to a considerable extent, but not in full, driven by a recovery of earnings forecasts (Panel B), with the remainder of the stock price increase driven by a decline in the ICC (Panel C). We furthermore observe that the linear trend in the ICC is in line with the linear trend in the German 10-year government bond yield, the latter being the closest indicator for the 10-year risk free interest rate in Europe. For the ICC, we obtain an average decline of 0.33 percentage points per year, compared to an average decline of 0.37 percentage points per year for the German 10-year government bond yield. Overall observed changes in the implied ICC are hence not substantially different from changes in the 10-year risk free interest rate.[11] This observation suggests that monetary policy has effectively reduced interest rates and thereby boosted the stock market through a decrease in discount rates.

Table 6 reports the outcomes of our stress test using the counterfactual scenario in which we keep discount rates constant between March 2020 and July 2021. Comparing to the

[11] We note that there could be potentially offsetting effects that we cannot capture in our analysis, which would for example occur if at the same time the ICC and long-term growth forecasts would decrease (not driven by the risk-free interest rate).

main outcomes in Table 5 (third column), we find that estimated losses in July 2021 are substantially larger for the scenario with constant discount rates, between 4% and 21% of available capital and reserves. For the two scenarios with constant volatility, this represents more than a doubling of expected losses compared to the main outcomes. In absolute figures, total expected losses for the euro area banking sector in July 2021 would have expected to range between €94 billion and €534 billion if discount rates would have stayed the same. Given the primary importance of cash flow effects for banks' expected loan losses, the results of the analysis of the counterfactual scenario are arguably more informative about the true impact of the Covid-19 crisis on financial stability.

5. Conclusion and discussion

The Covid-19 crisis has caused a sharp and unprecedented contraction of economic activity, leading to losses in business valuation across industries. Our analysis shows that expected losses were particularly high in the period immediately after the Covid-19 pandemic broke out on March 18, 2020 (market low point) and did improve but were still high after the initial stimulus packages as announced by most major economies in April, 2020. For euro area banks, we estimate the expected loss on their current loan portfolio as a result of shocks between January 1, 2020 and March 18, 2020 (market low point) and between January 1, 2020 and April 20, 2020 (post-stimulus shock). We show that at the market low point, expected losses for banks range between 12.3% and 38.2% of their available capital and reserves, depending on the post-shock amount of volatility and recovery rates on defaulted businesses. This improves to a range between 7.9% and 31.2% a month later, after the announcement of substantial stimulus packages by public sector authorities. These estimates have improved over time as governments enacted unprecedented support packages and more information on Covid-19 became available. In July 2021 estimated losses on corporate loans had improved to between

1% and 15% of available capital and reserves. However, we find that the stock market recovery between March 2020 and July 2021 is partly attributable to a lower cost of capital, in line with the easing of monetary policy and a lower long-term risk-free interest rate (as proxied by the 10-year German government bond yield). In a counterfactual scenario, in which we keep the discount rate constant from the start of the pandemic, we find that estimated losses in July 2021 are substantially larger, between 4% and 21% of available capital and reserves. This represents more than a doubling of expected losses in two out of the four scenarios.

Our results are subject to several limitations. By using the Merton model to estimate the probability of default we make several simplifying assumptions, including on the liability structure of firms (i.e., consisting of equity and one homogeneous category of plain vanilla debt) and the process that describes firm value over time (i.e., geometric Brownian motion). Some of these assumptions been challenged in the literature (e.g., Merton, 1976, Cai and Kou, 2011) and may lead to some model error in our outcomes. We partially address potential modelling errors in our approach by using the difference between PDs before and after the shock. Furthermore, we recognize that there are differences between listed and non-listed firms that could affect the change in PD that we estimate per industry based on our listed-firms sample. Chief of these potentially relevant differences is firm size, since bigger firms tend to be listed more often. We control for this and other potential differences using a predictive regression model. We find no evidence of a size effect in our sample of listed firms. We do find that liquidity and leverage are significant predictors of a PD change emanating from the Covid-19 shock and we adjust for those factors in our non-listed sample. Lastly, we focus in our approach on corporate credit only and do not consider other potentially relevant channels that could affect bank's their solvency. These include effects of Covid-19 on consumer lending, equity portfolios, and sovereign debt. The full impact of Covid-19 on banking sector capital adequacy is likely higher when taking those channels into account and our results are hence likely conservative.

Our results are relevant for both financial sector authorities and financial institutions. Although we find that estimated market-value losses have diminished substantially, our analysis shows that there are still industries and subsectors that pose increased risks of loan losses to banks. Financial sector authorities can use our findings to compare market-based expected losses to currently announced loss-provisions by euro area banks in different economic sectors. Our observation that earnings forecasts alone have in most cases not yet recovered to pre-pandemic levels is relevant to euro area banks, since short-term earnings are an important indicator of the ability of firms to meet their periodic loan instalments – especially when government support packages are phased out. For financial institutions, and in particular banks, our results can provide a benchmark to their own loan portfolios to estimate a plausible range of expected losses in their loan portfolios. Furthermore, our approach provides a real-time assessment of potential losses in bank's corporate loan portfolios after a major economic shock and could be applied to any type of future stock market shock.

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Figure 1 – Stock price development in the euro area

This figure shows the development of the STOXX Europe 50 and STOXX Europe 600 indices, compared to a broader euro area sample containing 2,157 listed firms. For each firm we obtain daily stock prices (return index) from Thomson Reuters Datastream. To aggregate our sample to an overall index, we weigh firms by their total assets as obtained from the Bureau van Dijk Orbis database. We define three periods for our analysis, consisting of the initial shock between January 1, 2020 and March 18, 2020 (1), the initial recovery during the month thereafter between March 18, 2020 and April 20, 2020 (2), and the recovery from thereon until July 1st, 2021 (3).

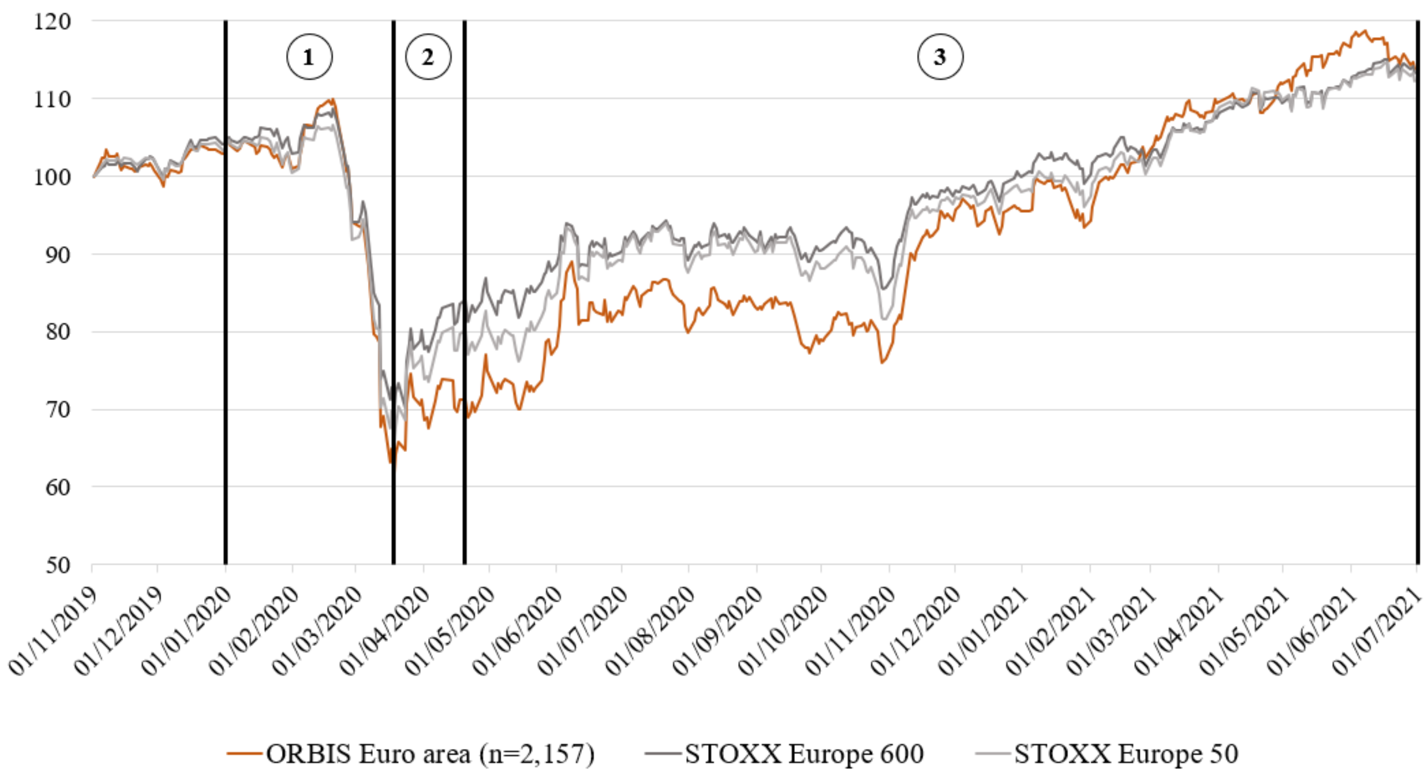

Figure 2 – Implied cost of capital (ICC)

This figure reports the aggregate results for 152 firms in the euro area for which complete data is available to calculate the implied cost of capital (ICC) according to equation (2), following Chen, Da, and Zhao (2013). Panel A and B show the market capitalization and earnings per share forecasts obtained from the IBES database. Panel C shows the calculated ICC including the best fitting linear trend line (slope = -0.0009). For comparison, panel D shows the German 10-year government bond yield (slope = -0.0010) which is a close indicator for the 10-year risk-free rate.

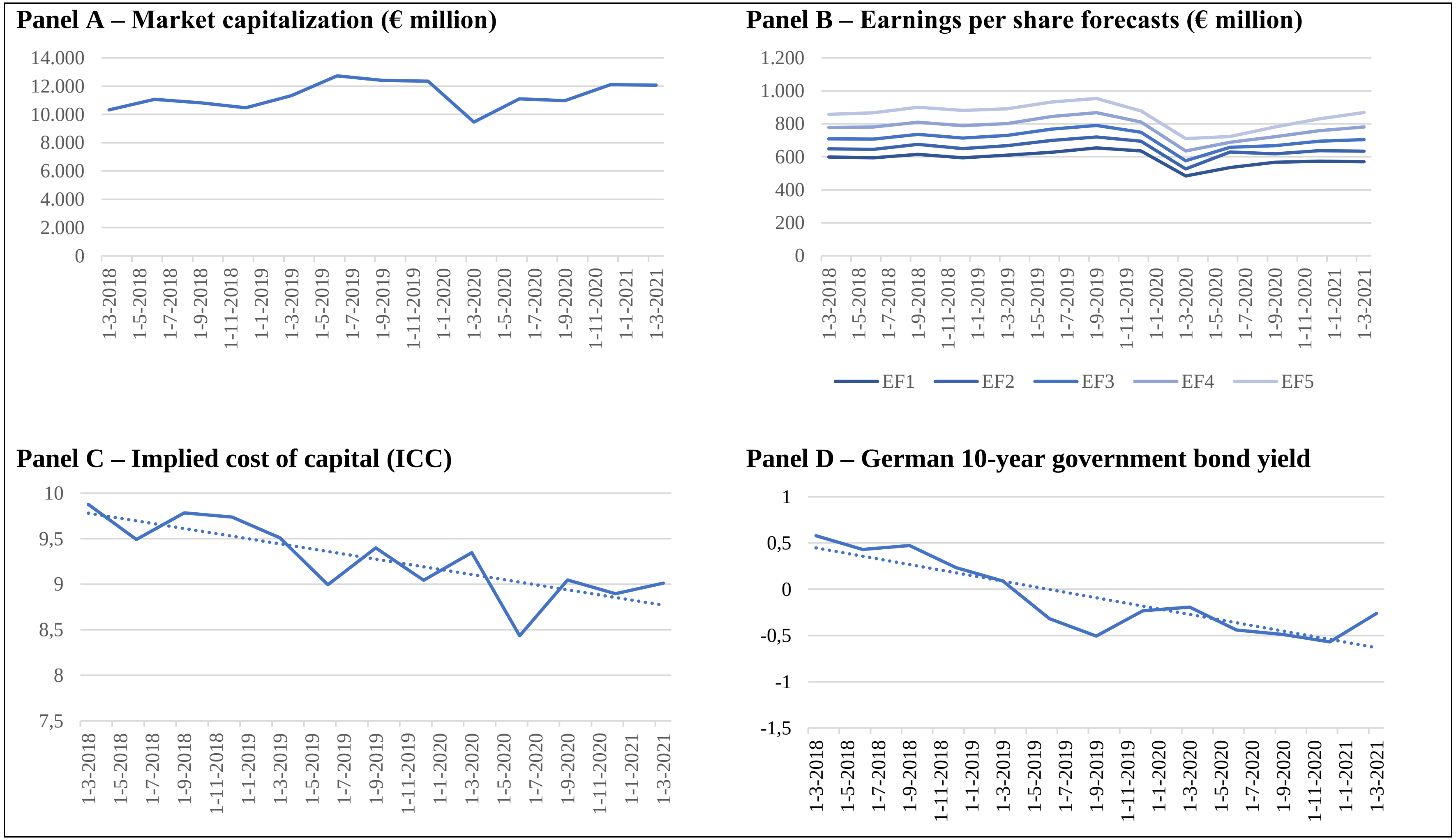

Table 1 – Observed Covid-19 sectoral equity shocks and changes in equity volatility

This table reports the change in the return index obtained from Thomson Reuters Datastream per NACE-1 sector between January 1st, 2020 and March 18, 2020, April 20, 2020 and July 1st, 2021. It also reports the yearly long-term equity volatility for the period between 2010 and 2020 and the daily equity volatility pre-shock (November 1st, 2019 to February 1st, 2020) and post-shock (April 20, 2020 until July 1st, 2021). Daily volatilities are annualized by taking the square root of the number of working days in a year (252). Firm-level data is aggregated using asset weighted averages.

Industry		**Change in return index (RI)**			**Equity volatility**			
	Number of firms	Equity shock March '20 (1)	Equity shock April '20 (1+2)	Equity shock July '21 (1+2+3)	Pre-shock long-term equity volatility (yearly)	Pre-shock equity volatility (daily, annualized)	Post-shock equity volatility (daily, annualized)	Change in daily equity volatility (factor)
A - Agriculture, forestry and fishing	24	-24%	-22%	11%	28%	22%	32%	1.4
B - Mining and quarrying	27	-53%	-38%	-11%	22%	17%	38%	2.2
C - Manufacturing	802	-39%	-24%	28%	33%	21%	35%	1.7
D - Electricity, gas, steam and air conditioning supply	60	-22%	-17%	17%	27%	21%	29%	1.4
E - Water supply; sewerage, waste management and remediation activities	13	-27%	-24%	33%	32%	17%	32%	1.8
F - Construction	51	-42%	-26%	-3%	33%	19%	37%	1.9
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	152	-26%	-15%	19%	31%	32%	38%	1.2
H - Transportation and storage	57	-42%	-33%	10%	33%	24%	43%	1.8
I - Accommodation and food service activities	31	-49%	-38%	-23%	27%	25%	52%	2.1
J - Information and communication	265	-28%	-18%	4%	27%	19%	32%	1.7
K - Financial and insurance activities	253	-43%	-36%	7%	31%	24%	38%	1.6
L - Real estate activities	146	-30%	-20%	5%	27%	25%	44%	1.8
M - Professional, scientific and technical activities	123	-19%	-9%	14%	28%	25%	29%	1.1
N - Administrative and support service activities	44	-53%	-45%	-13%	32%	29%	60%	2.1
O - Public administration and defence; compulsory social security	7	-32%	-21%	11%	28%	19%	38%	2.0
P - Education	3	-33%	-15%	7%	47%	40%	49%	1.2
Q - Human health and social work activities	26	-25%	-14%	-1%	29%	19%	30%	1.6
R - Arts, entertainment and recreation	32	-42%	-23%	12%	33%	24%	41%	1.7
S - Other service activities	41	-38%	-29%	-5%	21%	17%	33%	1.9
Total	**2,157**	**-38%**	**-29%**	**14%**	**30%**	**22%**	**37%**	**1.6**

Table 2 - Market-implied changes in probabilities of default (by industry)

This table reports the increase (decrease in parentheses) of the probability of default (in percentage points) that is implied by the Merton (1974) model as put forward in section 2.2. We report outcomes using both constant volatility and assuming increased volatility based on the change in daily equity volatility before and after the initial Covid-19 shock (last column in Table 1). Results are obtained for three points in time on March 18, 2020 (March), April 20, 2020 (April), and July 1, 2021 (July) compared to the January 1, 2020 baseline. The Merton model is calibrated using values for the equity shocks (March, April, and July), leverage, and standard deviation of equity as reported in Appendix I. Furthermore, we assume an average time to maturity of three years (in line with the duration of the loan portfolio of banks) and a risk-free interest rate of zero per cent during those three years. Results are reported for all firms for which a complete set of calibration parameters is available (1,732). Firm-level data is aggregated using asset weighted averages.

	Number of firms	Listed firms sample (constant volatility)			Listed firms sample (increased volatility)		
		March	April	July	March	April	July
A - Agriculture, forestry and fishing	23	0.13	0.07	(0.01)	0.29	0.24	0.06
B - Mining and quarrying	22	0.28	0.13	0.04	0.81	0.62	0.37
C – Manufacturing	698	0.17	0.09	(0.01)	0.41	0.30	0.10
D - Electricity, gas, steam and air conditioning supply	53	0.05	0.03	(0.03)	0.19	0.16	0.05
E - Water supply; sewerage, waste management and remediation activities	12	0.11	0.09	(0.03)	0.39	0.37	0.17
F – Construction	43	0.27	0.12	0.02	0.55	0.45	0.30
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	131	0.13	0.07	0.02	0.22	0.16	0.09
H - Transportation and storage	49	0.27	0.15	0.01	0.60	0.50	0.21
I - Accommodation and food service activities	20	0.30	0.18	0.10	0.70	0.60	0.49
J - Information and communication	230	0.14	0.11	0.06	0.40	0.34	0.26
K - Financial and insurance activities	107	0.16	0.10	0.00	0.32	0.27	0.14
L - Real estate activities	129	0.17	0.12	0.02	0.46	0.41	0.27
M - Professional, scientific and technical activities	92	0.17	0.10	0.02	0.23	0.15	0.05
N - Administrative and support service activities	32	0.26	0.17	(0.01)	0.72	0.63	0.26
O - Public administration and defence; compulsory social security	5	0.28	0.15	(0.05)	0.72	0.65	0.40
P – Education	3	0.29	0.17	0.12	0.41	0.29	0.22
Q - Human health and social work activities	21	0.08	0.03	0.00	0.31	0.22	0.14
R - Arts, entertainment and recreation	25	0.30	0.05	(0.06)	0.65	0.35	0.07
S - Other service activities	37	0.30	0.20	0.05	0.68	0.60	0.41
Weighted average	**1,732**	**0.17**	**0.10**	**0.01**	**0.41**	**0.32**	**0.16**

Table 3 – Prediction model changes in probability of default

This table reports the OLS-regression results for different models to predict changes in probability of default (in percentage points) at different points in time on March 18, 2020 (March), April 20, 2020 (April), and July 1, 2021 (July). We test the predictive capacity of four variables including size (total assets in billion USD), profitability (return on assets) and financial structure (leverage and liquidity ratios). We include industry fixed effects to account for substantial differences in shocks across economic sectors. The analysis is based on a same sample of 1,732 listed firms in the euro area for which complete market and calibration data is available. T-values are reported within brackets, * denotes a significance-level of 10%, ** a significance-level of 5%, and *** a significance-level of 1%.

	Full model (March)	Reduced model (March)	Reduced model (April)	Reduced model (July)
Constant volatility				
Assets	0.009	-	-	-
	(0.62)			
Return on assets	0.000	-	-	-
	(0.21)			
Leverage ratio	0.150***	-0.151***	-0.107***	-0.043***
	(7.87)	(8.11)	(7.14)	(2.76)
Liquidity ratio	-0.001*	-0.001*	-0.001	-0.000
	(-1.73)	(-1.74)	(-1.20)	(0.52)
Industry fixed effects	Yes	Yes	Yes	Yes
R-squared	0.07	0.07	0.06	0.03
N	1,732	1,732	1,732	1,732
Increased volatility				
Assets	0.005	-	-	-
	(-0.24)			
Return on assets	0.000	-	-	-
	(0.69)			
Leverage ratio	0.258***	0.254***	-0.237***	-0.183***
	(9.13)	(9.20)	(9.25)	(7.85)
Liquidity ratio	-0.003***	-0.003***	-0.002**	-0.001
	(-3.12)	(-3.15)	(-2.37)	(0.426)
Industry fixed effects	Yes	Yes	Yes	Yes
R-squared	0.17	0.17	0.17	0.12
N	1,732	1,732	1,732	1,732

Table 4 - Estimated market-implied changes in probabilities of default (by industry, random sample)

This table reports the estimated increase (decrease in parentheses) of the probability of default (in percentage points) per industry. Estimates are based on a random sample of 50,000 firms from the Bureau van Dijk Orbis database. The sample is drawn from the full set of 3,564,023 active firms in the euro area that have a non-zero value for "bank loans" and non-missing values for industry classification, leverage ratio, and liquidity ratio. For each of the firms in our sample we estimate the change in probability of default according to the reduced-form models in Table 3. Firm-level data is aggregated using bank loan weighted averages.

		Listed firms sample (constant volatility)			**Listed firms sample (increased volatility)**		
	Number of firms	March	April	July	March	April	July
A - Agriculture, forestry and fishing	1,344	0.13	0.06	(0.02)	0.31	0.22	0.08
B - Mining and quarrying	92	0.20	0.14	0.08	0.66	0.59	0.35
C – Manufacturing	7,297	0.16	0.09	0.00	0.43	0.34	0.15
D - Electricity, gas, steam and air conditioning supply	435	0.08	0.03	(0.03)	0.23	0.17	0.06
E - Water supply; sewerage, waste management and remediation activities	316	0.14	0.11	(0.01	0.41	0.38	0.16
F – Construction	5,944	0.17	0.11	0.01	0.50	0.44	0.21
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	11,465	0.17	0.11	0.01	0.27	0.21	0.07
H - Transportation and storage	2,428	0.15	0.09	0.01	0.46	0.38	0.19
I - Accommodation and food service activities	2,614	0.17	0.14	0.09	0.49	0.46	0.36
J - Information and communication	1,682	0.16	0.09	(0.01)	0.43	0.33	0.14
K - Financial and insurance activities	2,298	0.14	0.09	0.01	0.35	0.29	0.14
L - Real estate activities	3,421	0.13	0.09	0.03	0.41	0.36	0.24
M - Professional, scientific and technical activities	4,593	0.18	0.13	0.04	0.24	0.19	0.09
N - Administrative and support service activities	2,251	0.17	0.12	0.00	0.55	0.49	0.29
O - Public administration and defence; compulsory social security	11	0.20	0.13	(0.08)	0.59	0.55	0.22
P – Education	515	0.28	0.13	0.03	0.39	0.22	0.08
Q - Human health and social work activities	1,292	0.09	0.03	(0.03)	0.33	0.23	0.10
R - Arts, entertainment and recreation	629	0.13	0.09	0.00	0.39	0.32	0.19
S - Other service activities	628	0.08	0.06	0.02	0.36	0.33	0.25
Other	745	0.11	0.04	(0.02)	0.26	0.18	0.05
Weighted average	**50,000**	**0.16**	**0.10**	**0.01**	**0.38**	**0.31**	**0.16**

Table 5 – Covid-19 stress test of euro area banks' corporate credit portfolios (by industry)

This table shows the implied market value losses on corporate credit portfolios on March 18, 2020 , April 20, 2020, and July 1, 2021 using four different sets of scenario parameters. It shows the multiplication of the changes in the probability of default assuming either constant or increased (higher) equity volatility, the exposure amounts in Appendix I, and a loss given default (*LGD*) of either 45% (baseline) and 60% (downturn). We also report totals and their fractions of capital and reserves and total corporate loan exposures. Capital and reserves for all euro area banks totalled € 2,555,855 million in 2019 as obtained from the ECB statistical data warehouse. Some industries are grouped in the ECB exposure data and hence are taken together. All amounts are in € million.

	March '20				April '20				July '21			
Equity volatility:	Constant	Constant	Higher	Higher	Constant	Constant	Higher	Higher	Constant	Constant	Higher	Higher
LGD:	0.45	0.6	0.45	0.6	0.45	0.6	0.45	0.6	0.45	0.6	0.45	0.6
A – Agriculture, forestry and fishing	11,256	15,640	25,769	34,991	4,796	7,027	18,112	24,782	-1,348	-1,164	7,119	10,124
B – Mining and quarrying	1,913	2,551	6,238	8,317	1,274	1,699	5,505	7,339	765	1,019	3,248	4,330
C – Manufacturing	46,069	62,764	122,220	164,298	25,806	35,746	95,576	128,773	-1,344	-454	43,323	59,103
D – Electricity, gas, steam and air conditioning supply E – Water supply; sewerage, waste management and remediation activities	8,805	12,280	26,051	35,274	4,121	6,035	19,444	26,465	-2,669	-3,018	7,193	10,130
F – Construction	23,565	31,659	70,814	94,657	15,871	21,399	61,648	82,436	1,174	1,803	30,410	40,786
G – Wholesale and retail trade; repair of motor vehicles and motorcycles	43,519	59,348	70,571	95,417	28,159	38,868	54,633	74,167	1,818	3,747	17,658	24,866
H – Transportation and storage J – Information and communication	25,365	34,146	75,826	101,427	14,414	19,544	61,986	82,973	1,749	2,658	29,836	40,107
I – Accommodation and food service activities	11,436	15,952	32,932	44,613	9,694	13,630	30,719	41,663	5,716	8,326	23,987	32,686
L – Real estate activities M – Professional, scientific and technical activities N – Administrative and support service activities	123,962	167,730	245,228	329,417	85,206	116,055	204,153	274,651	23,628	33,951	116,675	158,014
Other	19,365	26,271	49,705	66,725	12,021	16,479	40,614	54,603	1,356	2,259	19,460	26,398
Total	**315,255**	**428,340**	**725,352**	**975,136**	**201,361**	**276,481**	**592,389**	**797,853**	**30,845**	**49,127**	**298,908**	**406,545**
Percentage of total corporate loan exposures	7.1%	9.6%	16.3%	21.8%	4.5%	6.2%	13.3%	17.9%	0.7%	1.1%	6.7%	9.1%
Percentage of capital and reserves	12.3%	16.8%	28.4%	38.2%	7.9%	10.8%	23.2%	31.2%	1.2%	1.9%	11.7%	15.9%

Table 6 – Counterfactual Covid-19 stress test of euro area banks' corporate credit portfolios (by industry)

This table shows the implied market value losses on corporate credit portfolios on July 1, 2021 based on a counterfactual scenario keeping discount rates constant from March 1, 2020. It shows the multiplication of the changes in the probability of default assuming either constant or increased (higher) equity volatility, the exposure amounts in Appendix I, and a loss given default (*LGD*) of either 45% (baseline) and 60% (downturn). We also report totals and their fractions of capital and reserves and total corporate loan exposures. Capital and reserves for all euro area banks totalled € 2,555,855 million in 2019 as obtained from the ECB statistical data warehouse. Some industries are grouped in the ECB exposure data and hence are taken together. All amounts are in € million.

	July '21			
Equity volatility:	Constant	Constant	Higher	Higher
LGD:	0.45	0.6	0.45	0.6
A – Agriculture, forestry and fishing	897	1,829	10,599	14,765
B – Mining and quarrying	1,004	1,338	3,636	4,847
C – Manufacturing	6,242	9,661	57,143	77,529
D – Electricity, gas, steam and air conditioning supply E – Water supply; sewerage, waste management and remediation activities	-778	-497	10,433	14,451
F – Construction	5,365	7,392	39,423	52,802
G – Wholesale and retail trade; repair of motor vehicles and motorcycles	9,493	13,980	26,523	36,686
H – Transportation and storage J – Information and communication	5,511	7,674	38,131	51,167
I – Accommodation and food service activities	9,491	13,358	28,151	38,238
L – Real estate activities M – Professional, scientific and technical activities N – Administrative and support service activities	53,306	73,522	155,993	210,438
Other	4,365	6,271	24,451	33,053
Total	**94,896**	**134,528**	**394,483**	**533,977**
Percentage of total corporate loan exposures	2.1%	3.0%	8.8%	12.0%
Percentage of capital and reserves	3.7%	5.3%	15.4%	20.9%

Appendix I – Corporate loan exposures of banks in the Euro area (by sector)

This Table shows the total loans on the balance sheets of euro area banks (exposure) broken down by sector, pre-shock on December 31, 2019. Exposure data is obtained from the European Central Bank (ECB) statistical data warehouse and covers all Monetary Financial Institutions (MFIs) excluding central banks. Monetary Financial Institutions (MFIs), as in a definition provided by the ECB, are defined as central banks, resident credit institutions as defined in Community Law, and other resident financial institutions whose business is to take deposits or close substitutes for deposits from entities other than MFIs and, for their own account (at least in economic terms), to grant credits and/or make investments in securities. Money market funds are also classified as MFIs. Some industries are grouped in the ECB exposure data and hence are taken together. All amounts are in € million.

Category	**Exposure**
A - Agriculture, forestry and fishing	187,089
B - Mining and quarrying	20,903
C - Manufacturing	627,586
D - Electricity, gas, steam and air conditioning supply E - Water supply; sewerage, waste management and remediation activities	231,601
F - Construction	314,602
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	572,444
H - Transportation and storage J - Information and communication	366,680
I - Accommodation and food service activities	149,294
L - Real estate activities M - Professional, scientific and technical activities N - Administrative and support service activities	1,678,960
Other	314,115
Total	**4,463,274**