QUANTITATIVE INVESTING

Real-life experience: Using ML and distance-to-default to predict distress risk

- Machine learning and distance-to-default signals are strong tail risk predictors
- Since inception, these distress signals have beaten standard risk factors
- Our year-by-year analysis includes real-life stock examples

Tail risk is extremely relevant for investors. While small wins and losses are inherent to stock market investing, significant price crashes can be highly detrimental. Identifying stocks that are likely to experience severe price crashes is crucial.

Commonly used measures such as a stock's beta and return volatility are effective risk indicators. Avoiding stocks with the highest beta and volatility can reduce the tail risk of an investment portfolio. However, these metrics rely on historical data. For a more forward-looking approach to estimating tail risk, incorporating distress risk measures such as Robeco's proprietary distance-to-default (DtD) measure can be beneficial. This measure has been part of our quantitative strategies since 2011. In 2021, we started including a machine learning (ML) risk signal that captures complex patterns in the stock market.

This note examines the performance of these signals, focusing on their out-of-sample performance. We provide further intuition and real-life examples of these enhanced risk measures and confirm that the DtD and ML risk signals have beaten traditional return-based measures since their introduction in real-life investment strategies.

What are the DtD and ML signals?

The distance-to-default (DtD) signal, inspired by the Merton model[1], captures how close a firm is to defaulting on its debt. It's a key concept in credit risk modelling, used by analysts and bond investors to assess a company's financial stability and the likelihood of credit default. In this model, stock equity is seen as a call option on the company's total value, including liabilities. This value is influenced by the volatility of the company's asset market value. The forward-looking nature of DtD offers additional insights compared to traditional metrics. Since 2011, an enhanced version of this proprietary distress risk measure is a negative screening tool for all our Quantitative Equity strategies, and has been integral to our stock selection model for Conservative Equities.[2]

[1] Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of finance*, 29(2), 449-470.
[2] How distress risk improves low volatility strategies: lessons learned since 2006, Joop Huij, Pim van Vliet, Weili Zhou and Wilma de Groot, Robeco Research Paper, February 2012

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The machine learning risk signal, introduced to our Quantitative Equity models in 2021, is trained to identify firms likely to suffer severe stock price crashes. ML techniques have several advantages, such as adapting to data patterns and capturing complex relationships like nonlinearities and interaction effects.[3] For example, the empirical relationship between a firm's financial leverage and its risk level is not linear. While firms with low or average leverage tend to have an average distress risk, those with high leverage are much more likely to experience significant price crashes. ML techniques excel at identifying such nonlinear relationships.[4]

Our evaluation focuses on comparing the out-of-sample performance of three distress indicators since their incorporation into real-life investment strategies:

1. 50/50 combination of beta and volatility
2. DtD signal
3. ML distress signal

For this we include a year-by-year analysis, examples of individual stock price crashes, power curves and portfolio sorts.

Year-by-year analysis

Since 2011, when DtD was integrated into Robeco's Quantitative Equity strategies, we have tracked the annual performance of the riskiest stocks. Table 1 illustrates the average yearly returns of the bottom 10% of stocks, as ranked by their beta & volatility and DtD scores. These are contrasted with the overall returns of stocks in the MSCI World and MSCI Emerging Markets indexes. In this case, lower means better, since these are the stocks which are avoided in our various Quantitative Equity strategies.

It is interesting to note that in strong market years like 2013 and 2019, the most risky stocks also performed well and sometimes even better than the market average. However, during downturns such as 2018 and 2022, these stocks experienced more significant losses, especially those scoring poorly on tail risk measures.

During negative market years, denoted in red, the most risky stocks underperformed the market while the least risky stocks outperformed. In this period emerging markets experienced harsher drawdowns in negative years than their developed market counterparts. For example, in 2013, while global emerging markets declined by 6%, the worst DtD stocks in EM plummeted 21%; this measure thus outperforming beta & volatility. This DtD outperformance repeated in 2015, a year in which both DM and EM went down.

In 2018, all risk measures did well again, but with mixed evidence in DM and EM for DtD versus volatility & beta. This shows that traditional risk measures should not be dismissed altogether, since they still have predictive power that complements DtD signals. Finally, 2022 was a showcase year in which all risk measures did well, with DtD again beating the traditional risk measures in both DM and EM. On average, the outperformance of DtD versus traditional beta/volatility is around 2 to 3% per annum for both developed and emerging markets.

[3] For an overview of the use of Machine Learning for asset management we refer to: Blitz, D., Hoogteijling, T., Lohre, H., & Messow, P. (2023). How can machine learning advance quantitative asset management? *The Journal of Portfolio Management*, 49(9), 78-95.
[4] A more extensive description of the Machine Learning approach was published in 2021, at the time of introduction in our Quantitative Models, and can be found on the Robeco website.

Table 1 | Yearly returns of 10% of stocks scoring poorest on risk indicators

	Global developed markets			Global emerging markets		
Return per year	*All stocks*	*Worst beta/vol*	*Worst DtD*	*All stocks*	*Worst beta/vol*	*Worst DtD*
2012	16%	19%	20%	21%	14%	15%
2013	24%	26%	29%	-6%	-15%	-21%
2014	16%	4%	3%	13%	-1%	7%
2015	11%	-7%	-9%	-1%	-12%	-14%
2016	15%	27%	23%	12%	16%	15%
2017	9%	6%	5%	18%	28%	25%
2018	-8%	-21%	-15%	-12%	-19%	-20%
2019	29%	31%	28%	19%	28%	26%
2020	6%	30%	29%	8%	40%	27%
2021	25%	38%	24%	19%	15%	7%
2022	-13%	-23%	-34%	-10%	-18%	-16%
2023	3%	6%	4%	2%	-2%	-5%
Negative years	-11%	-22%	-24%	-7%	-16%	-18%
All years	11%	10%	7%	6%	4%	2%

Source: Robeco, MSCI, DataStream, Compustat and Worldscope, 2023.

Individual stock examples

It is very insightful to look at companies that were subject to considerable downside risk and drops in share price. In 2022 many companies saw their market value drop by -50% or more. Table 2 includes the ten stocks with the most negative 2022 return, some of which are included in the largest 500 constituents of MSCI World. These ten stocks went down by 69.8% on average (euro-denominated). To make up for such large losses, they would have needed to make a staggering +330% the subsequent year to break even.

For each stock the beta, volatility, distance-to-default and ML rank at the beginning of the year are reported. The most significant losers of 2022 generally all had poor DtD and ML risk signal scores at the beginning of the year; indicating a high risk of underperformance. Notable examples include Silicon Valley Bank (SVB) and Snap, which scored very poorly on all risk metrics. SVB also consequently defaulted on its loans in 2023. Interestingly, the list contains two stocks with low betas: Okta and Cloudflare. They were thus not risky according to their beta. Furthermore, SVB did not rank in the bottom 10% based on historical volatility.

Table 2 | Stocks with the largest negative returns over 2022*

Company name	Return 2022	Beta	Volatility	Distance-to-Default	Machine Learning rank
Twilio	-80.2%	1.15	64.0%	2.87	0.98
Snap	-79.7%	1.49	69.3%	1.98	0.99
Sea Ltd	-75.2%	1.31	58.5%	2.36	0.98
Shopify	-73.2%	1.24	55.3%	3.02	0.95
Okta	-67.5%	0.78	45.7%	3.42	0.97
Match Group	-66.6%	1.26	45.0%	2.75	0.95
Align Technology	-65.8%	1.80	56.8%	4.18	0.83
Silicon Valley Bank	-63.8%	1.54	45.2%	2.89	0.94
Cloudflare	-63.4%	0.53	59.9%	1.99	0.98
Tesla	-62.7%	1.80	69.4%	2.36	0.95
Median of 500 stocks	*-9.2%*	*1.00*	*23.8%*	*5.62*	*0.50*

*The 10 stocks with the largest negative return over 2022 within the largest 500 stocks in the MSCI World Index. Source: Robeco, MSCI, DataStream, Compustat and Worldscope, 2023.

However, these three companies had the worst bottom 10% scores based on their DtD and ML risk rank, which ultimately proved correct, underscoring how these novel distress measures might better predict individual stock crashes compared to traditional risk factors. Next, we examine how these individual observations are supported by a broader equity return analysis.

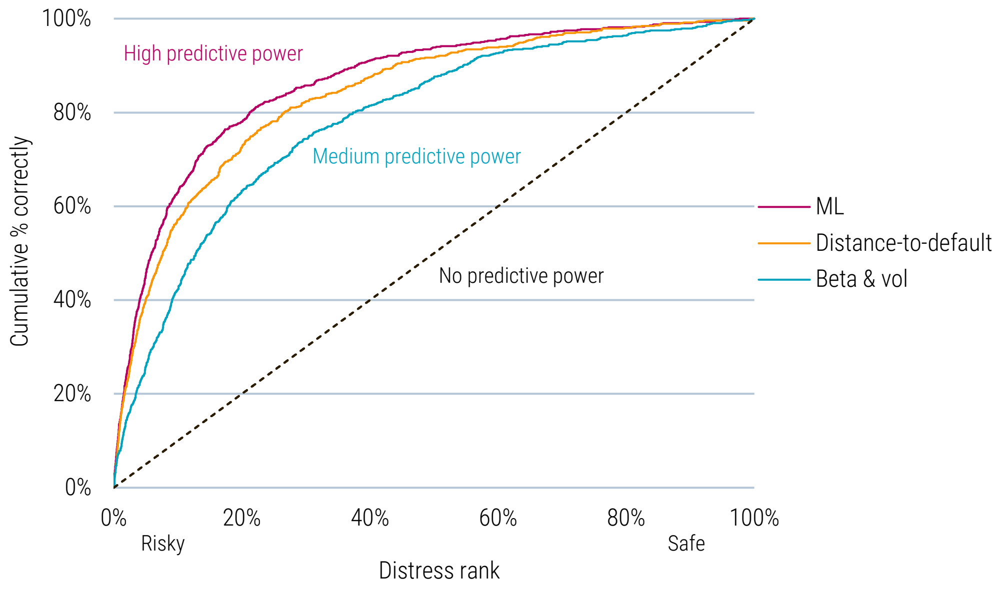
Power curves

In statistics, a tool commonly used to assess prediction accuracy is the power curve.[5] For every probability threshold, it shows the number of observations correctly classified as belong to a certain group, as a percentage of the total number of observations in that group. Without any predictive power, a 45 degree line is expected, as shown as a dotted line in Figure 1. The further away a power curve gets from the 45 degree line, the better the predictions of the investigated indicator. In our case, we rank all stocks separately on beta & volatility, DtD and ML risk predictions, and then use those ranks to predict whether stocks will belong to the lowest return group. The sample is global developed markets, consisting of 3000-4000 stocks, for the period 2002-2023.

Figure 1 shows that all three indicators clearly beat the no-predictability benchmark. We also find that the power curves for distance-to-default and ML are further from the 45-degree line than the power curve of the beta & volatility combination, indicating they are better predictors of tail risk. In numbers, we can express this by looking at the area under the curve (AUC), with a larger area indicating stronger predictability. The AUC numbers confirm the visual picture, with ML obtaining the highest AUC of 86.4%, followed by DtD (83.9%) and the beta-volatility combination (78.6%). For the out-of-sample 2022-2023 period, DtD and ML distress are also stronger predictors. This confirms the added value of using forward-looking risk factors, also in real-life scenarios.[6]

[5] Specifically, the Cumulative Accuracy Profile (CAP), see https://en.wikipedia.org/wiki/Cumulative_accuracy_profile.
[6] We focus on the 1% of stocks with the poorest 12-month subsequent returns to offer the clearest insight. The graphs depicting the worst 5% and 10% of stocks, as well as those covering the 2021-2023 period, show similar patterns

Figure 1 | Power curves for various predictors of distress*



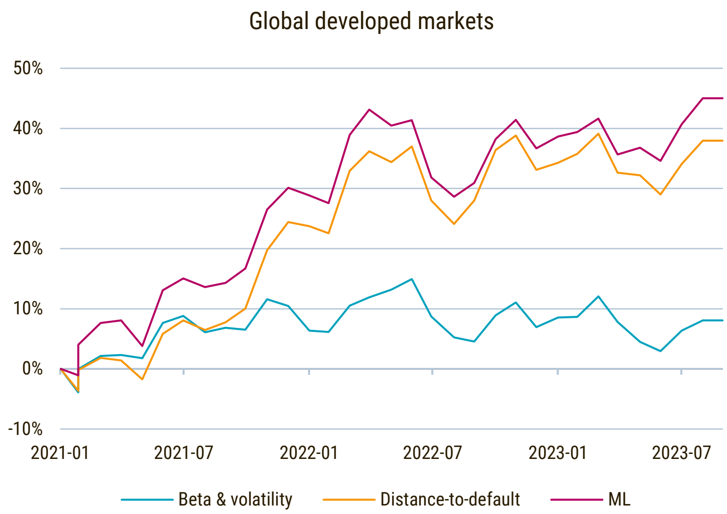
*Global Developed Markets 2002-2023. Source: Robeco, MSCI, DataStream, Compustat and Worldscope, 2023.

Portfolio sorts

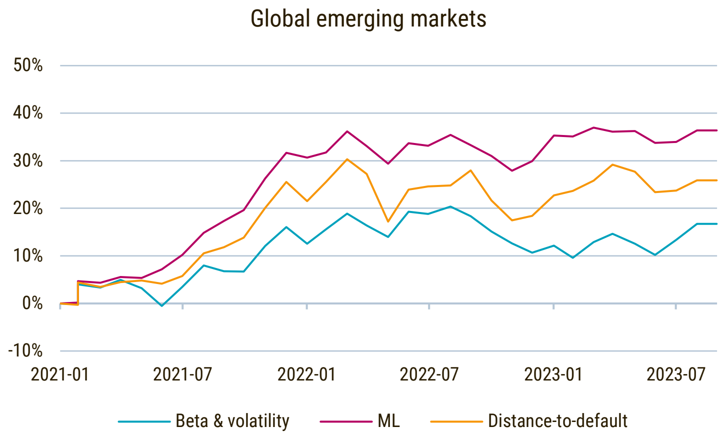
Finally, we look at the 10% of stocks with the highest beta & volatility, DtD and ML risk scores. If their subsequent stock performance is weak, we have evidence of a strong distress indicator. For all three risk indicators considered, we find that the most risky portfolios underperform the market on average. In Figure 2, we show the cumulative alpha obtained from a short position in the worst 10% of stocks, for both global DM and EM.

The sample range is from January 2021 to October 2023, resonating with the real-life out-of-sample period for the ML-based distress signals. In both cases, the underperformance of the bottom 10% is more pronounced for DtD and ML than for the classic beta-volatility basket. This indicates that moving beyond traditional measures helps to better detect the most risky stocks and avoiding (or shorting) these would historically have been rewarded with higher returns as a result.

Figure 2 | Cumulative alpha from a short position in the most risky stocks



Source: Robeco, MSCI, DataStream, Compustat and Worldscope, 2023.



Source: Robeco, MSCI, DataStream, and Worldscope, 2023.

Conclusion

This article presents detailed evaluations of proprietary distress risk predictors used in all of our Quantitative Equity strategies in general and Conservative Equities in particular, focusing on the comparison between traditional and advanced measures. Our analysis, which includes a year-by-year review, individual stock examinations, power curves and portfolio sorts, indicates that DtD and ML risk signals have added a distinct dimension to risk prediction since their inclusion in 2011 and 2021 respectively. These findings suggest a potential for improved identification of distressed stocks, which is a key consideration in strategy development and risk management.