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Keywords: Covid-19 pandemic, stress test, Financial Stability, bank capital

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Is COVID-19 a threat to financial stability in Europe?*

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Abstract

The severe economic impact of the COVID-19 pandemic could threaten financial stability. However, assessing the gravity of this threat is challenging, since banks' accounting-based loan loss provisions are sluggish. We use a Merton contingent claims model to provide a real-time, market valuation-based assessment of the impact of COVID-19 on euro area banks' corporate loan portfolios. We calibrate the model based on observed stock price responses and use different scenarios for future volatility and incurred losses in case of default. Based on stock prices as of April 20, 2020, we estimate that the market-implied losses for euro area banks could reach over €1 trillion, or 4 to 25% of corporate credits' book value (7 to 43% of available capital and reserves). Our analysis can be viewed as an early warning indicator of potential accounting losses to follow.

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1. Introduction

Besides the human toll of the COVID-19 pandemic, measures to fight the spread of the severe acute respiratory syndrome coronavirus 2 (SARS-Cov-2) have had a severe impact on the global economy as well as its future outlook. The pandemic has led to both large supply shocks (e.g., due to factory and business shutdowns, including interruptions in supply chains) and large demand shocks (e.g., due to unemployment, 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 at its low point on March 18. The global economy is expected to shrink by 6% in 2020, which constitutes a larger negative economic shock than the 2008-2009 "Great Recession" (OECD, 2020).

For policymakers and financial regulators, a key question is whether current bank capital buffers are sufficient to cover potential losses. After all, an ensuing banking crisis has the potential to deepen the economic crisis further. Given the central role of the banking sector in the economy, 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). Banks' capital buffers have been boosted since 2008-2009, but, overall, it is not clear whether banks can cope with the unprecedented current crisis and whether additional measures are needed to safeguard financial stability. If COVID-19 indeed constitutes a threat to banks and financial stability, it is imperative for financial regulators to find this out as soon as possible, such that appropriate policy actions can be taken.

One important obstacle to assessing the impact of the COVID-19 crisis on the solvency of banks is that current loan loss provisioning practices may severely underestimate the potential impact of COVID-19 on the banking sector. It is common practice for banks to make provisions for bad loans based on accounting rules. However, such 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). Furthermore, there is uncertainty about future economic developments and hence also about the magnitude of future realised losses for banks. This uncertainty is ignored when making loan-loss provisions, as they are best (point) estimates (Walter, 1991). We show the effect of different scenarios on the magnitude of future losses, to show a range of uncertainty as well as showing outcomes in worst-case scenarios that are of specific interest when analysing bank solvency (Ong, 2014).

The key contribution of our research is that we estimate the potential size of banks' loan losses in the euro area based on real-time stock market data. 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 affects the value of both equity and debt in a non-linear way.

The Merton model allows us to take a forward-looking perspective on banks' balance sheets and make predictions about the size of provisions and write-offs that banks will have to make over the coming years. Since our implementation of the Merton model relies on observed (real-time) stock market responses rather than accounting data, our analysis provides an early warning indicator of accounting losses to follow. Another innovation in this paper is that we use a large sample of firms to build a representative sample and apply our model to each firm. 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 heterogeneity (including differences in leverage across firms), which is critical for an appropriate implementation of the Merton model to large portfolios of loans.

Our analysis focuses on the banking sector in the euro area, using data on aggregated industry-level loan exposure (1-digit NACE) of euro area banks from the European Central

Bank (ECB) data warehouse. Using our calibrated model, we estimate changes in the default probabilities of 1,981 publicly listed firms in the euro area implied by their stock price response to the COVID-19 crisis in the period January through April 2020. We then aggregate the firm-level results to 19 industries (1-digit NACE). Subsequently, we apply these estimated changes in default probabilities to the aggregated corporate debt portfolio of euro area banks under four different scenarios. These four scenarios reflect the uncertainty around the structural change in equity volatility as a result of the COVID-19 crisis as well as around the fraction of defaulted loans that are recovered by the bank. We note that both of these factors depend to a large extent on the development of the public policy response.

Our results indicate that the market value losses in the corporate debt portfolio of euro area banks range from 4 to 25% of the book value of the loans (or up to more than €1 trillion in absolute numbers), depending on the scenario. As a fraction of available capital and reserves, the estimated losses range from 7% to 43% across the four scenarios. Our analysis also sheds light on the industries whose default probabilities are elevated the most as a result of the COVID-19 crisis, including financial and insurance activities, administrative and support service activities, accommodation and food service activities, construction, manufacturing, and transportation.

Our paper contributes to a burgeoning literature on bank stress testing (e.g., Upper, 2011; Henry et al., 2013; Ong, 2014). A recent strand of this literature extends these bank stress tests to the potential impact of climate risk, with a focus on industry-specific impacts (e.g., Battiston et al., 2017; Vermeulen et al. 2019). Building upon Reinders et al. (2020), we add to these and other studies by using a Merton contingent claim approach to assessing the impact of COVID-19 on banks' corporate credit portfolios. This approach is not only appealing because loans constitute a much more significant part of bank balance sheets than equity investments, but also because this stress test is based on market valuations instead of accounting data and thus offers a real-time assessment of bank solvency.

The results of our research are relevant for regulators, banks, other financial market participants, and their supervisors. Especially banking regulators and supervisors currently have to walk a tight line between, on the one hand, keeping credit available to those economic agents who need it and, on the other hand, safeguarding trust in the financial system by demanding ample capital reserves (Fratzscher et al., 2016). Adequate estimates of the size of potential loan losses within the European banking sector contribute to making this trade-off. Furthermore, individual banks and other financial market participants may use our industry-level estimates to inform their own analyses and loan loss provisioning.

We believe that our approach potentially has much broader applicability beyond the COVID-19 crisis, because it enables financial sector executives and regulators to immediately assess the impact of any type of economic shock on the balance sheets of financial institutions based on real-time stock market valuations. The approach is particularly valuable for large debt exposures for which market valuations are not readily available and in case the impact of the economic shock is asymmetric or heterogenous across sectors or firms.

2. Methodology

2.1. General set-up

In this section, we describe the method that we employ to estimate market-based expected losses to banks their credit portfolios as a result of the COVID-19 crisis. 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

$$\Delta PD = PD_{post-shock} - PD_{pre-shock} \tag{2}$$

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

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.[1]

2.2. Market-based estimation of ΔPD

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:

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

where $N(\cdot)$ 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).

[1] 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.

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

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

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

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:

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

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

3. Data and calibration

3.1 Exposure data (EAD)

For the exposure at default (*EAD*), we use 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 (C) with loans totalling €0.63 trillion in exposure and Wholesale and retail trade; repair of motor vehicles and motorcycles (G) totalling €0.57 trillion.

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

To calibrate the Merton model, we use a set of 3,867 public firms in the euro area obtained from the Bureau van Dijk Orbis database. This sample includes all firms in the Orbis database in the euro area region that are listed and have an ISIN code. For each firm, we obtain parameters for leverage and the book value of long-term debt, as well as the industry classification of the firm (1-digit NACE) and its associated ISIN code. Using the ISIN code, we link our Orbis sample to Thomson Reuters Datastream to obtain firm-level parameters for equity volatility and changes in the stock price of the firm between January 1, 2020 and March 18, 2020 (market low point) and January 1, 2020 and April 20, 2020 (post-stimulus shock).[2]

It is important to emphasise that we estimate the impact of COVID-19 on the probability of default for each of the individual firms in our sample, before aggregating these default probabilities to the industry-level. Accounting for within-industry heterogeneity is crucial because of the non-linear nature of the impact of asset valuation shocks on the market value of loans as per the Merton model. Such heterogeneity would be ignored when applying the Merton model to a representative firm. A representative firm might be far away from default, while a non-negligible subset of firms within the industry may not, and these firms could be a source of considerable risk for banks' portfolios of corporate loans. We nevertheless still base our calibration on a sample of listed firms only, which may suffer from a bias towards larger firms. As shown in Reinders et al. (2020), this may lead to an underestimation of losses, since smaller firms typically are riskier (i.e., have a higher asset value volatility). This also applies to our estimates, and hence our results are likely at least somewhat conservative.

We exclude firms for which the stock price remained constant during the shock period, indicating that the stock was not actively traded. We also exclude all firms that have missing values for one or more of the calibration parameters. This results in a sample size of 1,981 firms. Table 2 provides summary statistics of our calibration parameters for 19 industries. Per industry, Panel A reports the long-term debt weighted average of stock price shocks in March and April, respectively, the leverage, and the standard deviation of equity. Stock price shocks range between plus 11% for Education (P) in April to minus 51% for Accommodation and food service activities (I) in March. The average stock price shocks across all industries are minus 36% in March and minus 24% in April. The average leverage across all firms in the sample is

[2] We base the stock price response on the return index (RI) in Thomson Reuters Datastream, which accounts for dividend payments.

0.68, and the average standard deviation of equity is 0.30. We also report the standard deviation of those parameters across individual firms within the industry in Panel B.[3]

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. The post-shock value of the standard deviation of equity is however not known yet, as it depends amongst others on future policy actions to reduce economic volatility (e.g., due to further supportive measures). To incorporate this uncertainty, 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 doubles as a result of the COVID-19 shock, which we deem to be a plausible upper bound. Furthermore, we assume that the duration of loans for euro area banks is three years.[4] We also assume a flat risk-free interest rate of zero per cent during those three years.

3.3 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.[5] Since this scenario has a non-zero change in the *LGD* as a

[3] We note that the observed average standard deviation of stock price shocks across all industries increased substantially between March (0.24) and April (0.38). This indicates that the stock price shock has become more disperse during that time period, which one could interpret as investors becoming more precise in their appreciation of individual firms' their loss in value as a result of the COVID-19 shock.

[4] 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

[5] 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.

result of the shock, we obtain our expected loss estimate through equation (3). This requires a 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%.[6] 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.[7] We thus (conservatively) use a lower bound *LGD* of 45% across all industries.[8]

4. Results

Tables 3 and 4 present our main results. Table 3 reports estimated market-implied changes in probabilities of default (ΔPD) per industry, estimated using the Merton structural credit risk model. The table show shocks for March 18, 2020 ("March") and April 20, 2020 ("April") compared to the January 1, 2020 baseline. We also show 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 doubles ("double volatility").

[6] 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.

[7] 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.

[8] 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.

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 administrative and support service activities (46 ppt), accommodation and food service activities (28 ppt), construction (26 ppt), manufacturing (25 ppt), transportation and storage (25 ppt), and arts, entertainment and recreation (22 ppt). These numbers suggest a considerable worsening of default probabilities for many industries as a result of the COVID-19 crisis, as reflected in the stock prices of firms in these industries. As the probability of default is affected by a combination of a firm's equity shock and leverage, the results in Table 2 and 3 differ. While accommodation and food service activities experience the largest equity shock, administrative and support service activities are hardest hit due to its high leverage (0.75 in Table 2).

In the month after that, until April 20, 2020, the probabilities of default of all of these industries improve. Especially construction and administrative and support service activities (both plus 16 ppt) and manufacturing (plus 13 ppt) recover strongly in their implied probabilities of default during that period.

A similar pattern arises when assuming a doubling of the equity volatility and looking at the stock market low-point on March 18, 2020, for which we find the highest increases in implied probabilities of defaults. However, financial and insurance activities (68 ppt) now arises as the industry that is most severely impacted, followed by administrative and support service activities (67 ppt), construction (67 ppt), and accommodation and food service activities (65 ppt). The tremendous impact of COVID-19 on the default probability of financial and insurance activities under this scenario reflects the high leverage under which this industry operates (0.78 in our calibration, see Table 2) and illustrates the non-linearity in the Merton model, in which a doubling of the valuation shock typically leads to (much) more than a doubling of the default probability. 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.

Table 4 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. Panel A 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). Panel B presents the market value losses based on the stock price response as of April 20, 2020 under the same four scenarios.

The results in Table 4 suggest that banks will experience substantial additional losses on their corporate credit portfolios as a result of the COVID-19 crisis. Based on the post-stimulus shock to stock markets observed on April 20, 2020, these losses range from 4.0% to 24.6% 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 4.0% of current book value. In more pessimistic scenarios, in which the LGD increases to 60% or equity volatility doubles, these losses are 5.7% and 18.2%, respectively. In the most severe scenario, in which the LGD increases to 60% and equity volatility doubles, losses amount to 24.6% 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 7.0% (most optimistic) and 42.9% (most severe), which indicates that the loan losses for euro area banks as a result of COVID-19 are potentially very large.

Furthermore, we compare the post-stimulus shock to the shock at the market low-point observed at March 18, 2020. We believe that this comparison is relevant for at least two reasons. First, one could argue that the stock market recovery after March 18 was at least in part a response to the various policy actions to mitigate the economic damages, in which case our analysis can provide a sense of the loan losses prevented by such actions. Second, we note that several market observers (e.g., Financial Times, 2020ab) have questioned whether the stock market recovery after March 18, 2020 can be justified in light of the huge economic repercussions of the COVID-19 crisis. If indeed current stock market valuations are overly optimistic, the March 18, 2020 low-point may be a useful benchmark for more realistic assessments of loan losses.

Based on the stock market shock observed on that date, the most optimistic scenario would have led to a loss on corporate loans of 7.4% of current book value. In the intermediate scenarios in which LGDs increase to 60% or equity volatility doubles, these losses are 10.2% and 22.3%, respectively. In the most severe scenario, losses would have amounted to 30.0% of the book value of the corporate loan portfolio. 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 €153 billion (most optimistic) and €242 billion (most pessimistic) in market value credit losses for euro area banks.

Finally, we can also compare our scenario results with the decline in banks' market value (Vickers, 2019). During the first months of 2020, the STOXX Europe banks (a leading stock market index for banks) declined from January 1, 2020 to April 20, 2020 with 42.5%, which exceeds the average equity shock of 24% reported in Table 2. The 42.5% decline in market value corresponds with the upper part of our scenarios, which range from 7 to 43%.[9]

[9] It should be noted that our scenarios only include losses on the corporate loan portfolio, which is the most relevant part of banks' assets for COVID-19 related losses. Nevertheless, losses may also arise on banks' consumer loans, equity portfolios and sovereign exposures.

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 corporate industries. Our analysis shows that the impact on business valuation is uneven across industries and affects the value of the instruments that finance those businesses (e.g., equity and debt). The impact on the expected losses on debt instruments is largely driven by increased probabilities that firms will default. For euro area banks, we estimate the expected losses 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 13% and 52% 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% and 43% a month later, after the announcement of substantial stimulus packages by public sector authorities. But even these numbers indicate overall losses to euro area banks ranging up to more than €1 trillion.

Our results are important for both financial sector authorities and financial institutions. Financial sector authorities can use our findings to compare market-based expected losses to currently announced loss-provisions by euro area banks. In some jurisdictions, this may reveal gaps between the more accounting-based supervisory practices and market expectations and could be part of the rationale to implement additional measures to safeguard financial stability. Our results with potential declines in bank capital of up to 43% support the ECB’s ban on dividend payments and share buy-backs during the COVID-19 pandemic (ECB, 2020). 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. The impact on individual banks may vary, amongst others because the industry distribution of their loan portfolio differs.

Our research has several limitations. The Merton (1974) model is based on a number of assumptions, some of which have been challenged in subsequent research. One fundamental assumption is that asset value follows a geometric Brownian motion, which implies that in a short interval of time, asset value can only change by a small amount (Merton, 1976).[10] Several authors have noted that this is inconsistent with empirical observation, namely that in a short interval of time there can be substantial changes in stock prices or "jumps" (e.g., Cai and Kou, 2011). Part of this problem is addressed in our analysis by using differences between pre-shock and post-shock estimates (instead of absolute values for the probability of default). A second limitation is that our estimations relate to losses on the corporate credit portfolio only. Other channels should be considered to obtain a more complete picture of the impact of COVID-19 on euro area banks their stability. Three further channels to consider are the impact of COVID-19 on consumer lending (e.g., through increased unemployment), on equity portfolios, and on sovereign instruments (e.g., through credit rating downgrades). We believe that an in-depth investigation of these channels is a promising avenue for further research.

[10] For a full list of assumptions, see Merton (1974).

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Figure 1 – STOXX Europe 600 price index

This figure shows the STOXX Europe 600 price index between November 1, 2019 and April 20, 2020. Data is obtained from Thomsom Reuters Datastream.

Table 1 – Corporate loan exposures of banks in the Euro area (by industry)

This table shows the total loans on the balance sheets of euro area banks (exposure) broken down by industry, 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**

Table 2 – Calibration sample summary statistics

This table shows the summary statistics for the three main calibration parameters for the Merton model (equity valuation shock, leverage, and standard deviation of equity) for our sample of 1,981 public firms in the euro area, which we obtained from the Orbis database by Bureau van Dijk. We report both the weighted average values (weighted by the firm's long-term debt) for each calibration parameter (Panel A) and the standard deviations of each parameter across firms (Panel B). The equity shocks and standard deviation of equity are obtained by linking the sample to Thomson Reuters Datastream using ISIN codes. For the equity shocks, we take the difference in the return index (RI) between January 1, 2020 and, respectively, the stock market low-point on March 18, 2020 (March) and the stock market post-stimulus on April 20, 2020 (April). All calibration data is for 2019 (or the last available year for a given firm). We report leverage as total debt over total assets.

		Panel A: Weighted average				**Panel B: Standard deviation**			
Industry	Number of firms	Equity shock March	Equity shock April	Leverage	Standard deviation of equity	Equity shock March	Equity shock April	Leverage	Standard deviation of equity
A - Agriculture, forestry and fishing	24	-0.25	-0.24	0.56	0.28	0.19	0.20	0.20	0.19
B - Mining and quarrying	23	-0.53	-0.38	0.58	0.22	0.15	0.12	0.23	0.20
C - Manufacturing	789	-0.41	-0.27	0.65	0.33	0.22	0.38	0.20	0.20
D - Electricity, gas, steam and air conditioning supply	60	-0.20	-0.15	0.73	0.27	0.16	0.16	0.26	0.21
E - Water supply; sewerage, waste management and remediation activities	13	-0.28	-0.23	0.77	0.32	0.14	0.15	0.15	0.12
F - Construction	50	-0.42	-0.24	0.78	0.33	0.26	0.32	0.23	0.22
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	149	-0.26	-0.18	0.69	0.31	0.20	0.20	0.21	0.19
H - Transportation and storage	56	-0.43	-0.33	0.71	0.33	0.20	0.18	0.19	0.18
I - Accommodation and food service activities	30	-0.51	-0.40	0.63	0.27	0.43	0.33	0.19	0.16
J - Information and communication	259	-0.27	-0.19	0.69	0.27	0.28	0.56	0.20	0.20
K - Financial and insurance activities	119	-0.41	-0.26	0.78	0.31	0.23	0.30	0.29	0.24
L - Real estate activities	141	-0.30	-0.19	0.59	0.27	0.19	0.21	0.20	0.23
M - Professional, scientific and technical activities	119	-0.29	-0.21	0.73	0.28	0.32	0.34	0.23	0.23
N - Administrative and support service activities	43	-0.50	-0.39	0.75	0.32	0.28	0.25	0.21	0.20
O - Public administration and defence; compulsory social security	7	-0.33	-0.21	0.80	0.28	0.16	0.07	0.20	0.34
P - Education	3	-0.18	0.11	0.55	0.47	0.15	0.19	0.05	0.07
Q - Human health and social work activities	26	-0.25	-0.15	0.71	0.29	0.21	1.06	0.22	0.18
R - Arts, entertainment and recreation	31	-0.44	-0.36	0.79	0.33	0.22	0.18	0.24	0.19
S - Other service activities	39	-0.40	-0.32	0.49	0.21	0.23	0.21	0.20	0.19
Total	**1981**	**-0.36**	**-0.24**	**0.68**	**0.30**	**0.24**	**0.38**	**0.22**	**0.21**

Table 3 – Estimated 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 model as put forward in section 2.2. We report outcomes for March 18, 2020 (March) and April 20, 2020 (April) compared to the January 1, 2020 baseline. We also report outcomes assuming constant equity volatility (constant volatility) and a doubling of the observed equity volatility (double volatility). The Merton model is calibrated using values for the equity shocks (March and April), leverage, and standard deviation of equity according to Table 2. Furthermore, we assume an average time to maturity of three years and a risk-free interest rate of zero per cent during those three years.

	Constant volatility		**Double volatility**	
	March	April	March	April
A - Agriculture, forestry and fishing	0.08	0.05	0.42	0.39
B - Mining and quarrying	0.14	0.08	0.43	0.27
C - Manufacturing	0.25	0.12	0.64	0.51
D - Electricity, gas, steam and air conditioning supply	0.07	0.05	0.33	0.30
E - Water supply; sewerage, waste management and remediation activities	0.09	0.07	0.55	0.50
F - Construction	0.26	0.10	0.67	0.48
G - Wholesale and retail trade; repair of motor vehicles and motorcycles	0.13	0.07	0.43	0.36
H - Transportation and storage	0.25	0.17	0.62	0.51
I - Accommodation and food service activities	0.28	0.16	0.65	0.53
J - Information and communication	0.06	0.03	0.40	0.33
K - Financial and insurance activities	0.21	0.09	0.68	0.52
L - Real estate activities	0.11	0.06	0.40	0.32
M - Professional, scientific and technical activities	0.16	0.10	0.46	0.40
N - Administrative and support service activities	0.46	0.30	0.67	0.64
O - Public administration and defence; compulsory social security	0.11	0.05	0.54	0.41
P – Education	0.12	(0.02)	0.61	0.35
Q - Human health and social work activities	0.06	0.04	0.46	0.37
R - Arts, entertainment and recreation	0.22	0.18	0.44	0.41
S - Other service activities	0.06	0.02	0.38	0.27
Weighted average	**0.19**	**0.10**	**0.53**	**0.43**

Table 4 – COVID-19 stress test of euro area banks' corporate credit portfolios (by industry)

This table shows the market value losses on March 18, 2020 (Panel A) and on April 20, 2020 (Panel B) based on the implied shock to the market value of debt. It shows the multiplication of the changes in the probability of default assuming either constant or double equity volatility as in Table 3, the exposure amounts in Table 1, 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.

Industry	**Panel A: Loss on March 18 2020**				**Panel B: Loss on April 20 2020**			
Equity volatility:	Constant	Constant	Double	Double	Constant	Constant	Double	Double
LGD:	0.45	0.60	0.45	0.60	0.45	0.60	0.45	0.60
A – Agriculture, forestry and fishing	6,873	9,725	35,322	47,658	4,478	6,531	32,453	43,832
B – Mining and quarrying	1,325	1,830	4,010	5,410	743	1053	2,538	3,447
C – Manufacturing	72,001	97,884	179,567	241,306	35,107	48,692	142,653	192,086
D – Electricity, gas, steam and air conditioning supply E – Water supply; sewerage, waste management and remediation activities	7,103	10,165	36,171	48,923	5,085	7,475	32,997	44,691
F – Construction	36,509	49,622	94,371	126,771	14,134	19,790	68,221	91,905
G – Wholesale and retail trade; repair of motor vehicles and motorcycles	33,211	45,999	110,991	149,705	19,266	27,405	93,331	126,159
H – Transportation and storage J – Information and communication	21,718	30,057	78,875	106,267	13,492	19,089	64,802	87,503
I – Accommodation and food service activities	18,946	25,710	43,438	58,365	10,734	14,760	35,734	48,093
L – Real estate activities M – Professional, scientific and technical activities N – Administrative and support service activities	110,463	152,321	327,577	441,806	65,767	92,727	275,690	372,624
Other	23,798	32,672	83,675	112,508	10,538	14,993	63,865	86,095
Total	**331,946**	**455,985**	**993,997**	**1,338,719**	**179,343**	**252,515**	**812,284**	**1,096,435**
Percentage of total corporate loan exposures	7.4%	10.2%	22.3%	30.0%	4.0%	5.7%	18.2%	24.6%
Percentage of capital and reserves	13.0%	17.8%	38.9%	52.4%	7.0%	9.9%	31.8%	42.9%