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Towards an optimal bank balance sheet after Covid

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Overview

The Covid-19 pandemic has dominated the agenda for banks for most of 2020 and a number of economic sectors are experiencing seismic shifts. The use of historical data in risk modelling, stress testing and portfolio allocation has been questioned in a crisis that differs fundamentally from previous periods of economic stress. Bank stress test models are often linked to GDP growth and the unemployment rate and for the severe recession experienced during 2020 these models predict dramatic increases in loan defaults and losses. However, the expected increases in defaults and losses have not yet materialised due to government support measures and payment moratoria that econometric models do not capture. In this article, we discuss how reporting tools and advanced analytics with alternative challenger models can be used to create forward-looking performance indicators of bank loan portfolios. We focus on lending to European non-financial corporates and the asymmetric impact of Covid on different industry sectors. We explain how such projections can help optimise bank lending including the use of expert overrides to better account for the uniqueness of the current crisis. Once forward-looking measures of risk and return are in place, portfolio theory can be used for optimal portfolio allocation and management.

"Delayed recognition and poor management of deteriorating asset quality could easily clog up bank balance sheets with non-performing loans for a fairly long period of time, making it more difficult for the banks to support viable customers and underpin a faster economic recovery." Andrea Enria, Chair of the ECB Supervisory Board

Credit portfolio management (CPM) after Covid

Every crisis is different and suffers from unique challenges. The global financial crisis of 2009 revealed severe deficiencies in the analysis of subprime mortgages and related structured securities. The Covid pandemic of 2020 resulted in unprecedented lockdowns and disruptions to economic activity combined with numerous government intervention measures to mitigate the economic impact of the pandemic. The result was a steep economic recession in many countries that coexisted with stable or even declining corporate insolvencies and loan defaults contrary to econometric credit models which predicted large

increases in non-performing loans based on historically observed elasticities. Many credit portfolio managers wonder how to react to this apparent model failure and how to best stir the bank's balance sheet through these challenging times.

Naturally given the circumstance, European banking supervisors pay close attention to the asset performance as low asset quality affects bank capital. The Single Supervisory Mechanism specifies the priorities for 2021 regarding credit risk: focus on credit risk management, operations, monitoring and reporting. Credit portfolio managers must identify, measure and mitigate the impact of credit risk, as well as assess the bank's operational capacity to manage the expected increase in distressed borrowers. Furthermore, the ECB places particular emphasis on the banks' capacity to identify any deterioration in asset quality at an early stage as well as on the bank's capacity to continue taking the necessary actions to appropriately manage loan arrears and non-performing loans.

As an overview, we see the following steps towards an optimal bank balance sheet:

1) Data preparation and enrichment. Identify the minimum data sets required for an impactful CPM analysis. This includes data from finance and risk as well as operational data like staffing in the workout department. For corporate borrowers, up to date financials as well as market prices from the loan, bond, CDS and equity markets are important.
2) Continuous monitoring of actual loan performance, borrower behaviour and collateral values including the use of government support programs and payment moratoria. Interactive reporting of watchlist, forbearance and workout exposures including the monitoring of detailed recovery cash flows and workout expenses. The latter will greatly facilitate any non-performing loan (NPL) disposal or securitisation strategies.
3) Flexible report generation to compare actual performance with predicted performance from existing or newly adjusted models. Use of flexible and simpler challenger models that are easier to adjust and explore than champion models in production (challenger model sandbox).
4) Automated market valuations to explore exit strategies also for illiquid loan exposures.
5) Interactive evaluation of the economic benefits of the three main management strategies:
    a) on-balance sheet management with organic run-off of suboptimal exposures based on internal workout with restructuring and real estate owned strategies of NPL,
    b) outright single or portfolio sales, and
    c) structured risk transfer transactions in form of synthetic or true sale securitisations.
6) Combine risk model predictions, expert views and market valuations to quantify the impact on the future balance sheet including risk and return profile of all relevant portfolio segments. Include the relevant regulatory changes from the prudential backstop and Basel III/IV.
7) Translate the predicted performance into optimal action steps by selecting the most efficient portfolio segments for each management strategy.
8) Use advanced analytics for structured transactions balancing investor demands with regulatory and accounting benefits using cash flow models for tranched liabilities (cash & synthetic securitisation).

In this article we investigate how data and adjusted risk models can be used to update the credit portfolio management tool box and account for the Covid effects more accurately. We offer a management framework and analytics platform to support decisions towards an optimal balance sheet through a number of remediating actions. The suggested steps to improve the risk-return profile in the bank book are largely based on best practice CPM and should be equally useful after the pandemic has been overcome. Here, we comment on different challenger models for corporate default risk (step 3) and outline the use of portfolio theory for portfolio allocation (step 6). Data preparation (step 1) including standardisation and validation is available in the NPL Markets analytics platform. Continuous performance monitoring with user defined segmentations and drill downs are a recent addition to the platform (step 2). Evaluated corporate loan pricing in step 4 is discussed in a separate article available upon request. The interactive analysis of different management strategies (steps 5 and 7) is available in the investor and bank balance sheet analytics on the platform. The analytics for structured transactions (step 8) will be available on the platform shortly. For further research and information visit nplmarkets.com/en/research.

Champion model failure

Machine learning methods such as regressions, decision trees or neural networks are widely used techniques to model credit risk. They all rely on the principle that patterns and behaviors from the past will likely repeat in the future. Models identify these patterns in historical data and use them for predictions. Much work has gone in the development of credit models using these machine learning methods to link credit risk measures such as the probability of default or loss given default to macroeconomic variables. The primary motivation for lenders to develop these models is to calculate regulatory capital charges under the internal ratings based approach, run supervisor stress test scenarios, and calculate loan loss provisions under IFRS 9. It appears that point-in-time models predicting default based on the macro environment are not performing well during Covid. Those models would translate the unprecedented and repeated lockdowns, travel bans, physical distancing measures and the resulting slump in economic activity into steep increases in loan defaults and bankruptcies. On the other hand, extensive government support measures have been successful in shielding households and companies from the worst consequences of the pandemic. While companies in the hardest hit economic sectors have suffered dramatic reductions in total sales, the support measures thus far have prevented a new wave of bankruptcies and non-performing loans. Most credit models are not designed to capture the unprecedented relief measures as they had no precedent in the past.

In April 2020 during the lockdown of the first Covid wave, we predicted a doubling or tripling of the NPL ratio in Europe and the US for 2020 and 2021 based on historical data and macro forecasts from the IMF. In Europe overall, the predicted large increase in loan defaults did not materialize in 2020. According to Moody's, the US saw a doubling of the corporate default rate from 1.5% in 2019 to 3.1% in 2020, the highest level since the financial crisis of 2009. For US consumer lending, however, default models would

translate the dramatic spike in the unemployment rate in Q2 2020 into a jump in delinquencies that was not observed. The flow into 90 days plus auto loan delinquencies actually declined throughout 2020. In Europe according to Q3 2020 data from EBA, the non-performing loan ratio has barely increased neither for loans to corporates nor to households. Given the continued economic stress with renewed lockdowns in Q4 2020 and Q1 2021, there is an expectation that the low NPL ratios will increase eventually once the support measures are phased out. Nevertheless, banks have found that many of their credit models did not work well in this crisis.

To demonstrate the problem with point-in-time models in the current crisis, we pick the Accommodation and Food Services sector in Italy. The Bank of Italy publishes the annual rate of flows into non-performing loans for major industry sectors and regions on a quarterly basis. The latest available data point is Q3 2020. To project this proxy measure for the probability of default (PD) for 2021 to 2023, we use the baseline scenario for Italy published by EBA for the 2021 EU-wide stress test that is currently ongoing. Figure 1 highlights a particular challenge that banks face for the 2021 stress test namely that the main macroeconomic stress lies in the year 2020 before the actual stress test period 2021-2023. When running an automated model calibration and selection exercise, models with different time lags in the macroeconomic variables can show a very similar in-sample fit and out-of-sample prediction error. Figure 1 shows three such models with similar fit and prediction errors. Model 1 uses the unemployment rate only with a one year lag and predicts a peak PD below 5%. Models 2 and 3 in addition use real GDP growth with a six month and one year lag, respectively, and show a PD spike of above 20% in 2021 caused by the extreme GDP contraction in Q2 2020.

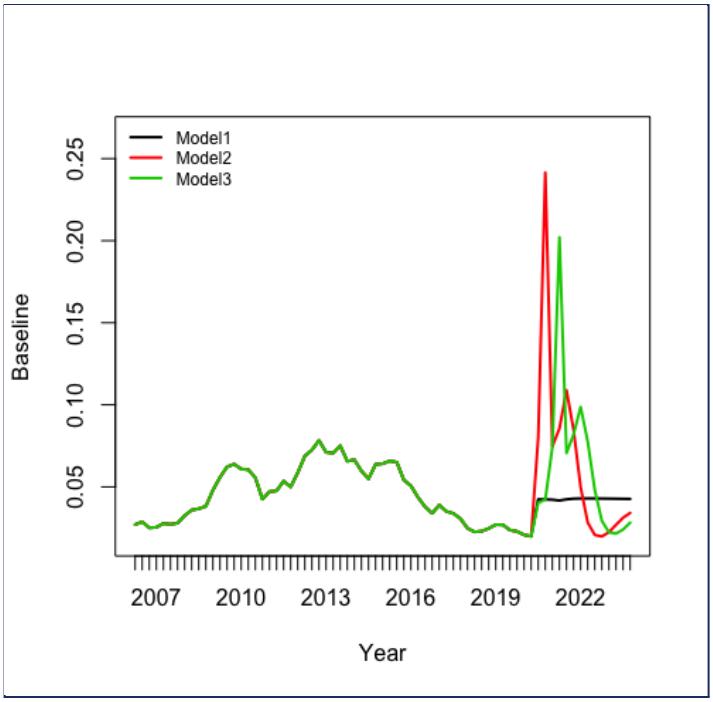

Figure 1: Annual flow of non-performing loans in Italy forecasted under the baseline scenario of the EBA 2021 bank stress test. Own calculations based on data from Bank of Italy.

For further reference we note the relative increase in the average PD over 2021-2023 caused by Covid is a factor of 2 for Model 1 and a factor of 3.5 for Models 2 and 3.

Accommodation and food service activities have been hit hard by the repeated lockdowns and travel bans. It is now clear that the Covid pandemic has hit some economic sectors much worse than others. We quantify the asymmetric impact of the current crisis on different industry sectors and explore how credit portfolio managers could tackle some of the main challenges arising from these unprecedented structural breaks encountered in the pandemic.

Challenger models for challenging times

The failure of macroeconometric time-series regression based models has motivated credit risk experts to explore other corporate credit risk model types that are well known in the financial industry. Merton-style structural models link credit risk to the volatility of equity prices and credit spreads can be used to derive a market implied PD. Altman Z-score-style models predict corporate distress based on selected financial ratios. Z-score models have been proven to successfully discriminate between healthy and distressed borrowers across countries and industries (e.g. Altman 2014). Bank internal rating models often include Z-score-like financial ratios which can help identify companies that are more likely to survive the current crisis. As they do not use macroeconomic variables as input, Z-score default models are considered more through-the-cycle and less suitable for macroeconomic stress testing. In past recessions, broadly speaking, Z-score models kept their discriminatory power but they did not accurately predict the cyclical swings in default rates.

The pandemic emphasized the importance of having readily available challenger models. Model choices are determined by the available data. Alternatives to the complex econometric champion models of large financial institutions help to estimate a range of expected losses given the current environment and under different scenarios for the speed of economic recovery after Covid. A challenger model can be used to estimate losses of an entire portfolio or a specific segment. For instance, loans subject to payment moratoria or forbearance did not play a major role pre-Covid, but are much more significant now justifying dedicated models for this segment. Another example for challenger models are industry sector specific models. Traditional Z-score models showed only modest variation by industry sector (Altman 2014) i.e. the sensitivities to the different financial ratios were fairly stable across countries and sectors. Point-in-time credit models, however, show that different sectors exhibit largely varying sensitivities to the economic cycle. The procyclical behaviour of some sectors is well known for cyclical equity sector indices (e.g. discretionary consumer goods, construction or manufacturing) and non-cyclicals (e.g. non-discretionary consumer goods, utilities, healthcare).

Managing performing and non-performing SME exposures

Banks face a new set of challenges regarding corporate borrower solvency, liquidity, and profitability. Macro-based projections don't reflect the highly heterogeneous impact on sectors. While food retailers and online gaming benefit, airlines and accommodation and food services are suffering dramatic reduction in sales. Historical financial statements, meanwhile, take time before they reflect the current impact on business and financials.

Sector-based cash flow analytics can help quantify risks and liquidity needs. Borrower cash flow forecasts should reflect liquidity positions and associated financing needs due to negative cash flows and help identify which firms won't be able to repay the debt. Banks need sector-based analytics for

numerous purposes, from identifying the most exposed sectors and clients to the projection of non-performing assets and rating migrations, and developing restructuring plans and asset disposals.

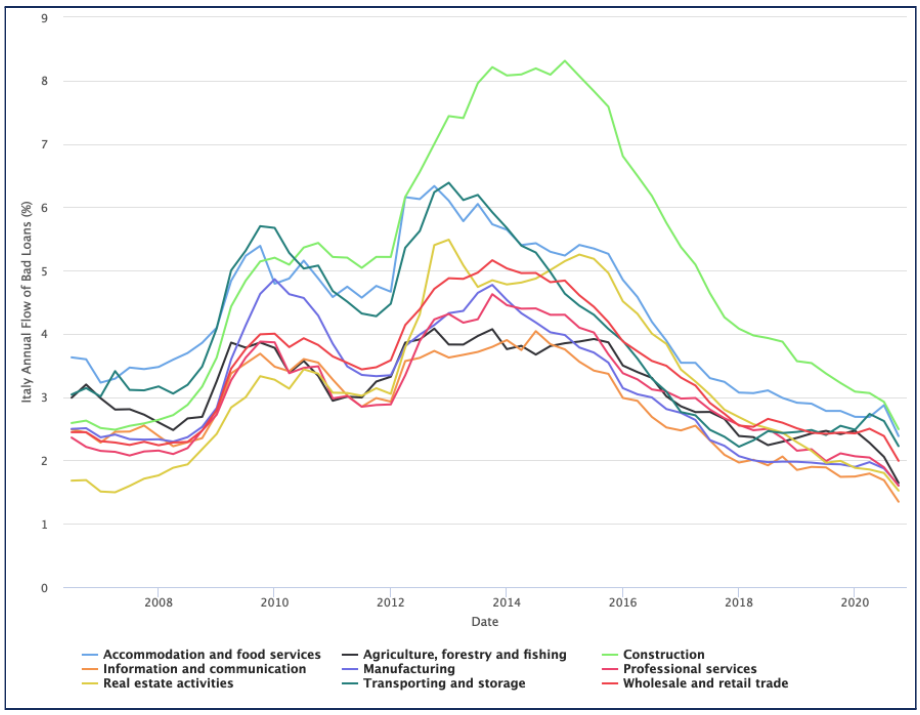

Figure 2: Annual adjusted non-performing loan rate for Italy by industry sector. Source: Bank of Italy

An important question in the prediction of the impact of Covid-19 on credit risk is to understand how quickly the economy will return to its pre-crisis level. The recovery will also depend on how many companies will go bankrupt due to the fall in sales. Bankruptcies have long lasting effects, prolonging the negative consequences of the economic shock. Therefore, European policymakers have generally taken the view to provide whatever liquidity is required to keep small, medium and large enterprises afloat (OECD 2020).

Since the summer of 2020 a number of studies have emerged that aim to predict the asymmetric impact of Covid on SME in different economic sectors by directly estimating corporate illiquidity or insolvency.

In Italy, Carletti et al (2020) employ a sample of 81,000 Italian firms to forecast the drop in profits and the equity shortfall triggered by the Covid lockdown. A 3-month lockdown generates an aggregate yearly drop in profits of about 10% of GDP, and 17% of sample firms become financially distressed. Distress is more frequent for SME as opposed to large corporates, for firms with high pre-Covid leverage, and for firms belonging to the manufacturing and wholesale trading sectors. Surprisingly, the profits and equity levels of firms in the recreation services and tourism sectors are relatively lightly affected by the lockdown in their analysis. This may be the case because these sectors are highly labor intensive; consequently, most of their labor cost was covered by public wage subsidies during the lockdown period. However, the profitability of these sectors may also be affected by social distancing policies for a longer time than other sectors, due to the lower physical distance between employees and customers in these sectors and, in general, by sluggish consumer demand for extended periods.

Another interesting study in Italy from Schivardi and Romano (2020) propose a simple method based on balance sheet data and sectoral predictions of sales growth from Cerved, a rating agency, to determine

the firms that will become illiquid. They apply the method to 650,000 Italian companies which produce three quarters of the Italian private sector output. Sales growth from more than 500 sectors is forecasted by Cerved. The authors develop a simple accounting framework to determine to what extent firms will have liquidity constraints. A well known data challenge for private SME is that balance sheet data are often outdated and published only annually and with significant delay. Hence, for many companies, lenders are still working with balance sheets and income information from the pre-Covid year end 2019. As of September 30, 2020, the predicted increase in illiquid and insolvent companies in Italy has not yet been observed. Figure 2 shows the annual flow of bad loans by borrower count and industry sector as reported by the Bank of Italy. The last two data points from Q2 and Q3 2020 show a drop in the rate of new non-performing loans which is helped by an increase in lending during the crisis.

NACE Sector	NPL Ratio Dec 2019	NPL Covid Factor	NPL Covid Ratio	EU Bank NFC Exposure (EUR bn)	EU Bank NFC NPL Covid (EUR bn)
A Agriculture, forestry and fishing	6.7%	1.43	9.7%		
B Mining and quarrying	6.5%	2.88	18.7%		
C Manufacturing	6.0%	1.97	11.9%	654	78
D Electricity, gas, steam	2.4%	1.21	2.9%	199	6
E Water supply	3.5%	1.00	3.5%		
F Construction	14.9%	1.28	19.1%		
G Wholesale and retail trade	6.5%	2.00	13.0%	565	74
H Transport and storage	6.5%	1.74	11.3%	225	25
I Accommodation and food services	8.6%	2.93	25.1%	120	30
J Information and communication	3.0%	1.59	4.8%		
L Real estate activities	3.1%	1.50	4.7%		
M Professional services	4.6%	1.84	8.4%		
N Administrative and support services	3.2%	2.33	7.4%	175	13
O Public administration and defence	1.0%	1.00	1.0%		
P Education	4.5%	2.77	12.4%		
Q Human health services and social work	2.9%	1.45	4.2%		
R Arts, entertainment and recreation	7.7%	2.82	21.8%	27	6
S Other services	4.6%	2.45	11.2%		

Table 1: Relative increases in SME failure rates for different industry sectors from Gourinchas et al. (2020) using data from seventeen EU countries. NPL ratios and exposure values for selected sectors from EBA and own calculation..

For 17 countries in the EU, Gourinchas et al (2020) estimate the impact of the Covid crisis on SME business failures. They use a simple model of firm cost-minimization and measure each firm's liquidity shortfall during and after Covid. The framework allows for a rich combination of sectoral and aggregate supply, productivity, and demand shocks. Gourinchas et al (2020) estimate a large increase in the failure rate of SME of nearly 9 percentage points, absent government support. Accommodation & Food Services, Arts, Entertainment & Recreation, Education, and Other Services are among the most affected sectors with a near threefold increase in the NPL ratio. Table 1 shows the ratio of the failure rates with and without Covid for the main NACE industry sectors. For Italian companies in the Accomodation and Food sector we had estimated a factor of 2 to 4 for the relative increase in the PD in Figure 1 above depending on the model choice.

In France, Guerini et al (2020) simulate the impact of the Covid crisis on corporate solvency using balance sheet data of one million French nonfinancial companies, assuming they minimize their production costs in the context of a sharp drop in demand. They find that the lockdown triggers an unprecedented increase

in the share of illiquid and insolvent firms, with the former more than doubling relative to a scenario without Covid (growing from 3.8% to more than 10%) and insolvencies increasing by 80% (from 1.8% to 3.2%). They find sectors such as hotels and restaurants, household services, and construction are the most vulnerable, while wholesale and retail trade, and manufacturing are more resilient.

At a country level, corporates have been impacted by Covid with different degrees of severity. Figure 3 shows the net percentage of corporates reporting the impact of the Covid lockdowns in the six months prior to October 2020 as reported in the European SAFE survey. In most countries a majority of companies reported turnover and profit declines whereas labour and other costs were mostly stable.

SAFE October 2020: Net % increase past six months	Turnover	Labour cost	Other cost	Interest expense	Profit	Fixed investment	Inventories and WC	Number employees	Debt to asset
EU27	-44%	5%	14%	5%	-45%	-8%	-14%	-10%	8%
Austria	-38%	1%	-2%	-4%	-41%	-18%	-8%	-10%	4%
Belgium	-39%	-4%	9%	0%	-34%	-12%	-9%	-14%	-5%
Bulgaria	-47%	19%	19%	7%	-48%	-1%	-13%	-19%	0%
Croatia	-57%	-1%	9%	3%	-49%	-17%	-6%	-18%	-8%
Cyprus	-51%	11%	-3%	1%	-58%	9%	-18%	-5%	8%
Czech Republic	-38%	-1%	16%	2%	-40%	-7%	-11%	-10%	1%
Denmark	-9%	9%	-3%	5%	-10%	1%	0%	-5%	-6%
Estonia	-24%	2%	-8%	5%	-34%	-20%	-8%	-10%	1%
Finland	-22%	13%	9%	2%	-18%	-7%	-5%	-7%	-7%
France	-54%	-1%	25%	5%	-51%	-11%	-17%	-7%	13%
Germany	-37%	6%	8%	2%	-40%	-13%	-13%	-11%	0%
Greece	-59%	-3%	11%	-1%	-66%	-11%	-29%	-6%	13%
Hungary	-41%	-6%	34%	0%	-48%	4%	-12%	-14%	6%
Ireland	-62%	-21%	10%	1%	-55%	-11%	-19%	-23%	2%
Italy	-56%	2%	11%	6%	-56%	-11%	-18%	-7%	19%
Latvia	-27%	12%	8%	6%	-35%	7%	-10%	-9%	-4%
Lithuania	-21%	19%	15%	5%	-21%	6%	-3%	-18%	1%
Luxembourg	-25%	8%	8%	2%	-40%	-10%	-11%	3%	-3%
Malta	-64%	8%	11%	4%	-70%	-20%	-21%	-13%	10%
Netherlands	-32%	18%	7%	-6%	-30%	-1%	-8%	-2%	-4%
Poland	-42%	32%	50%	-5%	-39%	-4%	-10%	-6%	2%
Portugal	-49%	8%	16%	10%	-49%	-2%	-27%	-7%	20%
Romania	-41%	25%	35%	6%	-48%	-3%	-10%	-13%	15%
Slovakia	-50%	23%	13%	3%	-46%	-2%	-5%	-15%	4%
Slovenia	-50%	-3%	-5%	-2%	-47%	-12%	-10%	-11%	-7%
Spain	-55%	-4%	4%	24%	-56%	-6%	-16%	-14%	26%
Sweden	-22%	-22%	-8%	0%	-25%	-10%	-13%	-12%	-3%
Albania	-50%	32%	30%	19%	-56%	4%	-3%	-7%	9%
Bosnia and Herzeg.	-52%	11%	5%	11%	-54%	-1%	4%	-9%	-15%
Iceland	-32%	37%	44%	-32%	-45%	-15%	-11%	-22%	5%
Kosovo	-67%	-2%	10%	18%	-77%	-13%	-4%	-29%	36%
Montenegro	-61%	4%	10%	13%	-66%	-11%	-14%	-15%	-8%
Serbia	-45%	16%	20%	2%	-43%	-6%	-4%	11%	2%
North Macedonia	-53%	16%	25%	-2%	-57%	-4%	-4%	-8%	4%
Turkey	-33%	33%	70%	50%	-53%	-13%	-14%	-7%	30%
United Kingdom	-50%	-8%	13%	-10%	-42%	-15%	-18%	-32%	0%

Figure 3: Data from the October 2020 SAFE survey. Numbers represent the net percentage of companies reporting an increase or decrease of activity.

While the quoted studies differ in the details for the impact by country-sector cohorts, it is likely that companies in accommodation and food services and arts, entertainment and recreation are suffering the most in many countries whereas utilities, technology and healthcare are doing much better.

Figure 4 shows a heatmap of the estimated NPL ratios after Covid for selected industry sectors by country in Europe. For Italy and selected other countries, detailed sector NPL data are available that allow

for an econometric forecast similar to Figure 1. To cover all European countries here we multiply the NPL ratios for each country-sector at December 2019 with the factor for the relative increase due to Covid in Table 1. Clearly, the high NPL countries Greece and Cyprus stand out, but more concerning ratios above 20% are also predicted for Croatia, Portugal and Italy in certain sectors.

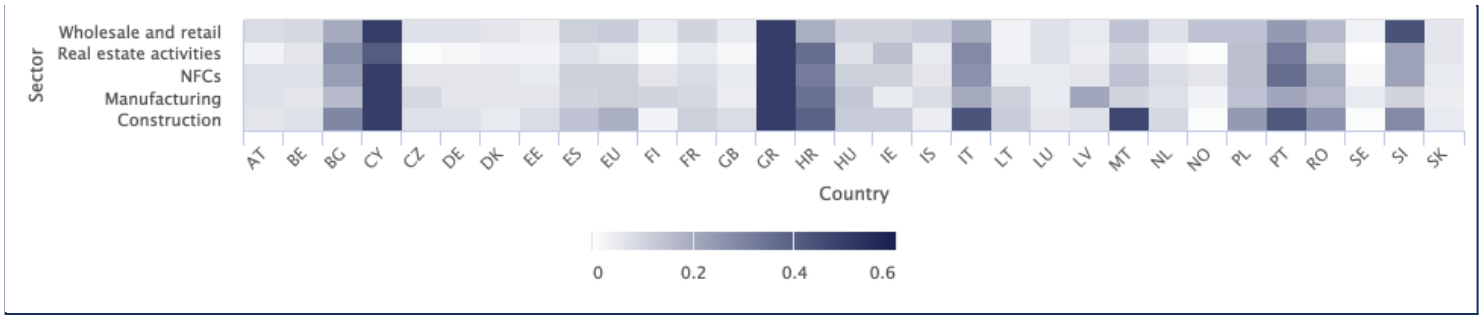

Figure 4: Heatmap for the NPL ratio after Covid for selected industry sectors by country in Europe.

Larger companies are more likely to have listed equity, external credit ratings and publicly available financial disclosures on a quarterly basis. We have recently analysed all large corporate loan tranches in the Loan Connector database from financial data provider Refinitiv (NPL Markets 2021). We calculated an estimated market value of the 28,000 active tranches to 13,600 borrowers in 115 countries. We found 3,500 tranches with a daily market price quotation, 6,300 tranches had a traded bond issued by the same borrower and 1,100 tranches are related to borrowers with a traded CDS. 7,800 loans are to borrowers with an external rating from at least one major rating agency. Of the unrated loans, 2,100 tranches are to borrowers with an equity-implied structural model implied rating and of the non-listed, non-rated tranches, 1,100 tranches had a borrower with private company rating based on financial ratios (similar to a Z-score). Around 300 tranches are trading at distressed levels with a market price below 80%.

Figure 5 shows the average discount spreads of large European loans in different industry sectors as reported in Refinitiv Loan Connector. Similar to equity markets, the initial Covid shock in March 2020 has largely been reversed and market prices for many traded loans are back to pre-Covid levels. Utilities and Healthcare show the lowest average spreads whereas loan spreads in sectors most hit by Covid such as Retail, Wholesale, Leisure and Hotel and Gaming remain elevated around the pre-Covid levels.

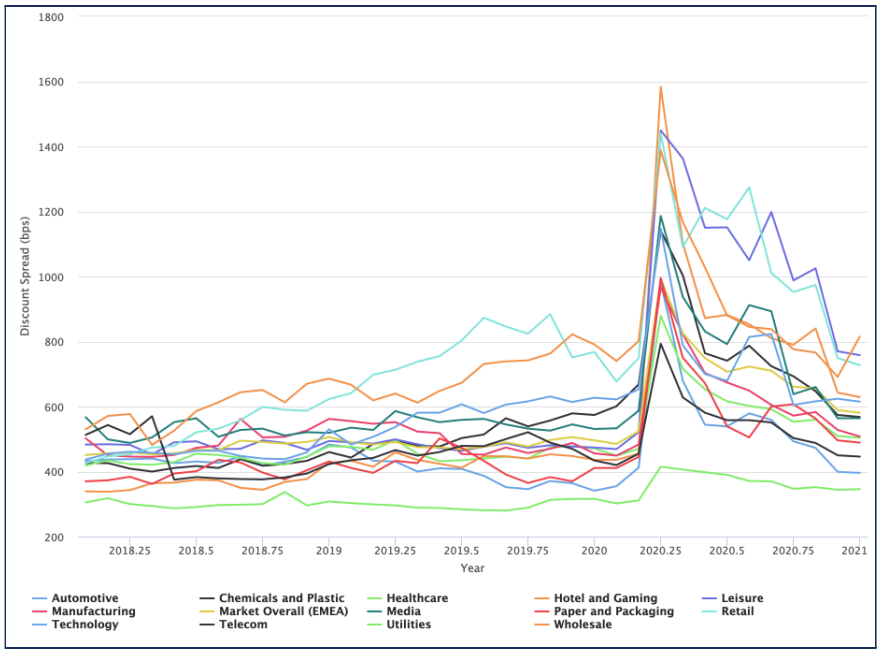

Figure 5: Discount spreads of European loans in the secondary market by industry sector. Source: Refinitiv.

To conclude this section, we reviewed a number of alternative challenger models and assess the asymmetric impact of Covid on different sectors. Market implied PDs derived from credit spreads are back to their pre-Covid levels after a steep increase and subsequent decline in 2020. Models predicting illiquidity or insolvency based on financial ratios predict large increases in the NPL ratio ranging from stable ratios for less affected sectors to a tripling of NPL in the most severely hit sectors.

Optimal bank portfolio allocation after Covid

Having discussed the need for different challenger models for credit risk predictions, we now sketch out how such predictions can be used to infer portfolio management decisions towards a balance sheet with an optimal risk-return pay-off and portfolio allocation. We offer an effective risk reducing method based on historical default and loss experience and current credit spreads by applying mean-variance portfolio theory to sub-portfolios in the bank book. Such sub-portfolios could be different customer or loan types or the sector-country segmentation of the previous section. The approach and its accompanying implementation is designed to help credit managers to make portfolio rebalancing decisions or provide quantitative guidance for the setting of sector, client or line of business risk limits. Forward-looking expert overrides from users can be included in a Bayesian framework made popular in the context of equity portfolios by Black and Litterman (1990, BL in short).

The strategy of managing effective diversification as a means to reduce unexpected losses through client, industry sector and country limits is well-known and remains of great importance. Much less is known about the interaction between diversification, risk and profitability as the risk and return of empirical loan portfolios has generally been analyzed separately. Since the pioneering work of Markowitz, portfolio theory has been applied to the risk-return analysis of equity portfolios. The traditional objectives of maximizing returns for given levels of risk or minimizing risk for given levels of return have guided efforts to achieve effective diversification of such tradable investments. Concepts such as individual stock and portfolio betas to indicate risk levels and the efficient frontier, with optimal weightings of the

portfolio assets, are common among investment professionals. The necessary data in terms of historical returns and correlations of returns between individual stocks are usually available to perform the portfolio optimization analysis.

The application of mean-variance analysis to loan portfolios is relatively rare as the typical assumptions of multivariate Gaussian returns do not apply to loans with their highly skewed loss distributions. In addition, long-term return data on loan pools are largely missing in the public domain and individual loan returns are mostly not observable given the limited number of loans that have actively quoted prices in the secondary loan market. Research has shown that mean-variance analysis may still be valid in a non-Gaussian context. The approach implemented by us follows the Basel-Vasicek framework and Mencia (2012) in using the non-linear probit transformation to generate negatively skewed loan returns, but at the same time remains a function of a vector of underlying Gaussian state variables. In other words, while the systematic risk factors are assumed (multivariate) normal, loss and return distributions are highly skewed as a result of the probit transformation. In this context, the means and variances of portfolio returns remain valid measures of profitability and risk, respectively. As shown by Mencia, simple single-period returns for a homogeneous sub-portfolio are given by the difference of the credit spread net of funding and operational costs less the expected loss rate. While individual loan returns are mostly not observable, the problem is usually addressed by bucketing loans with similar risk characteristics into segments (aka sub-portfolios or replines), for which the historical performance is easy to observe.

Different champion and challenger loss models will predict different outcomes under the selected macroeconomic recovery scenarios after Covid. Linking returns to point-in-time expected losses opens up the possibility to use the same model for stress testing as for portfolio optimization, i.e. find the optimal portfolio allocation for a given macroeconomic stress scenario. Forward-looking expert information can be included in a Bayesian BL style. Closed form expressions for the expected returns, variances, and covariances between different loans are available. The covariance matrix of returns does not only depend on the loss distribution, but also on the granularity of the portfolios. We calculate annualized returns (measured quarterly) as the difference between the currently observed credit spreads net of funding and other costs less the expected loss rate. Rather than minimizing risk as measured by the return variance, we could directly minimize downside risk measures such as value at risk or expected shortfall, which play a prominent role in the management of economic risk.

The approach pioneered by Black and Litterman, allows the users to blend their subjective views on individual asset returns into a normally distributed reference model. BL provides a clear Bayesian way to specify investors' views and to blend the investors' views with prior information. The assumption that the assets returns be normally distributed seems to prevent the application of BL to loan portfolios with highly skewed return distributions. However, it has been shown in the work of Meucci (2010) how this is not the case: as long as the systematic risk factors creating the randomness are normal, BL can be effectively used to process views on these risk factors. Here we use the BL formula to process views on the *repline-specific probit-transformed loss rate* that is assumed Gaussian as in the Basel-Vasicek model. BL addressed the important practical problem of how to include expert views in optimal asset allocation.

A view is a statement on the relative or absolute forward-looking performance of individual asset returns, which typically differs from the historical return or loss experience, a key feature in the current situation where prediction based on historical data may be misleading. A view corresponds to statements on the expected return, whereas the covariance is assumed known. The BL mean and covariance matrix are then used to determine the optimal allocation to the different portfolio segments that includes the expert's views.

As usual when optimizing portfolios certain boundary conditions and constraints must be obeyed. In practice a large number of constraints could be relevant like risk budgets, limits set by risk policy and box constraints which are effectively borrower, sector or country limits. The proposed framework and analytics offers an intuitive and path towards a more efficient bank balance sheet.

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About NPL Markets

NPL Markets is an innovative marketplace for illiquid loan trading, operating throughout Europe, that is based upon four pillars: Data preparation, Marketplace execution and investor reach, Valuation, and Reporting. NPL Markets helps sellers of NPL to prepare and standardize transaction data and select the optimal transaction portfolio based on balance sheet impact. Our platform also supports investors with deal screening and initial valuation with online revaluation and reporting tools.

With the help of its proprietary data mapping and transformation tool NPL Markets helps financial institutions to map their data to the data formats defined by EBA for NPL transactions, EBA for the valuation in resolution, and by ESMA for securitisation disclosures. Once standardized and validated the loan-level data can be uploaded to the NPL Markets valuation tool to conduct a detailed discounted cash flow analysis using pre-populated pricing parameters in different macroeconomic scenarios across all major asset classes.

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