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A Study of COVID-19's Impact on Concentration Risk

Abstract

This paper studies the impact of COVID on concentration risk, relevant in the context of limit setting, portfolio allocation, and other concentration-sensitive measures. Analysing two portfolios, one of European firms and the other of U.S. firms, we show how our solutions can be used to navigate the COVID crisis and better understand credit risk within a portfolio framework.

We leverage Moody's Analytics newly-developed Cross-sectional COVID-19 Overlay (the Overlay), introduced in Pospisil, Jiang, Levy, Li, and Zhao (2021). The Overlay is an adjustment to scenario-based ratings and probabilities of default (PDs) that accounts for COVID-specific impacts on credit risk across industries and countries, with applications for stress testing, provisioning, and early recognition of losses.

We use Overlay-adjusted scenario-based PDs in conjunction with the RiskFrontier™ portfolio solution to assess COVID's impact on concentration risk for benchmark credit portfolios. Namely, we decompose portfolio volatility (i.e. Unexpected Loss) into Sector Risk Contributions, once with the Overlay and once without. This enables us to quantify the effects of COVID on a sector's risk within a portfolio.

We find that changes in sector-expected losses, as measured by the Overlay, have a multiplicative effect on the changes in risk contribution. For instance, in the European portfolio, the change in risk contribution under a baseline scenario for banks is almost four times the change in expected loss. Moreover, the change in both expected loss and risk contribution can be material, even under a baseline scenario; for dine-in restaurants, in the U.S. benchmark portfolio, these are ~30% and ~16%, respectively.

This exercise helps uncover hidden risk and obtain a better understanding of its distribution across segments in a portfolio. Traditional models may underestimate risk for some sectors and overestimate it for others, when not taking into consideration the particular propagation macro-shocks exhibited during this pandemic.

We conclude by remarking how the exercise can be used as a blueprint to replicate the analysis on any other credit portfolio, recognising the need for a portfolio-specific analysis, to conclusively quantify the effects of COVID on portfolio concentration risk.

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1. Introduction

The COVID-19 pandemic and associated lockdown measures have brought to light new credit risk dynamics, leading financial institutions to reevaluate credit loss forecasting models, as well as to rethink how they segment and analyse their portfolios. For example, Hotels & Restaurants were hit more severely than Pharmaceuticals — more so than during pre-pandemic downturns, highlighting the need to reassess model performance in the current environment. Similarly, classifying Hotels & Restaurants as a single segment is now too coarse a segmentation, with Dine-in Restaurants having experienced a greater decrease in demand than Fast Food Restaurants. In general, businesses relying on prolonged customer physical proximity were hit harder than those that could deploy social distancing. This paper builds on Pospisil, Jiang, Levy, Li, and Zhao (2021), which explores these nuances and introduces the Overlay.

This paper analyses COVID-19's impact on concentration risk for a benchmark credit portfolio, quantifying cross-industry hidden risks associated with the pandemic. This framework can be used to gain a better understanding of new risk sources in portfolios, to introduce more granular sector segmentation, to revise risk-based limits, and to re-balance portfolios to better reflect risk appetite. For a discussion of concentration risk and its role in the allowance process during the pandemic period, see Levy, Muzyka, and Xu (2020).

For the analysis, we leverage Moody's Analytics GCorr™ Macro multi-period framework, [1] our model for "traditional" scenario-based credit loss forecasts, along with the Overlay, to produce single-name ratings and PD projections that recognise COVID-specific impacts. [2] The Overlay introduces more granular segmentation, enabling better distinction between industries commonly grouped together, such as Dine-in Restaurants and Fast Food Restaurants, to account for their different reactions to the crisis. [3]

We use Overlay-adjusted scenario-based PDs, in conjunction with the RiskFrontier™ portfolio solution, [4] to assess COVID's impact on concentration risk for a benchmark credit portfolio. We obtain the portfolio value volatility, i.e. Unexpected Loss (UL) over a one-year horizon, and decompose this UL into Sector Risk Contributions. We conduct this process twice: once with the Overlay, and once without, allowing us to quantify the effects of COVID on a sector's specific risk within a portfolio.

The purpose of this paper is twofold. First, it analyses COVID's impact on concentration risk for benchmark credit portfolio. Second, it serves as a generic "how-to" guide for institutions to analyse their portfolios, recognising that a portfolio-specific analysis is essential in understanding the ultimate effects of COVID on risk.

We organise the remainder of this paper as follows: Section 2 outlines the Overlay; Section 3 introduces the Sector Risk Contribution as a metric to measure concentration risk; Section 4 provides details on the exercise carried out to assess COVID's impact on our benchmark portfolios' concentration risk; Section 5 concludes.

[1] See Huang, Lanfranconi, Patel, and Pospisil (2012) for an overview of Moody's Analytics GCorr framework and Jiang, Xiao, and Xie (2020) for more details on the GCorr Macro model.
[2] See Xu and Liang (2020) for the rating transition model and Pospisil, Jiang, Levy, Li, and Zhao (2021) for the scenario-based PD methodology.
[3] In GCorr Corporate, both Fast Food Restaurants and Dine-in Restaurants are grouped within Hotels and Restaurants. When applying the Overlay, this sector is segmented further as Traveler Accommodation, Caterers & Food Trucks, Dine-in Restaurants, Fast Food Restaurants, and Coffee Shops & Snack Bars.
[4] See https://www.moodysanalytics.com/product-list/riskfrontier and Levy (2013) for an overview of RiskFrontier.

2. The Overlay

To address the pandemic's effects, Moody's Analytics developed the Overlay, which assesses credit risk in the context of COVID-19. The model adds increased granularity relative to a traditional model, offering 121 industry segmentations and global coverage. In addition to traditional macroeconomic and credit data, the Overlay incorporates alternative data, including mobility and epidemiological statistics, in describing COVID-credit risk dynamics. Traditional models, estimated using 20 years of historic data, mainly capture dynamics observed in the tech-telecom and financial crisis, rather than the considerably different contemporaneous effects caused by COVID. The Overlay has been designed and calibrated to reflect the stylised facts about the impact of the health crisis. In particular, it anchors to a traditional macroeconomic scenario, and distributes its impact across industries, reflecting the observed effects of the pandemic on different sectors. See Pospisil, Daly, Labowicz, Lanfranconi, Li, and Levy (2020) for a discussion of the implications of sociological reactions to COVID on credit risk.

For example, because Pharmaceuticals have been affected far less than Hotels & Restaurants by COVID, the Overlay adjusts the "traditional," historically observed effects of a macro shock to account for these new dynamics. In this case, a negative macroeconomic shock to Pharmaceuticals still has a negative effect on PDs, but of lower magnitude when compared to a pre-pandemic period. Conversely, a firm in the Dine-in Restaurants sector experiences magnification of the negative macro shock, reflecting the observation that this sector was hit more severely by the pandemic, and more so than during previous financial crises.

The Overlay provides much more granular segmentation than traditional risk assessment models. For example, we delineate Aircraft Manufacturing and Defense & Space, traditionally grouped into Aerospace & Defense, into separate segments. Aircraft Manufacturing demand and revenues were hit hard during the pandemic, while the Defence & Space sector was not affected much at all. Note, this particular scenario has not historically been the case. For instance, during the Great Financial Crisis 2007–2009, *both* sectors were impacted similarly. The difference in treatment then came from reliance on a more generic view of the Aerospace & Defense sector's overall risk composition. Today, we can see that the Aircraft Manufacturing sector has been affected by lockdowns and traveller demand, while Defense & Space does not face these issues. Similarly, Dine-in Restaurants responded quite differently to lockdown restrictions than Fast food Restaurants, the latter showing more resilience and warranting separation into two distinct segments. For more details on the Overlay, see Pospisil, Jiang, Levy, Li, and Zhao (2021).

3. Measuring Concentration Risk with Sector Risk Contribution

Concentration risk is a portfolio's possible loss in value when a group of exposures moves together. This risk is driven by common factors that can result in substantial losses to a particular segment in a credit portfolio. Concentration risk can be generated, for instance, by the degree to which an Oil & Gas portfolio has exposure to oil prices. Alternatively, it can manifest through high exposure to a corporate counterparty such as Nestlé or a municipality such as the City of London.

Concentration risk is impacted by borrower characteristics within a given segment, such as their PDs and exposures, as well as their correlation within the portfolio. As PDs increase, we generally observe an increase in that sector's concentration risk and, similarly, for the total exposure and correlations. However, PD levels, exposure amount, and correlations interact in non-trivial ways. For example, a very large exposure with very low PDs may contribute to concentration risk less than a very small exposure with very large PDs — a change in any of these attributes reflects a change in concentration risk.

In this study, we are particularly interested in the effects a change in PDs due to COVID — quantified by the Overlay — has on the change in concentration risk. We measure concentration risk using the widespread measure of Sector Risk Contribution, defined, for a sector S, as

$$RC^S = \sum_{i \in S} w_i \, RC_i,$$

where w_i and RC_i are the (monetary) holding amount and risk contribution, respectively, of exposure i. We have $RC_i = \frac{\partial UL}{\partial w_i} = \rho_{ip} UL_i$, i.e. a position's risk contribution is the sensitivity of the portfolio's volatility to its exposure or, equivalently, the product of the instrument-portfolio correlation, ρ_{ip}, and the instrument's unexpected loss, UL_i. The sum of the sector contributions equals the volatility — i.e. unexpected loss UL — of the portfolio value at horizon, namely $UL = \sum_S RC^S$. [5] From this decomposition of risk, we can then posit, for instance, that the Automotive sector is responsible for, say, 3% of the portfolio risk. See Kaplin, Levy, Meng, and Pospisil (2015) for more details on risk contribution and how it can be used for limit setting.

As discussed, the Overlay accounts for COVID's unique cross-sectional impact, anchoring to a specified macroeconomic scenario and producing scenario-based ratings and PDs. To study how the Overlay impacts concentration risk, we relate the changes in sector risk contributions to the ones in the segment's expected loss. We define the Expected Loss (EL) of sector S as

$$EL^S = \sum_{i \in S} w_i \, LGD_i PD_i,$$

where LGD_i and PD_i are the LGD and one-year PD of exposure i, respectively, and w_i its (monetary) exposure.

The next section relates the change in a segment's risk contribution, ΔRC^S, to the change in its expected loss, ΔEL^S, presenting charts depicting this relationship under a baseline scenario. This process allows us to quantify the effects of COVID on a segment's risk contribution as measured by the Overlay.

[5] This follows from the application of Euler's theorem for homogeneous functions to UL, which is positive homogeneous of degree 1 in the exposures w_i.

4. The Effects of COVID-19 on Benchmark Portfolios

4.1 European and U.S. Portfolios

We consider two credit portfolios: one of European counterparties and one of U.S. counterparties. We take EDF™ (Expected Default Frequency)-implied ratings and LGDs from Moody's Analytics CreditEdge™ as of the beginning of Q3 2020. We exclude firms with one-year PDs above 10%, ending up with 3,837 and 3,288 firms for the European and U.S. portfolios, respectively. For each counterparty, we parameterise a five-year maturity term loan, with holding amount given by the total liabilities of the counterparty, with the following adjustments:

- For firms in Banks and S&LS and Insurance Companies, we set the holding amounts to 10% of the total liabilities; and for Security Brokers and Dealers, we set the holding amounts to 40% of the total liabilities;
- Holding amounts are floored at 5 million USD (for the European portfolio, these are converted to EUR).

For the European portfolio, we select six countries: Germany, Spain, United Kingdom, Sweden, Italy, and France. Figure 1 shows that in this portfolio's country firm distribution most firms are in the UK, followed by France, Germany, Sweden, Italy, and Spain. Most firms have Aaa ad Baa1 EDF-implied ratings, as shown in Figure 2. [6] Figure 3 shows the industry segment distributions are quite varied; we include 30 of the 117 industries represented in the portfolio.

Figure 1 Country distribution of firms in European portfolio.

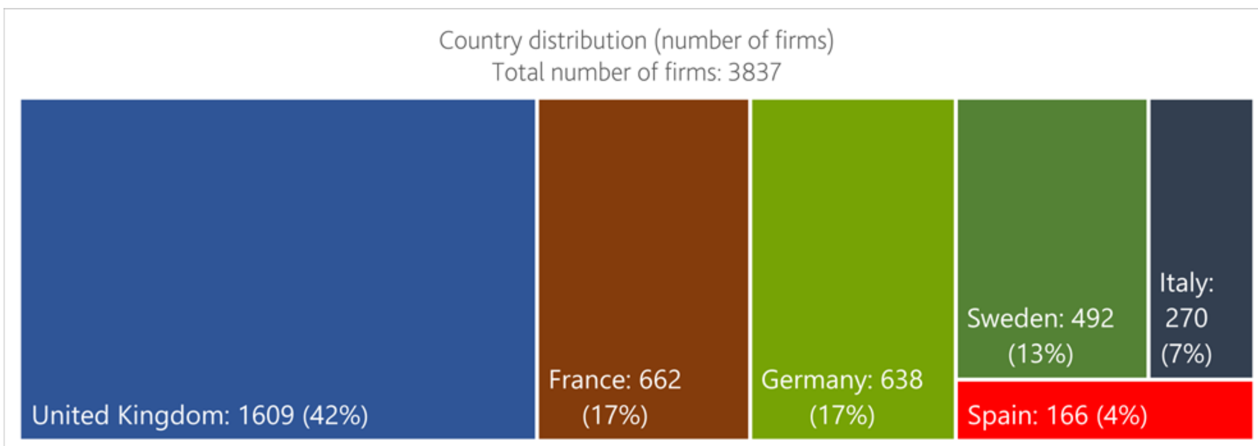
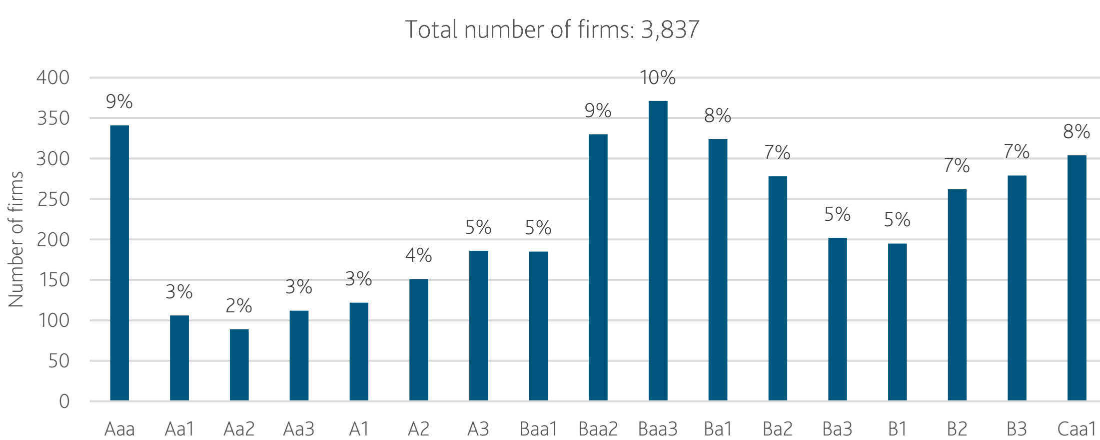
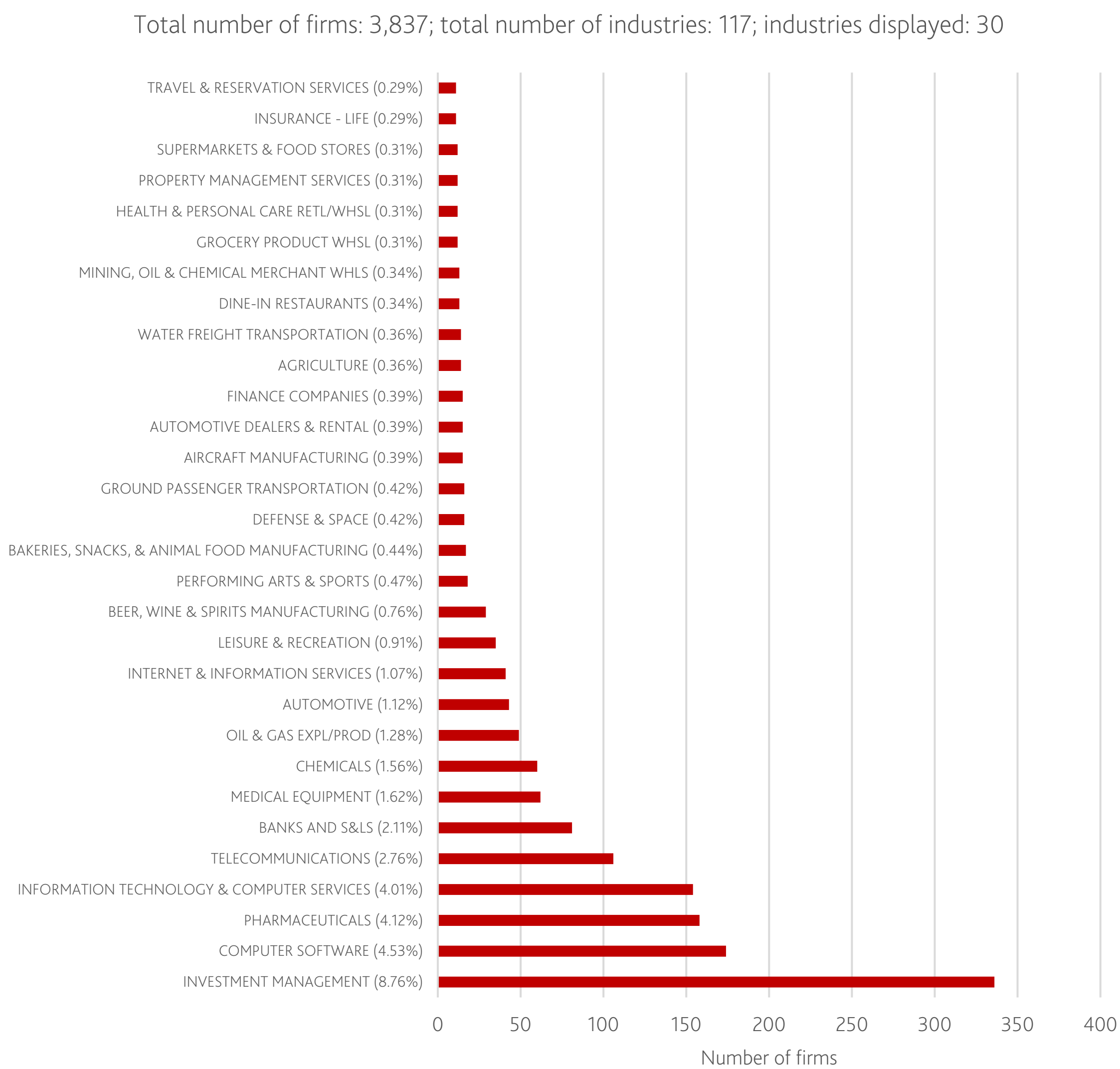


Figure 2 Distribution of EDF-implied ratings in European portfolio.



[6] See Moody's Analytics Research Teams (2015) for the methodology behind EDF-implied ratings.

Figure 3 Industry distribution of firms in European portfolio (30 of the industries with at least 10 firms).



Moving to the U.S. portfolio, Figure 4 shows the firm distribution in terms of EDF-implied ratings. Notice, this portfolio is akin to the European one, with one difference being a lower representation of Aaa rated firms — 9% in the European portfolio and 1% in the U.S. one. In both portfolios, Baa3 is the mode. Figure 5 shows the industry distribution by firm count in the U.S. portfolio (for the same 30 firms considered in the European portfolio, see Figure 3). Notice how the U.S. portfolio has a higher concentration of banks and pharmaceutical firms.

Figure 4 Distribution of EDF-implied ratings in U.S. portfolio.

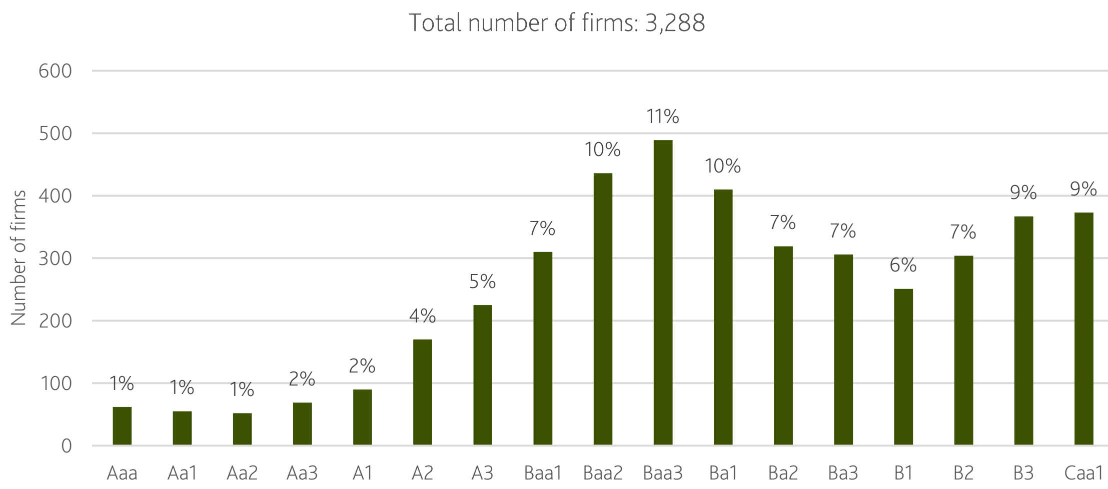
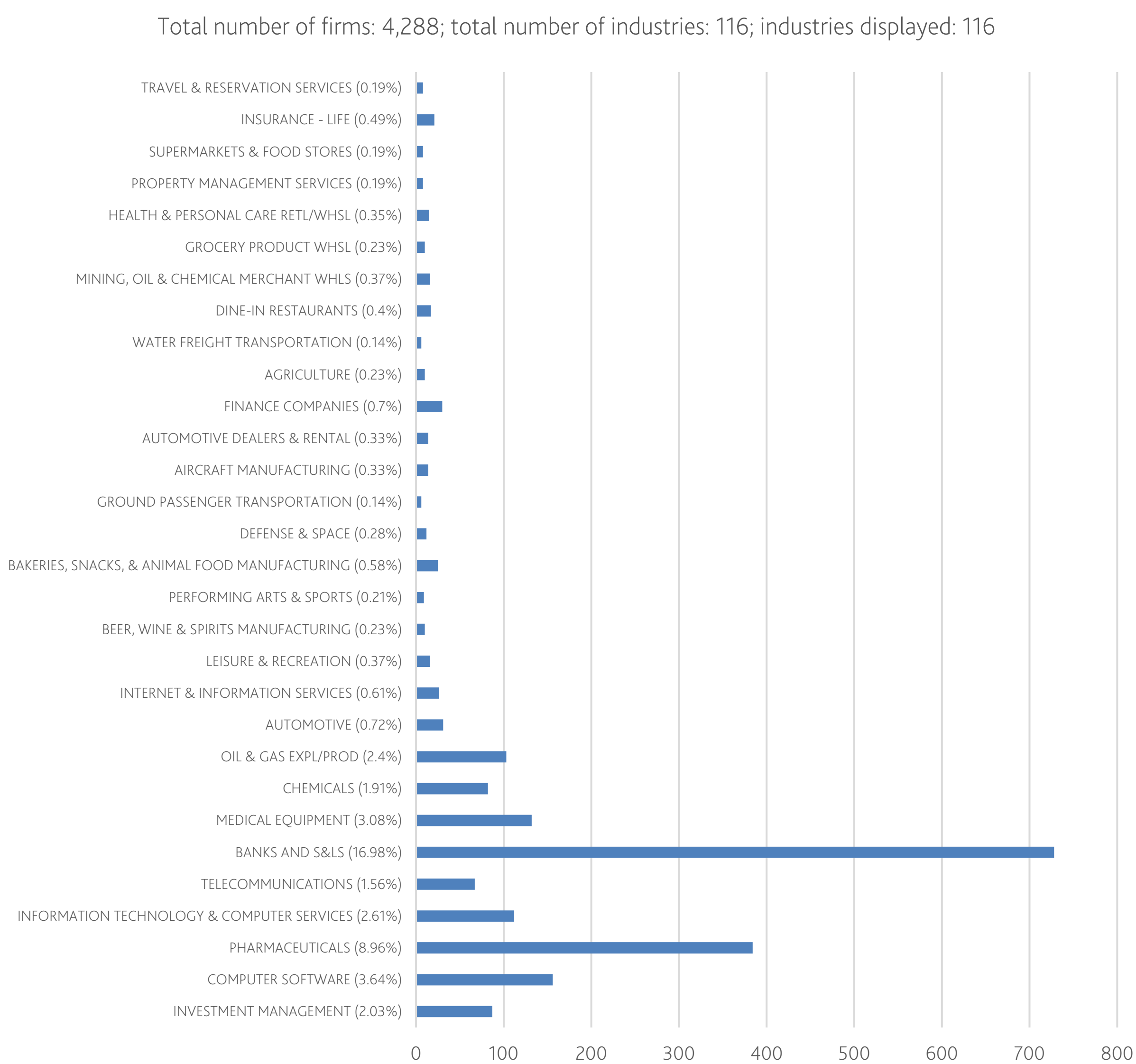


Figure 5 Industry distribution of firms in U.S. portfolio (30 industries).



4.2 Exercise Structure

We run the two portfolios described above under a baseline scenario, obtaining the following two parameterisations:

A. Scenario-based rating distributions with Overlay
B. Scenario-based rating distributions without Overlay

Comparing A to B, we can assess the effects a baseline scenario has in the pandemic crisis, compared to other periods, measured by the Overlay. From this, we can see how scenarios can have a very different impact on different industries.

We use the scenario-based rating distributions produced with and without the Overlay to obtain instrument-level TTC (Through-the-Cycle) PDs, following the rating mapping in Dwyer et al. (2017). We then estimate the expected TTC PD as a weighted average, as follows:

$$PD(Scenario) = \sum_r TP_{r_0 \to r}(Scenario) \times PD_r,$$

where $TP_{r_0 \to r}(Scenario)$ is the scenario-based migration probability from the firm's initial rating r_0 to rating r, and PD_r is the probability of default from rating r. [7]

We use baseline scenarios from Moody's Analytics, from the end of Q3 2020 until the end of Q3 2021 (one year) for GDP, Unemployment Rate, and Equity for Germany, Spain, UK, France, Italy, and Sweden. [8] Figure 6 depicts the equity quarterly percentage change under the baseline scenarios. [9] The chart shows percentage changes of average quarterly values. Note, the first two quarters in the plot correspond to realised values, whereas the remaining quarters are projections used for the scenario-based PDs. Notice how U.S. Equity had a larger drop in the first quarter compared to European countries. Moreover, see how Spain and Italy suffered a more severe drop in Q2 2020 compared to Germany or Sweden, and the scenario projects a higher recovery during the following two quarters, leading to a convergence of all countries to a similar quarterly percentage change by Q2 2021.

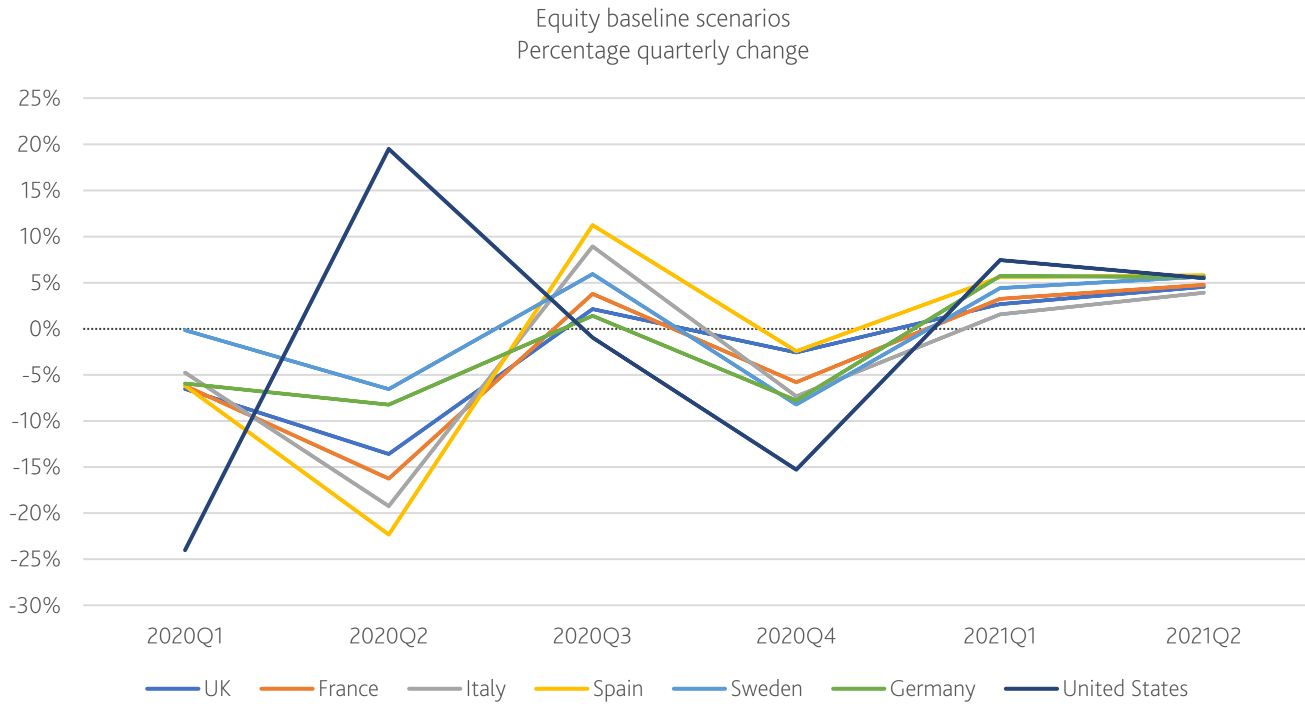
[7] The probability $TP_{r_0 \to r}(Scenario)$ is produced by PCDA whereas PD_r is given by the mapping found in Dwyer et al. (2017). The initial rating r_0 is obtained from CreditEdge.

[8] Moody's Analytics offers baseline and alternative macroscenarios for an extensive range of geographies. Scenarios defined according to the following narratives:

- S0: Alternative Scenario 0 – Upside – 4th Percentile. This above-baseline scenario is designed so there is a 4% probability the economy will perform better than in this scenario, broadly speaking, and a 96% probability it will perform worse. Similarly, for S1, S2, S3, and S4.
- S1: Alternative Scenario 1 – Upside – 10th Percentile
- S2: Alternative Scenario 2 – Downside – 75th Percentile
- S3: Alternative Scenario 3 – Downside – 90th Percentile
- S4: Alternative Scenario 4 – Downside – 96th Percentile
- S5: Slower-Trend Growth Scenario. In this low-performance, long-term scenario, the economy underperforms its potential indefinitely
- S6: Stagflation Scenario. In this scenario, inflation accelerates even as the economy remains weak
- S8: Low Oil Price Scenario. Designed as a benchmark to reflect the impact on the economy under the assumption of lower oil prices
- Consensus ("CF") Scenario. Designed to incorporate the central tendency of a range of baseline forecasts produced by various institutions

[9] Equity corresponds to indices, namely: the DAX for Germany, the FTSE MIB for Italy, the IBEX 35 for Spain, the FTSE 100 for the United Kingdom, the CAC 40 for France, the OMXS All Share for Sweden, and the S&P 500 for the USA.

Figure 6 Moody's Analytics equity baseline scenarios as of the end of Q3 2020.



These scenario-based PDs, along with par spreads and the other portfolio information (e.g., exposure, maturity, etc.) parameterize RiskFrontier. [10] Using the beginning of Q3 2020 analysis date, we conduct two sets of analyses over a one-year risk horizon: one using PDs obtained with the Overlay and one without. We then study the relationship between changes in expected loss, ΔEL^S, to changes in risk contribution, ΔRC^S, complied by the Overlay. Fitting the simple linear regression model

$$\Delta RC^S = \alpha + \beta \Delta EL^S + \epsilon,$$

helps us understand whether a change in expected loss has an amplified effect on the change in risk contribution. Namely, if $\hat{\beta} > 1$, it means that a change in expected loss leads, on average, to a more than proportional change in risk contribution.

4.3 Results

4.3.1 European Portfolio

We first look at results for the European portfolio. Figure 7 plots the change in monetary values of Expected Loss (x-axis) and Risk Contribution (y-axis) resulting from COVID, measured by the Overlay, for sectors in our European benchmark portfolio. The blue line represents a fitted regression line, and the red line is a 45-degree line, for reference.

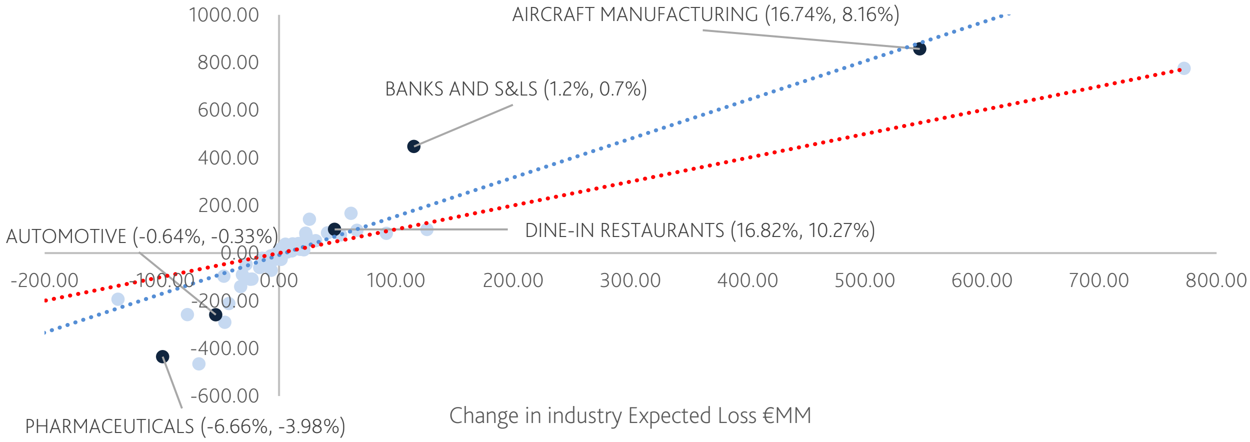
As the chart shows, when accounting for the Overlay, industries most negatively impacted by COVID, such as Dine-in Restaurants and Aircraft Manufacturing, find themselves on the right-hand side of the y-axis, and they experience an increase in € expected loss. Meanwhile, industries less affected by a macro shock, compared with past downturns, such as Automotive and Pharmaceuticals, find themselves on the left-hand side of the y-axis, and they experience a decrease in expected loss, after applying the Overlay.

Notice, the change in a sector's € risk contribution is, on average, more pronounced than the change in € expected loss. Namely, an increase (decrease) of 1€ in a sector's expected loss leads, on average, to an increase in its risk contribution being greater (lower) than 1€ — i.e. the blue regression line — is steeper than the red, 45-degree line. This dynamic is driven by the increased

[10] We use zero-EDF yield curves as reference curves and set spreads by marking-to-par all instruments. In particular, we use EUR ZERO EDF and USD ZERO EDF for the European and U.S. portfolios, respectively. RiskFrontier allows users to calculate the spread over a yield curve by setting "mark-to-par" when specifying *Data Settings*.

(decreased) levels of concentration risk in negatively (positively) impacted segments. A higher expected loss results in a higher likelihood of affected exposures moving together into default and loss. In parentheses, we show the expected loss and risk contribution percentage changes, respectively.

Figure 7 Relation between change in expected loss and change in risk contribution, due to Overlay, under baseline scenario (Europe portfolio).



In general, the direction of change in expected loss, after applying the Overlay, reflects what we have observed since the pandemic began. We now take a closer look at a few specific sectors.

Dine-in Restaurants (e.g. Whitbread, Autogrill, Mitchells & Nutlers, Domino's Pizza) have a relatively low RSQ (25%), resulting in lower correlations with other instruments and macro shocks. The holding amount, based on the counterparties' outstanding debt, is also relatively low, and so is the average initial PD (1%). The direction of change of the Overlay on PDs is positive and sizable — i.e. it leads to a large increase in PDs. Consequently, the percentage expected loss change is very high (17%). The relatively small size in the monetary change is mainly due to the low holding amount and correlations, mitigating the large effect of the Overlay.

For **Pharmaceuticals** (e.g. Bayer, Sanofi, Recordati) the situation is the opposite. Changes in expected loss and risk contribution due to COVID are negative and relatively small. The sector's average RSQ is high (40%) and so is its holding amount (16 times larger than Dine-in Restaurants). Its average initial PD (0.31%) is low. The effect of the Overlay on this sector reduces the impact of a macro shock. The percentage expected loss change is -6%. COVID's effect is negative, in the sense that the expected loss and risk contribution decrease after applying the Overlay. However, the relatively low PDs mitigate the monetary size of the change.

Some industries, such as **Banks and S&LS**, see a risk contribution change above average in relation to expected loss change, i.e. $\Delta RC^{Banks\ and\ S\&L} > \Delta RL^{Banks\ and\ S\&L}$. Banks and S&LS (e.g. HSBC, Unicredit, Santander, Société Générale) have high average RSQ (44%) and represent the largest exposure in the portfolio (124 times Dine-in Restaurants' exposure). The average initial PD (0.5%) is rather low, and the effect of the Overlay on PDs is positive, leading to a percentage expected loss increase of 1.2%. Low PDs, that have very large exposures, together with fairly high correlations, lead to a high change in risk contribution, indicating increased concentration risk in this sector.

The **Automotive** sector (e.g. VW, BMW, Audi, Fiat, Ferrari, Peugeot, Renault, Scania) experiences a decrease in expected loss and risk contribution. Its average RSQ is high (50%) and so is the holding amount (62 times Dine-in Restaurants). The initial PD is, however, low (0.48%), and the direction of change from the Overlay is slightly negative, i.e. leads to a decrease in PDs. Because of this result, and the low PD level, the percentage expected loss change is very low (-0.6%). The very large exposure and negative effect of the Overlay lead to an overall small and negative monetary change.

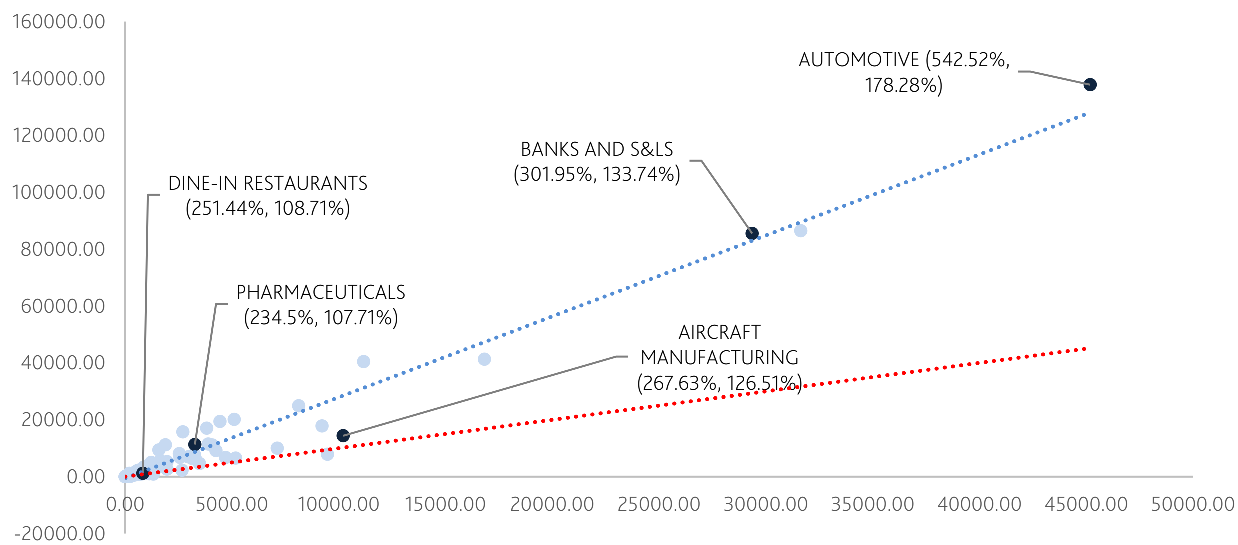
Aircraft Manufacturing, together with **Defence and Space**, was, in traditional segmentation, grouped into Aerospace & Defence. However, while Defence and Space was little-impacted by COVID, Aircraft Manufacturing was hit considerably — the Overlay reflects this difference. In our portfolio, Aircraft Manufacturing (e.g. Rolls Royce, BAE systems, Leonardo, Safran, Melrose) has an average RSQ (37%), and the holding amount is substantial (8 times Dine-in Restaurants). The initial PD is quite high (1.78%), as well as the (positive) effect of the Overlay. Consequently, the percentage expected loss change is also very high (17%). We can attribute the large monetary change in expected loss and risk contribution to the high holding amount, initial PD, and effect of Overlay on the PDs.

COVID's impact, as measured by the Overlay, can be quite significant. For example, for Dine-in Restaurants and Aircraft Manufacturing — two newly introduced industries [11] — the change in expected loss, even under a baseline scenario, measured by the Overlay, is around 17%. Under a severely adverse scenario, this percentage rises to more than 50% and, for some industries, we see increases in expected loss greater than 100%.

Exploring the impact of scenario severity, Figure 8 compares the changes in expected loss and risk contribution across the baseline to a severely adverse scenario using the Overlay. [12] Note how COVID's effects are accentuated when considering a more severe scenario — the slope of the regression line is more than double the red line, i.e. the effects on risk contribution are amplified.

Traditional models can underestimate expected and realised losses for certain industries and overestimate them for others. The Overlay helps to identify changes in the riskiness of segments and provides early warning signals for sectors more likely to experience severe credit losses. From a portfolio management perspective, the analysis sheds light on how risk is distributed among the sectors, relevant for setting risk-based limits and portfolio rebalancing.

Figure 8 Relation between change in expected loss and change in risk contribution, Baseline scenario to 96th percentile Downside (S4) scenario (European portfolio).



The magnitude of the effect of a sector's change in its average PD on its risk contribution, which we measure via the Overlay, depends on the sectoral instruments' and counterparties' characteristics (e.g. maturity, exposure, PD, etc.) and its correlation with the rest of the portfolio. Different combinations of these attributes lead to different results: their non-trivial interactions make a precise outcome difficult to predict a priori. Note, while the direction of change in expected loss — resulting from COVID and measured by the Overlay — is known in advance, and reflects the observations made from the onset of the pandemic, it is challenging to gauge the magnitude of this change and, more so, its effect on risk contributions. A portfolio-specific analysis is required to precisely quantify the effects of a change in single-name risk parameters on the overall risk of a portfolio and, ultimately, to get a better sense of the concentration risk effects created by COVID.

4.3.2 U.S. Portfolio

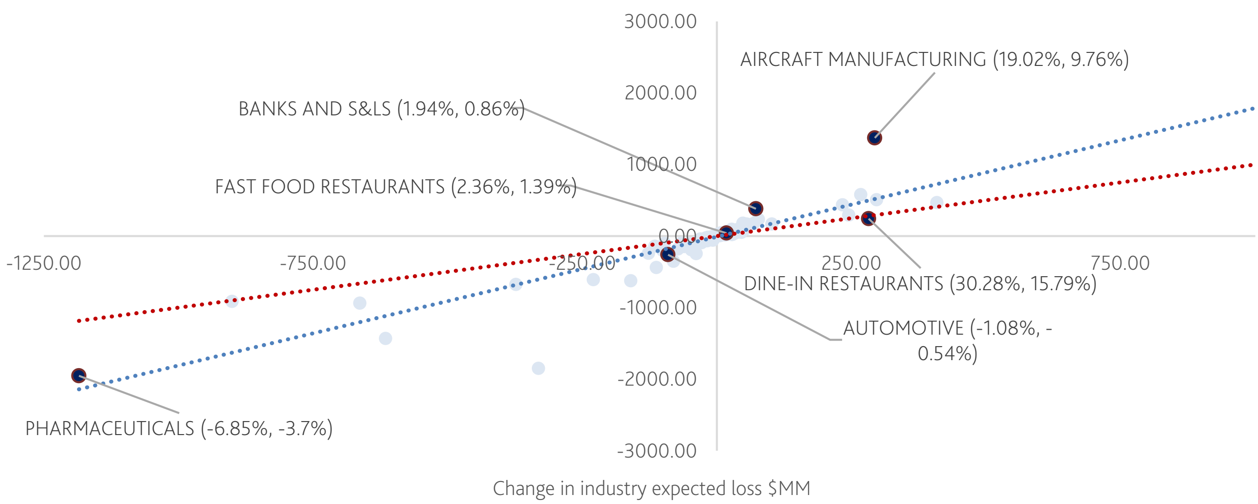
We now present results of the U.S. portfolio. Figure 9 compares the monetary changes in expected loss to the ones in risk contribution for the U.S. portfolio. The blue line represents a fitted regression line, and the red line is a 45-degree line, for

[11] The Overlay provides 121 industry segments, a more granular segmentation than traditional models. See Section 2 for more details.
[12] Here we use Moody's Analytics 96th percentile Downside (S4) scenarios for United Kingdom, France, Spain, Italy, Germany, and Sweden.

reference. Note how, similar to the European case, Aircraft Manufacturing, Banks and S&LS, and Dine-in Restaurants are in the northeast quadrant and Pharmaceuticals and Automotive in the southwest one. That is, the former three segments are particularly penalized by the pandemic, in opposition to the latter two.

In the U.S. portfolio, we include Fast Food Restaurants as there are 12 firms operating in this business. The difference between the percent change in expected loss and risk contribution between Fast Food and Dine-in Restaurants is noticeable, (~2%,~1%) against (~30%,16%). While this change is driven by different components, we highlight that the change in PD due to the Overlay is 30% for Dine-in Restaurants and 2% for Fast Food Restaurants, reflecting the greater dependence of the former on physical proximity. We now look more in detail at these six segments.

Figure 9 Relation between change in expected loss and change in risk contribution, due to Overlay, under baseline scenario (U.S. portfolio).



Dine-in Restaurants (e.g. Papa John's International, Darden Restaurants, Cheesecake Factory, Texas Roadhouse) has very low RSQ (~15%) resulting in low correlations with other instruments and macro shocks. The holding amount, based on the counterparties' outstanding debt, is also low (below the average and median values). The average initial PD is however quite high (3%). The direction of change of the Overlay on PDs is positive and sizable — i.e. it leads to a large increase in PDs. Consequently, the percentage expected loss change is very high (30%). The combination of holding amount, PD, correlations, and Overlay effects, leads to a relatively material monetary change in expected loss and risk contribution, due to COVID.

For **Pharmaceuticals** (e.g. Pfizer, Johnson & Johnson, Merck & Co., Bristol Myers Squibb Co.) the situation is different. Changes in expected loss and risk contribution due to COVID are negative and very large. The sector's average RSQ is within average (35%) and its holding amount very large (roughly 30 times larger than Dine-in Restaurants). Its average initial PD (0.34%) is low. The percentage expected loss change is -7%. The effect of the Overlay on this sector *reduces* the impact of a macro shock, i.e. COVID's effect is negative. This, together with a significant exposure, leads to a material decrease in the monetary value of expected loss and risk contribution.

Banks and S&LS (e.g. JPMorgan Chase & Co.) have a very high average RSQ (60%) and represent the third-largest exposure in the portfolio (60 times Dine-in Restaurants' exposure). The average initial PD (0.53%) is rather low, and the effect of the Overlay on PDs is positive but small, leading to a percentage expected loss increase of 1.9%. Low PDs, a large exposure, high correlations, together with a small positive effect of the Overlay, lead to a modest monetary change in risk contribution for this sector.

The Automotive sector (e.g. Ford Motor Co., General Motors Co., Tenneco Inc.) experiences a small monetary decrease in expected loss and risk contribution. Its average RSQ is high (43%) and so is the holding Amount (~24 times Dine-in Restaurants). The initial PD is quite high (1.25%), and the direction of change from the Overlay is slightly negative, which leads to a decrease in PDs. Because of this, the percentage expected loss change is fairly low (-1.08%). The large exposure and negative effect of the Overlay lead to an overall small and negative monetary change in expected losses and risk contribution.

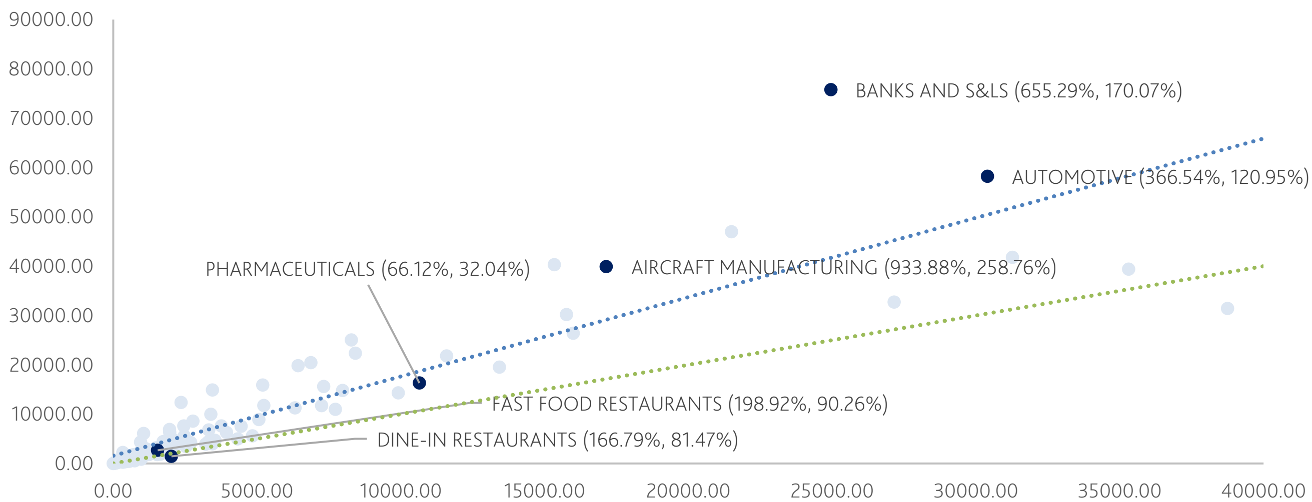
Aircraft Manufacturing, together with **Defence and Space**, was, in traditional segmentation, grouped into Aerospace & Defence. While Defence and Space was little-impacted by COVID, Aircraft Manufacturing was hit considerably — the Overlay reflects this difference. In our U.S. portfolio, Aircraft Manufacturing (e.g. The Boeing Co., Honeywell International, General Dynamics) has a high RSQ (50%) and a substantial holding amount (12 times Dine-in Restaurants). The initial PD is quite low (0.49%). The (positive) effect of the Overlay is quite large, following the arguments above. Consequently, the percentage expected loss change is also very high (19%). We can attribute the large monetary change in expected loss and risk contribution to the high holding amount, correlations, and effect of Overlay on the PDs.

Fast Food Restaurants (McDonald's, Shake Shack, Domino's Pizza) has a low RSQ (21%), close to that of Dine-in Restaurants. The holding amount is ~three times that of Dine-in Restaurants, and the initial PD low (0.73%). The effect of the Overlay on PDs is positive but modest compared to Dine-in Restaurants. This leads to a modest monetary change in expected losses and risk contributions.

The effect of COVID on expected losses, as measured by the Overlay, can be material. For Dine-in Restaurants and Aircraft Manufacturing for example, the increase is 30% and 19%, respectively.

Exploring the impact of scenario severity, Figure 10 compares the changes in expected loss and risk contribution from the baseline to a severely adverse scenario using the Overlay, for the U.S. portfolio. [13] Note how COVID's effects are accentuated when considering a more severe scenario — e.g. Aircraft Manufacturing increases almost 10 times.

Figure 10 Relation between change in expected loss and change in risk contribution, Baseline scenario to 96th percentile Downside (S4) scenario (U.S. portfolio).



[13] Here we use Moody's Analytics 96th percentile Downside (S4) scenarios for U.S.

5. Summary

COVID's impact on concentration risk for a benchmark portfolio, as measured by the Cross-sectional COVID-19 Overlay and RiskFrontier, can be significant, and requires a much more granular representation than provided by traditional models. The Overlay implies an amplification of the effects of macro-shocks on PDs for sectors such as Banks and S&LS, Dine-in Restaurants, and Aircraft Manufacturing and a mitigation of them for Pharmaceuticals and Automotive. This difference reflects observations from the pandemic's onset and on the variation in COVID's impact severity for different industry segments.

We analyse the effects of COVID on a European and a U.S. benchmark portfolio. The pictures drawn by these exercises are similar, in that a change in expected loss has a multiplicative effect on concentration risk: a 1€ increase (decrease) in the sector's expected loss leads, on average, to an increase (decrease) of more than 1€ in its risk contribution.

While the benchmark portfolio studies share similarities, we recognise it is the interplay between portfolio-specific attributes that determines the ultimate COVID effects on a portfolio. The magnitude of the changes in concentration risk, in particular, depend on a number of portfolio dimensions. It is clear, however, that traditional models underestimate expected and realised losses and credit risk for certain segments and overestimate them for others, when not accounting for COVID-specific effects. Our survey quantifies these effects, with applications for setting risk-based limits, portfolio allocation, and early recognition of losses.

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