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Quantitative Portfolio Strategy

2 January 2020

Using Signals from a Default Prediction Model in High Yield Portfolio Construction

- **We study the dependence of realized forward default rates of US HY bonds from public issuers on company fundamentals and additional signals from bond and equity markets.**
- **We choose a parsimonious model with five factors, using techniques from machine learning, and show that it achieves accurate forecasts on a default horizon of six months.**
- **In out-of-sample classification of bonds that will default within six months or not, the model correctly flags 94% of defaulting bonds and 94% of surviving bonds.**
- **We show how this model can be used to construct bond portfolios that minimize default risk – either outright or per unit of spread – and explore the historical performance of such portfolios.**
- **In strategy backtests from 2000-2019, long-only portfolios of the model's top-quintile bonds outperformed the HY index by 56bp/month, with a TEV of 124bp/month, for an information ratio of 1.57 before transaction costs. A corresponding long-short portfolio (top vs. bottom quintile) produced an average monthly return of 120bp with an IR of 1.45.**
- **We study the role of different aspects of the model (signal selection, portfolio construction) on strategy performance, and how performance varies over time.**
- **We find that while OAS can provide an accurate estimate of default probability, this (priced-in) estimate does not contribute much to strategy performance.**
- **An equity momentum signal contributes strongly to strategy performance and provides incremental improvement at estimating default probability.**
- **We also investigate how the model can be used to form default-screened portfolios that include all index bonds except for those in the top quintile by estimated default probability. Over 2000-2019, this strategy outperformed the HY index by 17bp/month, with a TEV of 56bp/month, for an IR of 1.04.**
- **We repeat the study limiting our bond universe to the most distressed part of the HY universe. These strategies typically have greater risk and reward, with information ratios similar to those on the entire HY index.**

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Motivation

Corporate bonds and other default-risky securities pay investors high interest rates to compensate them for the risk of default. For investment-grade bonds, while the possibility of default is the underlying source of risk, the realization of risk in the portfolio typically takes the form of widening and tightening spreads, or changes in credit ratings; actual defaults are quite rare. For high yield bonds, however, defaults are not nearly as uncommon, and can be quite damaging to portfolio returns. High yield investors therefore have a particular interest in estimating default risk as accurately as possible, and not taking any such risks unless they are more than adequately compensated.

Figure 1 shows the historical default rates experienced by bonds in the Bloomberg Barclays US HY index over different horizons[1]. On average, the realized default rate over the past 20 years was about 4% per year for HY bonds overall, but with substantial variation over time. Indeed, we find that the standard deviation of default rates over this period is roughly equal to the mean. The default distribution is also positively skewed, as evidenced by the difference between the mean and median default rates.

FIGURE 1

Statistics of Forward Realized Default Rates (by number of bonds) for the Bloomberg Barclays US HY Index, July 1998 – July 2018

	1M	3M	6M	9M	12M
Mean	0.3%	1.0%	2.1%	3.1%	4.1%
Median	0.2%	0.6%	1.2%	1.9%	2.4%
Min	0.0%	0.0%	0.2%	0.3%	0.4%
Max	2.4%	5.8%	9.9%	12.3%	13.7%
Std Dev	0.5%	1.1%	2.0%	2.8%	3.5%

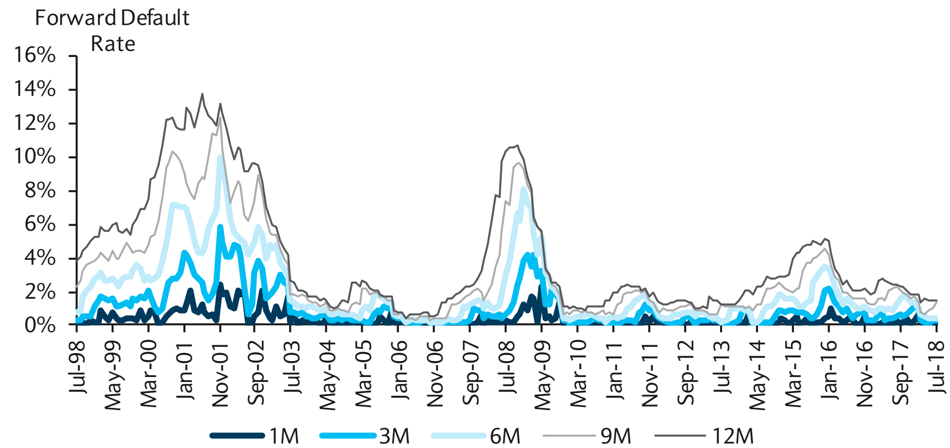
Source: Bloomberg Barclays Indices, Barclays Research

The time variation of default rates is brought into focus in Figure 2. We find that in two distinct episodes – the dot-com crisis and the global financial crisis – more than 10% of bonds that were in the index defaulted within 12 months. Between such events there were extended periods of relative calm, in which realized default rates were substantially below the overall averages.

[1] Please note that these default rates may differ in two ways from those found in other analyses of index default rates. Often, index default rates are calculated as the percentage of index MV that defaults in the coming month. Our calculation is based on the number of bonds defaulting as a percentage of the number of bonds in the index. Furthermore, Figure 1 features a look-ahead approach that freezes the set of bonds in the US High Yield Index at a given point in time and then checks how many of them default in the next *n* months. As a result, our figures include bonds that had already exited the index (perhaps due to index rules on maturity and amount outstanding) prior to the default event being triggered. We find this approach to be the most relevant to our task of estimating horizon default probabilities.

FIGURE 2

Realized Default Rates in Bloomberg Barclays US HY Index Over Different Horizons



Note: Default rates calculated over rolling windows of 3, 6, 9 and 12 months forward from the month-end date shown, as the ratio of the number of bonds defaulting during that window to the number of index bonds as of each date.
Source: Bloomberg Barclays Indices, Barclays Research

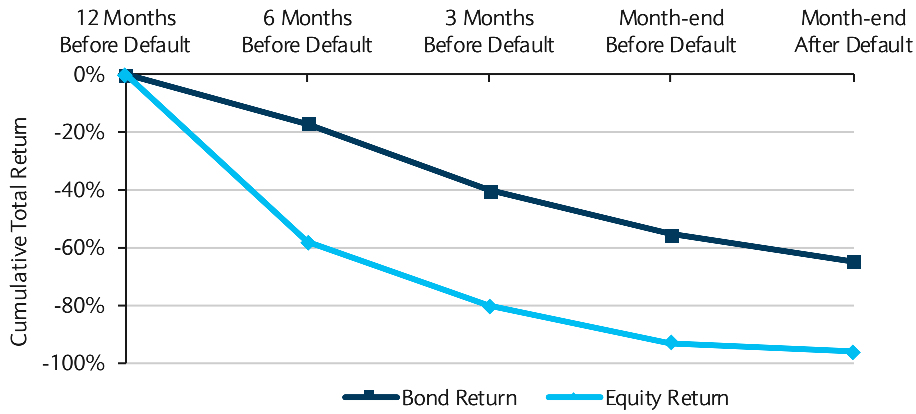
While some default events seem totally unpredictable (e.g. the accounting scandal at Enron), others follow a slow and steady course, such as consistently declining revenues (e.g. Sears Holdings). High yield markets naturally respond to bad news about a firm in the form of widening spreads and falling prices. One might suspect, then, that impending defaults are sufficiently priced in such that the losses upon default are not that significant[2]. This is true to some extent, but depends strongly on the time horizon. Defaults are financially material events that are typically accompanied by large losses over several months leading up to the default. For the default events in our study, Figure 3 plots the typical time course of these returns over the final 12 months of a bond's life. Starting 12 months before the month-end date on which each default is recorded in the index, we plot the median cumulative total returns over a growing window. We find that the median cumulative total return of a defaulting bond over the final year of its life was -65%, with the majority of this loss recorded during the six months prior to default, but relatively little in the final month. The loss for equities of defaulting firms was even greater, with a median total return of -96% over the final year[3], again with a small fraction of that coming in the last month before default. For both debt and equity investors, the conclusion is twofold: it is of primary importance to portfolio construction to avoid impending defaults; and to be useful, any such signal must arrive several months in advance of the actual default event.

[2] For example, if a bond is already trading at a price that reflects its estimated recovery value, then a default will not necessarily cause a further loss.

[3] We were surprised to find that the loss to equity holders was often less than 100%. It seems that even after bankruptcy, shares of common stock often continue to trade at (very low) prices above zero. For analysis of this phenomenon, see Li, Y. and Z. Zhong, "Investing in Chapter 11 stocks: Trading, value, and performance", *Journal of Financial Markets* (**16**:1), February 2013, pp. 33-60.

FIGURE 3

Development of Cumulative Total Returns of Defaulting Firms from the HY Bond Index, for Bonds and Equities, over the 12 Months before Default, July 1998 – January 2019



Source: Bloomberg Barclays Indices, Compustat, Barclays Research
Note: For each default event tracked in our data sample of public companies from the Bloomberg Barclays High Yield Index, we calculate the cumulative total returns starting 12 months before the month-end following default, for both the bond and the equity of the issuing company (as described below). We chart the median returns for each horizon.

Two main sources of information provide assessments of default risk from within the bond market: credit ratings and associated information from rating agencies, and market prices. In this report, we investigate the extent to which additional information from outside the bond market can help arrive at more accurate estimates. In particular, wherever possible, we seek to use both pricing information and fundamentals relating to the equity of a bond's issuer to get a more complete picture of the company's health. We are aided in this effort by our team's investment in maintaining a historical mapping of bonds to the appropriate equity at each point in time, adjusted for corporate actions. In this context, the goal of this research is to understand the drivers of default, and use these drivers as signals to develop a default forecasting model. The model is calibrated to historical realized defaults of a sample of HY index bonds from public issuers.

For a complete treatment of forward-looking default probabilities, producing a single number for each issuer is not sufficient; the results should ideally include a full set of default probabilities at multiple horizons. For this study, however, we have chosen to limit our focus to a single default horizon of six months. This horizon was selected based on a number of factors, including discussions with investors about typical holding periods for corporate bonds, and the above analysis indicating that a successful signal of impending default on a six-month horizon could provide a material advantage to portfolio managers. Figure 3 shows that a warning signal at a six-month horizon could help bond investors avoid nearly 75% of the ultimate default loss; and it also shows that by that time the equity market has typically shown ample signs of worry.

This paper is organized as follows. We first describe the construction of our sample dataset, including the rules we used to identify default events, and compare the properties of our sample to the full Bloomberg Barclays US HY index. We then present our model for estimating default. We identify a number of signals that are associated with default risk, and study how default rates depend on each one. We focus on the five signals that form the basis of our default model: OAS, equity volatility, short-term leverage, past equity return, and general market environment as measured by VIX. Next, we present the details of the model and its performance at predicting default. Once the model is complete, we apply it to the problem of portfolio construction, using several different variations: we look at the construction of long-only portfolios and their performance relative to the index, as well as at long-short portfolios. In both cases, in an idealized setting that does not include transaction costs, the portfolios constructed using the model were able to achieve excellent performance. We test model performance on the whole HY index as well as a subset of the most distressed bonds.

Dataset Coverage, Scope and Properties

Our dataset is essentially the public subset of the Bloomberg Barclays US High Yield Index. In particular, we consider all bonds with the following properties:

- Included in the Bloomberg Barclays US High Yield Index
- Not currently in default
- The firm that issued the bond also has actively traded equity

Our study is based on bond data from January 1998 through July 2019. However, much of the analysis presented here will be on slightly shorter periods. We use signals that are formed based on trailing market results, and we measure performance (e.g. realized subsequent defaults) over a forward-looking period of six months. Therefore, many of the results reported will be based on a shorter time window, trimmed at both ends to allow for signal formation and performance measurement.

Most of the key inputs to our model are based on data – both fundamentals and pricing – associated with the equity of the issuing firm. To link a bond with the correct issuing firm, and its associated pricing and fundamental data from Compustat, we made use of the unified debt-equity dataset used in Ben Dor and Xu (2014)[4] to study bond signals in equity momentum portfolios (BEAM). For private bonds – those that we are unable to map to a publicly traded firm – we do not have sufficient data to evaluate the issuer's financial condition, and we therefore exclude them from our dataset. An additional group of bonds that we exclude are those that are mapped to firms based outside of North America. We include bonds issued by Canadian firms, but exclude those from European or Asian companies. These limitations restrict the size of our dataset[5].

Figure 4 shows the average coverage percentage of the Bloomberg Barclays US HY index after application of each stage of filtering. In particular, the set of public bonds includes more than 70% of the index. The final coverage of our sample dataset is roughly 50% of the HY index. Much of the additional loss in coverage is due to the exclusion of bonds from European and Asian firms.

FIGURE 4

Coverage of Bloomberg Barclays US HY Index After Application of Each Data Source

	Initial Coverage	After Bond-Equity Mapping	After Equity Pricing & Fundamental Data
By Count	100.0%	71.83%	50.90%
By Market Value	100.0%	74.77%	51.88%

Source: Bloomberg Barclays Indices, Compustat, Barclays Research

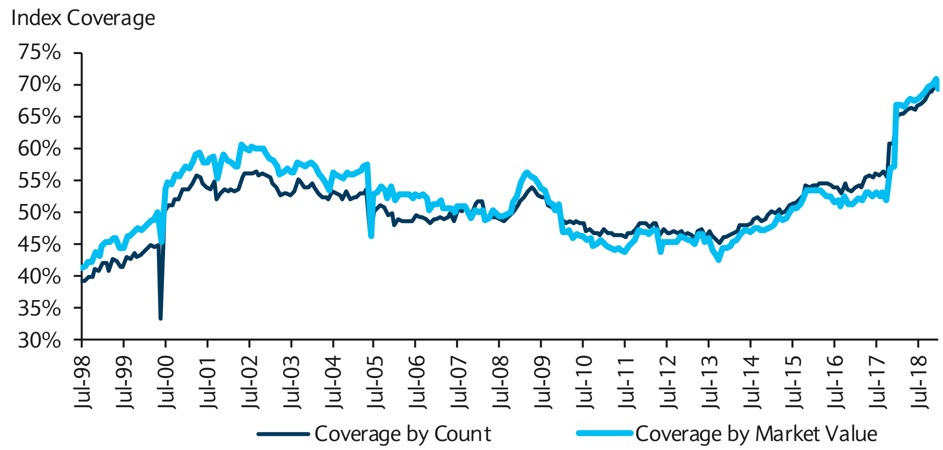
[4] See Ben Dor, A. and J. Xu, *BEAM (Bonds in Equity Asset Momentum) – Value of Bond Market Information in Equity Momentum Strategies*, Barclays Research, June 5, 2014. The bond-equity mapping process is described in detail on pages 6-10 of this article.

[5] We found that in a small number of cases, the fundamentals of the issuing company seemed quite out of synch with the pricing of the debt. We have applied some additional filters to try to minimize this occurrence. First, we removed all bonds that map to holding companies; these firms are typically high-quality firms that buy majority holdings in risky companies as an investment but do not necessarily stand behind their debt. Second, when faced with bonds of different qualities that map to the same issuer, we kept only those bonds in the quality with the largest market value. These filters removed a relatively small number of bonds from our dataset.

Figure 5 shows that the coverage is relatively consistent over time, with slightly less coverage at the beginning of our sample period. The graph also shows that coverage is not dominated by large or small issuers, since there is very little difference between the index coverage ratios calculated in terms of market values or numbers of bonds.

FIGURE 5

Coverage of Bloomberg Barclays US HY Index in our Sample Dataset



Source: Bloomberg Barclays Indices, Compustat, Barclays Research

We now describe the properties of our sample dataset and compare them to the properties of the full Bloomberg Barclays HY index. Our goal is to understand in what sense our sample represents bonds in the index. Figure 6 compares some of the key characteristics of the two universes, including OAS, market value, coupon, return and maturity. We find that the two line up very well in terms of average maturities and average returns. However, on average, the OAS of the index is 54bp higher than that of our data sample of public bonds, and the average yield is higher by a similar amount.

FIGURE 6

Comparison Between Time-Averaged Properties of the HY Index and the Sample Dataset (July 1998 – January 2019)

	Index	Sample
Number of Bonds	1733.0	892.3
Average Bond MV ($ MM)	432.3	432.0
OAS (bp)	551.9	497.9
Yield to Worst (%)	8.89	8.34
OASD	4.38	4.59
6M Default Rate	2.03%	1.77%

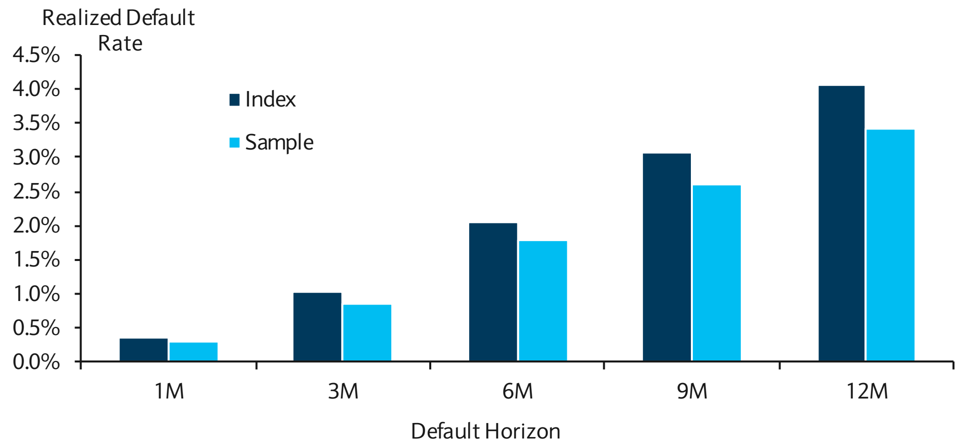
Source: Barclays Research

Next, since our study is focused on defaults, we compare the historical default experience in our data sample with that of the index as a whole. As shown in Figure 7, our sample of public bonds experienced a slightly lower incidence of default, at every horizon, than the overall HY index.

These two characteristics of our dataset – low OAS and low default rates compared to the index – are consistent with each other. The part of the index excluded from our dataset consists of bonds from private issuers. It makes sense that these carry greater risk, default more frequently, and as a result trade at wider spreads. In fact, this was the conclusion of a dedicated study carried out by Ben Dor and Xu (2015) on public vs. private bonds[6]. This study investigated why private bonds, which seem to steadily trade at a spread premium to public bonds, have not generated greater returns – and the answer was that they experience higher rates of default.

FIGURE 7

Comparison of Realized Forward Default Rates in Data Sample vs. HY Index



Source: Bloomberg Barclays Indices, Barclays Research

Defining and Detecting Default

The determination of exactly when a default event has occurred is not trivial; in fact, a number of different implementations are available. We have chosen to work with a definition based on information available from within the Bloomberg Barclays HY Index database. The index labels each bond with an Index Rating, based on an algorithm that combines ratings from Moody's, S&P, and Fitch[7]. Whenever Index Rating is changed to D (typically because one or more of the rating agencies changed their rating to D), we assume that a default has occurred. However, this rating-tracking process is not sufficient for determining default status in all cases. Sometimes, even without an official change of rating to D, a bond is marked as Trading to Default; in most cases, it is subsequently dropped from the index.[8] This implies that market participants are assuming that a default is imminent, even though it has not yet been confirmed by a ratings change announcement. This could correspond to cases in which a default is announced on a bond whose ratings have previously been withdrawn, so that it now appears in the index as NR. We have also observed in some cases that a bond was marked as Trading to Default when an issuer failed to make a coupon payment to bondholders, even though they would technically not be in default until the expiration of a grace period 30 days later. For the purposes of our study, we consider a default event to have taken place either when Index Rating is set to D or a bond is marked as Trading to Default.

[6] Ben Dor, A. and J. Xu, *An Empirical Analysis of the Difference between Public and Private Issuers of High Yield Bonds*, Barclays Research, March 25, 2015.

[7] The precise methodology used to compute index ratings have changed over time; we use the Index Rating that was reported at a given point in time based on the method then in effect.

[8] In the early days of the High Yield Index, defaulted bonds remained eligible for index inclusion. The rules were change to exclude defaulted bonds from the index as of June 30, 2000.

The Default Prediction Model

Modelling Framework

There is extensive literature on modelling default risk; this is not the place for a complete review[9]. Generally, such models are divided into two camps: structural models and reduced-form models.

Structural models, based on original work by Black and Scholes (1973) and Merton (1974), attempt to directly model the finances of a firm. Very simply, the firm's debt is considered fixed, while the value of its assets is volatile. Default is assumed to occur if and when the value of the assets dips below that of the outstanding debt. Structural models, based on some simplifying assumptions about the structure of the debt and how asset values may change, estimate the probability of this occurrence. Key inputs to such models include the leverage of a firm (debt to equity ratio), which determines how far the firm currently is from the default boundary, and the equity volatility, which is used to compute the asset volatility. There have been many extensions and commercial implementations of Merton's model. These include Barclays' CDP, Moody's KMV, JP Morgan's CreditMetrics, and Bloomberg's DRSK. While each of these models differ slightly in their implementation and adjustments, they are all essentially structural models with a Merton backbone.

Reduced-form models, pioneered by Jarrow and Turnbull (1995), do not attempt to model the structure of the firm or the process of default. Rather, they attempt to directly estimate the probability of default from traded instruments. A particularly successful implementation of a reduced-form model is the Kamakura Default Model.

We use a hybrid modelling approach that shares characteristics with each of the above categories. We directly estimate the probability of default based on a diverse set of explanatory variables, including – but not limited to – the same data that underpin structural models. However, unlike those models, we do not impose the specific functional form of the Merton model. Our model also includes bond spreads, making it more similar to reduced-form models, which estimate hazard rates (instantaneous default probabilities). We use logistic regression to calibrate our model to a historical dataset of observations of company attributes and subsequent default experience. One advantage of our default classification approach is its flexibility. Any variable that provides additional information – including either the inputs or the outputs of a structural model – can be included in the process. While our model is parsimonious in that it relies on only a few factors, it is able to successfully predict default at our selected six-month horizon.

Predictors of Default

In this section we motivate our model by studying the dependence of realized default rates on certain variables or transformations of variables. These variables include:

- OAS
- Equity Volatility
- Short Term Debt
- Equity Momentum
- VIX

[9] A brief and readable overview of the topic, with references, can be found in van Deventer, D.R., "An Introduction to Credit Risk Models", in Encyclopedia of Financial Models, Vol. 1, F. J. Fabozzi, ed., Wiley, 2013, pp. 299-311.

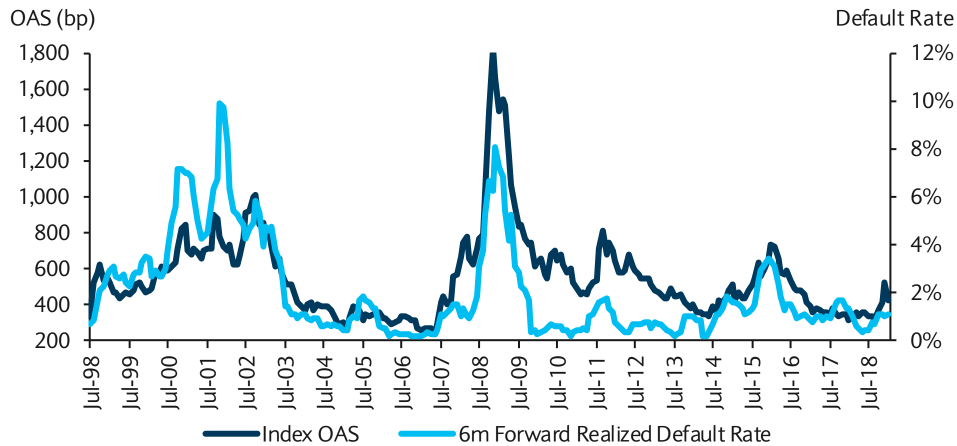
For each variable we plot and explain the causal relationship between the signal and subsequently realized default rates.

Option Adjusted Spread

The option-adjusted spread (OAS) of a defaultable bond is a measure of the premium over a comparable Treasury bond that an investor receives for assuming the extra credit risk. Therefore, on a security level, larger OAS should imply a larger default probability. Empirically however, this is not always the case. OAS is the net result of many different market effects; treating the full OAS as compensation for default risk may substantially over-estimate the inherent credit risk. For instance, Figure 8 shows that the index OAS was much larger during the 2008/9 financial crisis than during the 2000/1 crisis even though default rates were comparable – or even higher in 2001. Indeed, several studies have attempted to quantify how much of the OAS is attributable to credit risk versus other premiums such as liquidity or recovery risk (see for instance Dastidar & Phelps, 2010*)*.

FIGURE 8

Co-movement of OAS and 6M Realized Forward Default Rate of the Sample Dataset



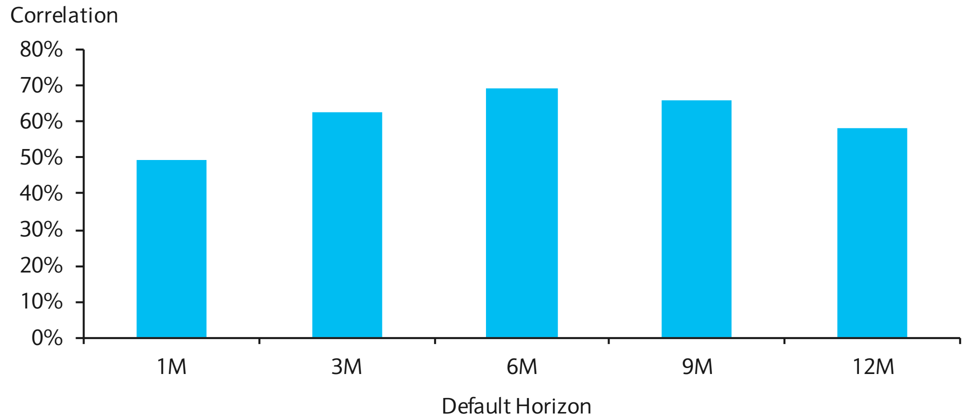
Note: For each month, we plot the HY Index OAS against the default rate realized in the subsequent six months
Source: Bloomberg Barclays Indices, Barclays Research

Nevertheless, OAS is a good predictor of default in that, on average – either temporally or cross-sectionally – larger OAS typically means a larger default probability. So while Figure 8 shows some time-variation in the relationship between OAS and default rates, there is still a clear indication of co-movement between the two quantities.

Figure 9 shows the correlation between sample OAS and the subsequently realized default rates for different time horizons. The correlation between OAS and default rates over the next six months is nearly 70%. This is slightly higher than at other horizons, but the correlation is strong at all horizons considered.

FIGURE 9

Correlation Between HY Index OAS and Realized Forward Default Rates



Source: Bloomberg Barclays Indices, Barclays Research

Beyond the systematic dependence of market-wide default rates on index-level OAS, there is a clear cross-sectional dependence as well. Bonds with higher spreads have greater rates of subsequent default. Figure 10 shows how the realized default rate for our sample depends on OAS.

This figure, as well as similar figures to follow in this section, was produced as follows:

i. Aggregate all bonds in the data sample.

ii. Sort the dataset by the value of the signal (in this case OAS) in ascending order.

iii. Group the dataset into 10 equal-count buckets by signal value.

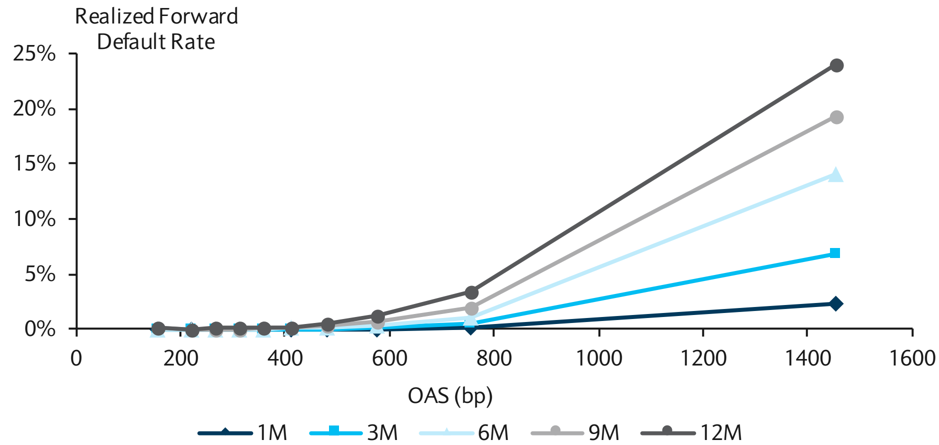
iv. Within each bucket, calculate the median of the signal, as well as the percentage of bonds in the bucket that default at horizons of 1, 3, 6, 9 and 12 months forward from the signal observation date.

v. Plot the realized default rates as a function of the median signal value.

We see that there is a marked increase in default rate for the top decile for all time horizons considered. For instance, while the median OAS for the 10th decile was roughly double that of the 9th decile (1456bp and 755bp respectively), the 6M default rate was roughly 14 times larger (14.02% and 1.01% respectively).

FIGURE 10

Realized Forward Default Rates by OAS Decile



Source: Bloomberg Barclays Indices, Barclays Research

Normalizing the OAS Signal

The decile plot shown in Figure 10, as described above, was produced using a pooled approach, in which a single ranking by OAS was carried out across observations of all index bonds from all time periods. However, as shown in Figure 8, the market environment changed drastically over time; this makes it problematic to compare bond spreads from different time periods. For instance, consider the following two hypothetical cases:

- a bond with OAS of 1000bp on November 30, 2008, when the average OAS of our sample was 1650bp
- a bond with OAS of 1000bp on May 31, 2007, when the average OAS of the sample was only 214bp

These two bonds would have the same ranking and thus be put into the same decile, even though they represent very different cases. The first is a better-than-average bond in a crisis period, while the second is a worse-than-average bond in a benign environment. In the pure OAS-based ranking shown in Figure 10, it is safe to assume that the 10th decile is dominated by observations from late 2008 and early 2009.

To neutralize the systematic market component of the bonds OAS and focus on the bond-specific idiosyncratic component, we normalize the bond OAS by representing it as a deviation from the cross-sectional average OAS for the sample month by first subtracting by the cross-sectional weighted average OAS of the index, and then dividing by the same quantity:

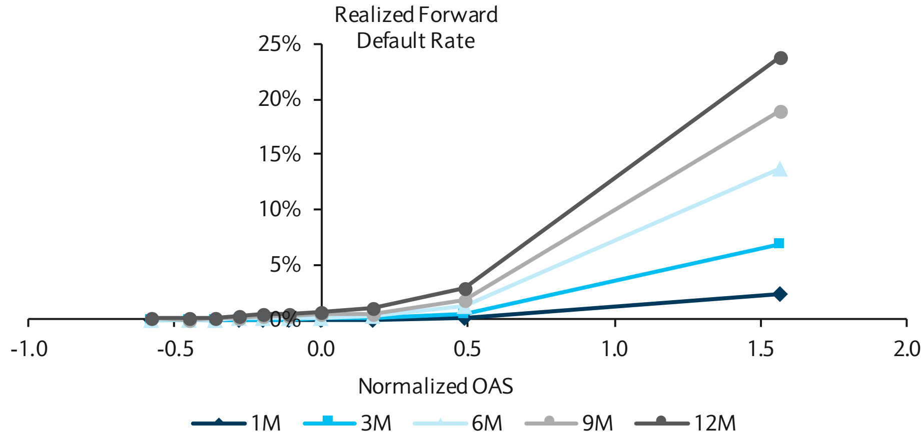
$$Normalized\ \ OAS_t^i = \frac{OAS_t^i - Avg\ \ OAS_t}{Avg\ \ OAS_t}$$

This normalization does not change the ranking within each month, but does change the ranking within the whole sample (and the magnitude of the OAS effect vs. other effects cross-sectionally). For example, returning to the example of the two bonds above, the first bond has a normalized OAS of -0.39 while the second has a normalized OAS of 3.67. Hence, when taking the market environment into account, the two bonds have very different rankings, and thus belong to different deciles.

Figure 11 shows the realized default rate for different time horizons as a function of normalized OAS.

FIGURE 11

Realized Forward Default Rates by Deciles of Normalized OAS



Source: Bloomberg Barclays Indices, Barclays Research

In our default model we will use the normalized variable since it isolates the idiosyncratic risk of the bond over different market environments. We introduce a separate signal to represent the market environment, namely VIX.

Equity Volatility

There is a strong theoretical underpinning to the idea that equity volatility is associated with default probability[10]. In fact, equity volatility is one of the key inputs to structural models of default, as high volatility implies a high probability of a steep drop in the value of a company's assets. This increases the probability that the equity value may fall to zero, an event that can be equated with default. At a given point in time, we estimate the (forward-looking) equity volatility of a given issuer by measuring its daily total return volatility over the trailing one month. Just as in the case of OAS, however, systematic effects can cause equity volatilities for all stocks to spike in times of crisis. We therefore again isolate the idiosyncratic component of volatility by considering the historical equity return volatility normalized by the median equity return volatility of all issuers in the sample over the same period:

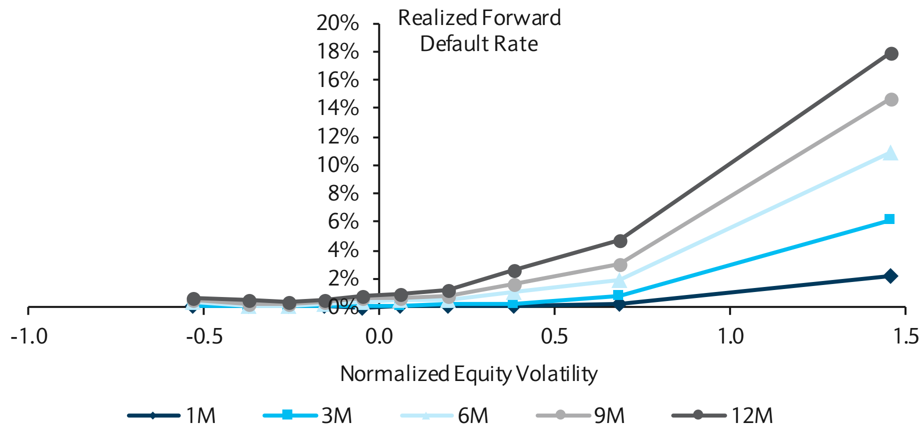
$$Normalized\ \ Equity\ \ Vol_t^i = \frac{Equity\ \ Vol_t^i - Median\ \ Equity\ \ Vol_t}{Median\ \ Equity\ \ Vol_t}$$

Figure 12 shows the dependence of realized default rate on normalized equity volatility. Again the plots show an almost monotonic relationship, with a marked increase in default rates in the 10th decile.

[10] Equity volatility is one of the key inputs to the model of Merton (1974), which models default as the probability that the value of a firm's assets falls below that of its outstanding liabilities. The Distance to Default in that approach is calculated by measuring how much a firm's asset value would need to drop to cross the threshold, and dividing that by the (unobservable) asset volatility, which is derived from the equity volatility. The net result is that increasing the estimate of equity volatility should result in an increased likelihood of default.

FIGURE 12

Realized Forward Default Rates by Deciles of Normalized Equity Volatility



Source: Bloomberg Barclays Indices, Barclays Research

We can understand the dependence of forward default probabilities on equity volatility several ways. One way is to equate the probability that a firm will default with the probability that the equity value becomes zero at some point in the future. That probability is due to the expected equity return as well as the equity return volatility. The larger the volatility, the larger the probability that the equity value can become zero.

Short-Term Leverage

Another strong predictor of default is short-term leverage (STL), which we define as the total debt due within the next 12 months relative to the total value of the firm's assets, i.e.

$$STL = \frac{Total\ \ Debt\ \ Due\ \ within\ \ 1Y}{Total\ \ Assets}$$

We calculate the total debt due with one year in two different ways: using the amount of short-term liabilities as reported by Compustat for the issuing corporation, and by taking the sum of the amounts outstanding of all bonds in our database with maturity dates within the following 12 months. We then take the larger of these two numbers as the total short term debt; a similar approach is used to estimate the total long term debt[11]. We add the total debt calculated in this way to the equity market value to arrive at an estimate of total assets for the denominator of our short-term leverage ratio[12].

A firm with a large amount of debt due in the near term relative to assets could find it difficult to either make the maturity payment or arrange refinancing. Indeed, Figure 13 shows a strong relationship between default rates and short-term leverage ratio, with 6.2% of bonds in the 10th decile experiencing default within 6M. This relationship is not monotonic; for healthy companies that are able to easily refinance, an upcoming bond maturity is a much less threatening signal. Only in the top decile by short term leverage do we see a decisive increase

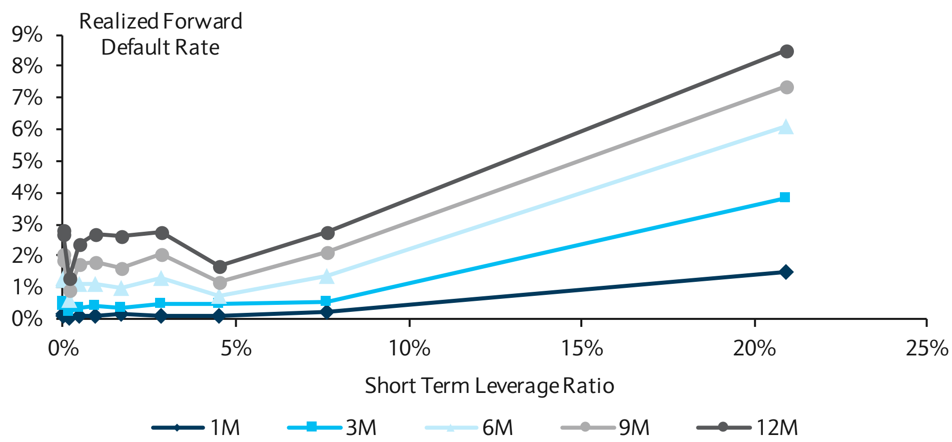
[11] Bond index data does not reflect all of a company's liabilities: bank loans and many other types of obligations will not be included. Therefore, the reported total liabilities from accounting data, both short-term and long-term, are usually – but not always – larger than the total face value of outstanding bonds. However, given that accounting data are updated only quarterly, and available only after some delay, the calculations of total debt based on index data can sometimes be quicker to reflect a new bond issuance or the approaching maturity of an outstanding bond.

[12] The leverage ratio of debt to assets is a key input to the Merton model. However, in its original form, the Merton model abstracts the debt of a firm to a single maturity date, thus requiring adjustments to match the more complex term structure of a firm's actual liabilities. Commercial implementations of the Merton model typically use a blend of short-term and long-term liabilities to calculate leverage. For instance, in Moody's KMV the default point is set to be short-term debt plus half of long-term debt. Our model relies solely on short-term debt (and thus short-term leverage) since we aim at forecasting default on a shorter time horizon.

in realized default rates. The median value of the short-term leverage ratio also jumps significantly, from 8% in decile 9 to 21% in decile 10.

FIGURE 13

Realized Forward Default Rates by Deciles of Short Term Leverage Ratio



Source: Bloomberg Barclays Indices, Barclays Research

A Note on Financials

Default models that use balance sheet signals typically have a separate model for financials since leverage ratios for financials are typically much higher than would be expected for their default probability compared to other sectors. However, we found that within our dataset, the statistics of the short-term leverage signal used in our model were relatively consistent across financials and non-financials. Therefore, bonds of financial companies are included in our model.

Equity Momentum

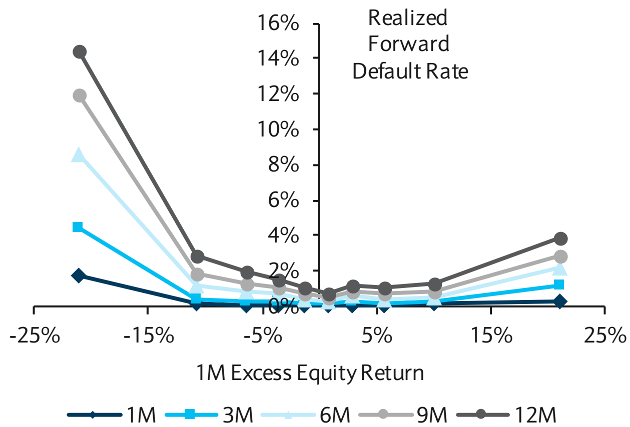
As mentioned in the “Equity Volatility” section, the probability of default can be seen as the probability that equity value will be zero at some time in the future. Market experience has shown that equity markets exhibit momentum – that is, they have a tendency to follow a trending pattern in which a stock’s past return is positively correlated with its future return. Thus, the more negative the trailing equity return, the more probable the equity value may be zero in the future and the greater the probability of default.

Once again, we attempt to isolate the issuer-specific part of the signal, to make sure that an equity market downturn does not result in a strong indication of default for all issuers. In this case, though, we do not rescale the returns, we simply remove the average return of the SP500 index from the equity return of each issuer. Thus, we define the normalized equity return as

$$6M\ \ Equity\ \ Momentum_t^i = Ret6M_t^i - Ret6M_t^{SPX}$$

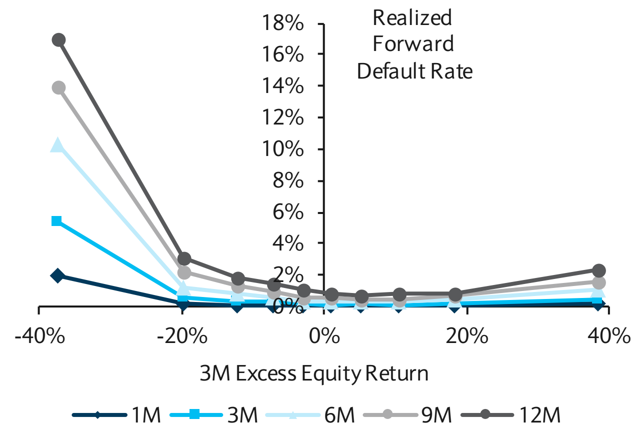
Clearly, a large recent drop in a company’s market value, especially in the absence of a market-wide crash, is a clear sign of danger. However, it is less obvious what the best time frame is for this look-back. Might we be better off using a shorter horizon? Figure 14 and Figure 15 examine alternative definitions based on equity returns over the past one month and three months, respectively. The “U” shape that appears in these charts shows that realized forward default rates do not depend monotonically on past 1M and 3M. While default rates are highest, as expected, in the decile with the most negative returns, we also see

FIGURE 14
Default Rates by Deciles of 1M Equity Momentum



Source: Bloomberg Barclays Indices, Compustat, Barclays Research

FIGURE 15
Default Rates by Deciles of 3M Equity Momentum

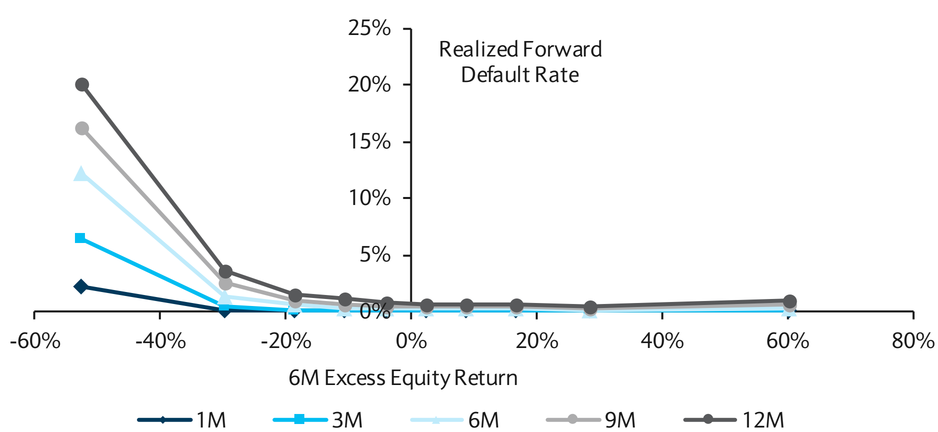


Source: Bloomberg Barclays Indices, Compustat, Barclays Research

elevated default rates for the top decile of returns. This is likely due to a short-term price rebound in stocks that have previously suffered large losses[13].

This is in contrast with the 6M time frame shown in Figure 16, which shows a consistent increase in default rates as returns decrease. This increase is not linear, with default rates spiking for the bottom decile of returns. For this study, we have chosen to use the 6-month horizon to define our equity momentum variable, since the dependence of forward default rates on momentum is closest to monotonic in Figure 16[14].

FIGURE 16
Realized Forward Default Rates as a Function of Past 6M Equity Momentum



Source: Bloomberg Barclays Indices, Compustat, Barclays Research

[13] This phenomenon is well-known in studies of equity momentum. This is the reason that the typical signal used in equity momentum strategies is based on a 12-month lookback that excludes the most recent month's return.

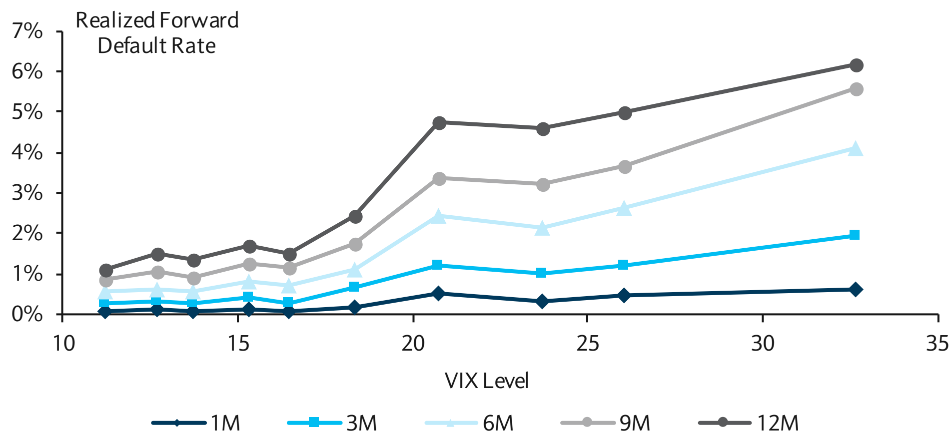
[14] Our group maintains a cross-asset momentum strategy that uses past equity momentum to project subsequent returns of corporate bonds. In that work, the equity momentum signal is formed using an average of signals at three different horizons – one, three and six months. For details, see Polbennikov, S. and A. Desclée, *Equity Momentum in Credit (EMC)*, Barclays Research, 18 August 2017. For the current study, with default prediction as the goal, we have decided to look for a sustained drop in a company's value over time, and hence use the pure six-month signal.

VIX

While the previous default predictors have all been at the issue level and carefully constructed to contain only idiosyncratic risk, VIX is a systemic risk factor which signals the general market condition. Figure 17 shows that forward default rates generally increase as VIX increases.

FIGURE 17

Realized Forward Default Rates as a Function of VIX Level



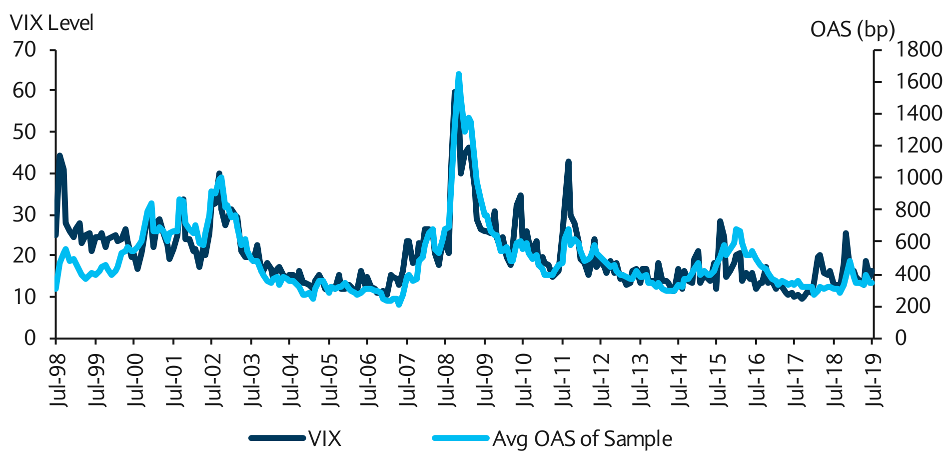
Source: Bloomberg Barclays Indices, Barclays Research

Correlations Among Signals

As discussed in the previous sections, one of our motivations for transforming the raw variables into normalized signals is to isolate the idiosyncratic component by subtracting the systemic component. This leads to signals that are much less correlated to each other, while still maintaining high correlation with the default signal. This is important as it allows us to more cleanly attribute incremental predictive power to each signal.

FIGURE 18

VIX and OAS of Sample are Highly Correlated



Source: Barclays Research

For instance, Figure 18 shows that VIX has a correlation of over 80% to the average OAS of the sample. Once we normalize the OAS, this relationship disappears, and the correlation between the two is near zero. The same pattern holds true with respect to correlation between the systematic VIX level and the other normalized or re-centered variables.

We also test for correlation among the four normalized variables in our model. We measure the cross-sectional correlations among these four variables each month. Figure 19 shows the time average for each of these correlations over the study period. We find, understandably, that some of our signals do seem to be related to each other: the companies with the highest OAS tend to be those with the greatest recent equity volatility (correlation 0.38) and the most negative past equity returns (correlation -0.22). We exclude the VIX because in each single-month calculation of correlations, the VIX observation is the same across all companies, and therefore its correlation with all of the other variables is zero by definition.

FIGURE 19

Correlations Among Signals

	Normalized OAS	Normalized Equity Volatility	Short Term Leverage Ratio	Equity 6M Momentum
Normalized OAS	1.00	0.38	0.13	-0.22
Normalized Equity Volatility	0.38	1.00	0.13	-0.13
Short Term Leverage Ratio	0.13	0.13	1.00	-0.07
Equity 6M Momentum	-0.22	-0.13	-0.07	1.00

Source: Barclays Research

Additional Signals

There is no question that there are other possible signals that we could have used in our model, either instead of or in addition to the selected five. Indeed, in the initial variable selection stage of this research we investigated quite a few others. These included traditional balance sheet metrics such as debt-to-equity, EBITDA to Assets, and relative changes in EBITDA. We found that over the relatively short time horizon considered here, many of the balance sheet variables have little predictive power. For instance, a company can have negative EBITDA for a long time before being insolvent. We chose to exclude other variables that do have a strong relationship with realized six-month default rates since they contain similar information as other variables in the model. For instance, there is a strong dependence between bond price and probability of default. Nevertheless, the model does not include it since the information from bond price is very similar to that contained in OAS. We sought to build a parsimonious model, and therefore included a variable in the model only if it was found to add incremental predictive power. Indeed, even the variables we selected can be highly correlated in their raw form, due to mutual dependence on underlying market conditions. We have mitigated this issue by decomposing the variables into a systematic and idiosyncratic component, keeping only the idiosyncratic information for most of the variables, and leaving just a single variable to capture the systematic variation in default rates.

The key criteria used in the variable selection stage was success at predicting default on the selected six-month horizon. Were we to look at default probabilities on a longer horizon, it is very likely that other variables would play a larger role. It is important to emphasize that variable selection and model construction were completed before we started the final stage of portfolio construction and strategy performance measurement.

The QPS Default Model

We have identified a number of variables that are positively associated with the rate of subsequent defaults. We now combine these variables into a single model for default probability.

The five variables included in our model are: VIX, Normalized OAS, Normalized Equity Volatility, Short-Term Leverage, and six-month Equity Momentum. We denote these factors as x_1 through x_5, and represent the combination of all factors for a given observation as a vector $\boldsymbol{x}$. To express the idea that each of these factors has an effect on the probability of subsequent default, we assume that the log-odds of default within six months takes the form of a linear function $f(\boldsymbol{x})$ of our variables,

$$f(\boldsymbol{x}) = \beta_0 + \sum_{i=1}^{5} \beta_i x_i$$

If default will occur with a probability p, then the odds of default are given by $p\ /\ (1-p)$, and the log-odds is the logarithm of the odds. Thus, while probabilities range from 0 to 1, the odds of an event occurring range from 0 to infinity (but must be positive), while the logarithm of the odds can take any value – from strongly negative for p near zero, to strongly positive for p near one, and taking a value of zero for the even-odds case of $p = \frac{1}{2}$. It can easily be shown that the event probability p can be obtained from the log-odds by way of the logistic function (from which logistic regression derives its name):

$$p(\boldsymbol{x}) = \frac{e^{f(x)}}{1 + e^{f(x)}}$$

This set of assumptions gives a simple way to map any set of variables into an estimate of default probability. The logistic function maps the linear function of our variables, $f(\boldsymbol{x})$, to a probability value between 0 and 1. What remains is to estimate the values of the coefficients β_i to our linear function $f(\boldsymbol{x})$. The mathematical framework used for this task is logistic regression.

Logistic Regression

Standard linear regression models are not applicable to the estimation of default probabilities because the correct answer is never really known, even after the fact. Were we to build a model to predict next month's return based on current characteristics, we could use linear regression based on a data sample of observations of beginning-of-month characteristics and subsequent monthly returns. The regression procedure would then find the parameters for which the model's predictions are closest to the realized returns. In our case, however, we are trying to estimate the probability that a bond will default within six months. This probability is never observed for an individual bond; after six months have passed, all we can see is whether or not the bond defaulted in the interim. However, a non-default event does not mean that the default probability was 0, and a default event does not mean that the probability was 1. In this type of problem, guidance about the correct value for the probability cannot be gleaned from a single event, but by the variations in realized frequencies of default among different groups of observations. For example, in observations with higher levels of OAS or equity volatility, realized default rates are higher. Logistic regression uses a maximum likelihood procedure to find the dependence of default probability on each of the input parameters. With the equations defined above, once we assign values to the parameters β_i, we can calculate the ex-ante probability of default, according to the model, for any observation. By looking at a large collection of observations, calculating the probabilities of default for each one, and observing what happened, we can form an estimate of the likelihood of this set of outcomes. The logistic regression procedure finds the model parameters that maximize the likelihood score of the actual set of outcomes.

Model Performance at Predicting Default

One way of looking at model performance is to view default prediction as a classification task. In this paradigm, the model is presented with the set of available bonds, and must categorize them into two groups: those expected to default within the specified time-horizon and those expected to survive. Once the horizon has passed (e.g. once six months have elapsed), the correct answers are known – each of those bonds has either defaulted or not. In a supervised machine-learning approach such as logistic regression, the model is trained using past observations consisting of the input variables (observable as of the time of classification) and the eventual result. The model may use a non-linear scoring function to indicate the likelihood of being in one class or the other, and the binary classification is then carried out using a threshold. Logistic regression is one such model, in which the logistic function is used as the nonlinear transformation.

The Confusion Matrix

When building such models, the data sample is typically divided into two pieces: a training set and a testing set. The model parameters are fitted to the observations in the training set, and then model performance is measured on the testing set. For a binary classification task, such as whether a bond will default or not, the performance of the model on the testing set can be summarized by a 2x2 matrix, known as a "confusion matrix". The rows of the confusion matrix represent the two possible model predictions, while the columns represent the two possible horizon outcomes. As shown in Figure 20, the matrix tallies the counts of each combination of predictions and outcomes. TP (True Positive) denotes the accurate prediction of default, TN (True Negative) denotes the accurate prediction of survival, FN (False Negative) denotes an inaccurate prediction of survival, and FP denotes an innacurate prediction of default. In our presentation of confusion matrices, we highlight the accuracy of predictions by color-coding correct predictions in green and incorrect predictions in red. Hence we want a model that maximizes the numbers in green and minimizes the numbers in red.

FIGURE 20

Structure of the Confusion Matrix

	Realized Survival	Realized Default
Predicted Survival	TN	FN
Predicted Default	FP	TP
Totals	N	P

Source: Barclays Research

Out-of-sample performance is typically measured by ratios of these event counts experienced on the test dataset. Figure 21 presents some of these quantities. The simplest approach to performance is to compute the Accuracy Ratio (AR), the total percentage of correct predictions. However, the Accuracy Ratio may not be the best measure of performance for two reasons. First, our dataset is very unbalanced. The number of realized default events (positives) is much smaller than the number of observations in which the bond survives (N). Second, the Accuracy Ratio does not distinguish between the two types of errors, false positives and false negatives. Yet, one type of error may have much more severe consequences than the other. In missile detection, for example, a Type I error, or false positive, may result in an inconvenience, while a Type II error, or false negative, could result in a missile striking its target without a warning. Similarly, for a HY portfolio manager using default prediction as a screening tool, the cost of a false positive (survival of a bond predicted to default) is largely an opportunity cost (the additional carry one could have earned by buying the bond), while the cost of a false negative (default of a bond predicted to survive) could be a large portfolio write-down[15].

[15] The determination of the relative cost of different error types depends on how the model will be used. This example assumes that the screen is being used to select bonds in a long-only portfolio. If a hedge fund is using the model to establish short positions in bonds expected to default, a very different cost assignment might be relevant.

FIGURE 21

Quantities for Measuring Classifier Performance

Quantity	Description	Formula
P	Total Positives	$P = TP + FN$
N	Total Negatives	$N = TN + FP$
T	Total Observations	$T = P + N = TP + FN + TN + FP$
TPR	True Positive Rate	$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$
TNR	True Negative Rate	$TNR = \frac{TN}{TN + FP}$
FPR	False Positive Rate	$FPR = 1 - TNR = \frac{TP}{N}$
FNR	False Negative Rate	$FNR = 1 - TPR = \frac{FN}{P}$
AR	Accuracy Ratio	$AR = \frac{TP + TN}{T}$
BM	Bookmaker Informedness	$BM = TPR + TNR - 1$

Source: Barclays Research

To illustrate how the Accuracy Ratio can provide a misleading measure of performance on unbalanced datasets such at the one we are considering, consider the two hypothetical models in Figure 22.

FIGURE 22

Confusion Matrices for Two Hypothetical Models

Model A			Model B		
	Realized Survivals	Realized Defaults		Realized Survivals	Realized Defaults
Predicted Survivals	990	10	Predicted Survivals	900	1
Predicted Defaults	0	0	Predicted Defaults	90	9

Source: Barclays Research

In this example, default is a rare event, occurring in just 1% of observations. Model A is therefore able to achieve an Accuracy Ratio of 99% by simply predicting that no bond ever defaults. However, what this means is that while it correctly predicts 100% of the cases in which the bond survives, it is correct in 0% of the cases in which a bond defaults! Model B takes a more discriminating approach, and is able to correctly classify 91% of the survivals and 90% of the defaults. Intuitively, Model B seems to be a better classifier; yet its Accuracy Ratio is only 90.9%, substantially lower than that of Model A.

In this unbalanced sample, the AR, based on simple counts of all correct events, is not affected much by the incorrect prediction of all defaults, because they are rare events. Model B, in contrast, does a reasonably good job at predicting both defaults and survivals in terms of percentage of each accurately predicted; but since there are so few defaults, the AR is affected by the relatively large number of incorrect predictions of survival. Hence if using the Accuracy Ratio to measure model performance, we would rate the performance of Model A better than that of Model B, even though intuitively we may feel that that the performance of Model B is closer to what we are looking for.

To overcome this bias, other performance measures have been proposed for evaluating the results of a binary classification. Informedness, or Bookmaker Informedness (BM), first looks separately at the success of the model at classifying each type of event (TPR and TNR), and then gives equal weight to these two results in the overall measure. In this measure, a model based on random guessing, or indiscriminately applying a fixed rule as in Model A, should be shown to add no information. Indeed, Model A shows up as having 0 informedness, while Model B, which has relatively high success rates at correctly predicting both surviving and defaulting bonds, displays an informedness of 80.9%. Figure 23 compares the classification accuracy of Model A and Model B by these various metrics.

FIGURE 23

Performance Metrics for our Two Hypothetical Models

	Accuracy (AR)	True Negative Rate (TNR)	True Positive Rate (TPR)	Informedness (BM)
Model A	99.0%	100.0%	0.0%	0.0%
Model B	90.9%	90.9%	90.0%	80.9%

Source: Barclays Research

One more thing to consider about these models is the total number of predicted and realized defaults. The total number of default events in our sample was 10; yet Model A predicted 0 defaults and Model B predicted 99 defaults. Another metric that reflects this aspect of the problem is precision, the ratio of true positives to total predicted positives, $Precision = TP/(TP + FP)$. For Model A, with no predicted positives, this quantity is undefined; for Model B, the precision of the default prediction is just 9/99, or 9.1%.

The mathematical procedure for logistic regression uses a maximum likelihood approach[16]. Once a set of model parameters are specified, the model provides a function that estimates the default probability based on bond characteristics. To see how well such a function fits the data, we construct a scoring function based on the known outcomes for the training dataset. For each default (survival) event, higher (lower) projected default probabilities result in higher scores. These scores are aggregated across all observations to provide an overall score for a given candidate set of model parameters. The higher the overall likelihood score, the more likely it is that the observed data could have been generated at random from the modelled set of probabilities. The fitting procedure finds the parameter set with the maximum likelihood. However, like the simple Accuracy measure, the standard fitting procedure gives equal weight to each event. Thus, in an unbalanced data sample, the results may not give sufficient weight to the rare events – the defaults that are the focus of our study. To remedy this, it is possible to specify weights to the procedure, rewarding the correct classification of a default event by more than a correct classification of a survival event. To help prevent a bias towards the survival events which dominate the data sample, we can instruct the model to give default events a greater weight than survival events by a factor w.

Model Performance at Default Detection (Classification)

We now examine the performance of our five-factor default model in terms of its ability to correctly classify bonds into those that will default within 6 months and those that will survive. For the purposes of this section, we divide our dataset into two pieces: a training set used to fit the model parameters, and a testing set used to measure model performance. We trained the model on bond observations from July 1998 through December 2010 (including knowledge of the subsequent 6-month default experience, which would be known by June 2011), and we measured performance using data from June 2011 through January 2019. Figure 24 presents the out-of-sample confusion matrices and associated statistics for four different classifiers based on our model. Panel A uses the model in its vanilla form: the model

[16] The mathematical details of the maximum likelihood estimation used in logistic regression are provided in the Appendix, for both the unweighted and weighted cases.

is estimated with a weight ratio of 1 (with equal weight to all observations), and the classification of the bonds into "default" and "survive" categories is carried out using a threshold default probability of 50%. If it is more than 50% likely to default, we predict default; below 50% we predict survival[17]. The problem here is that very few observations have default probabilities of 50% or above, so this approach, if unweighted, will tend to mark almost all observations as "survive". The results show that while correctly classifying 99.8% of the surviving bonds, it flagged less than 50% of the default events.

As described above, one way to control the sensitivity of the model is to increase the weight given to default observations as we fit the model to the training dataset. As we push the weight ratio higher, we increase the probabilities produced by the model, and our 50% threshold is able to detect more and more of the defaults. To illustrate this, Panel B uses a weight ratio of 50. However, the downside is that as we do this, we produce more and more false positives. This approach achieves a much more balanced performance, accurately predicting over 96% of the default events. Of the 820 observations in our test sample that correspond to default events, we now correctly predict default for 771 of them, up from 389 in Panel A. The trade-off is an increase in the number of false alarms – bonds flagged as defaults that subsequently survive; but the balancing of the error rates in the two directions increases the Informedness measure to over 90%.

FIGURE 24

Confusion Matrices and Classification Statistics for Different Parameter Settings

Panel A: Full Model, Weight = 1, PD Threshold = 50%					
	Realized Survivals	**Realized Defaults**	**True Negative Rate (TNR)**	**True Positive Rate (TPR)**	**Informedness (BM)**
Predicted Survivals	99,718	411	99.8%	48.6%	48.4%
Predicted Defaults	208	389			
Panel B: Full Model, Weight = 50, PD Threshold = 50%					
	Realized Survivals	**Realized Defaults**	**True Negative Rate (TNR)**	**True Positive Rate (TPR)**	**Informedness (BM)**
Predicted Survivals	94,308	29	94.4%	96.4%	90.8%
Predicted Defaults	5,618	771			
Panel C: Full Model, Weight = 1, PD Threshold = 2%					
	Realized Survivals	**Realized Defaults**	**True Negative Rate (TNR)**	**True Positive Rate (TPR)**	**Informedness (BM)**
Predicted Survivals	93,977	45	94.0%	94.4%	88.4%
Predicted Defaults	5,949	755			
Panel D: 2-Factor Model Based only on OAS and VIX, Weight = 1, PD Threshold = 2%					
	Realized Survivals	**Realized Defaults**	**True Negative Rate (TNR)**	**True Positive Rate (TPR)**	**Informedness (BM)**
Predicted Survivals	95,394	33	95.5%	95.9%	91.3%
Predicted Defaults	4,532	767			

Source: Barclays Research

[17] Using 50% as the cutoff level is the standard approach used in machine learning for classification tasks. The advantage is that the 50% mark is at the steepest part of the logistic function, which then forms the cleanest break into two categories.

Panel C in Figure 24 illustrates a different way of arriving at a similar result. Here, instead of raising the weight ratio used to train the model (which can severely distort the estimated default probabilities), we keep the weight at 1 and instead change the threshold at which we flag a bond as a default risk. Instead of requiring a default probability of 50% or higher in order to flag a default, we can lower the threshold, flagging more bonds as being at risk of default. Similarly to when we adjusted the weight ratio, lowering this threshold increases our True Positive Rate while lowering the True Negative Rate. In Panel C, using a weight ratio of 1 and a default probability threshold of 2% or more to classify a bond as a likely default, we obtain results roughly similar to those in Panel B, with both TPR and TNR at 94% or better, and Informedness close to 90%.

For the pure classification task illustrated here, the approach taken in Panel B seems to provide slightly better performance. However, the introduction of the weight ratio biases the estimation procedure such that the model systematically over-estimates default probability. Furthermore, when we proceed to portfolio construction, we will see that projections of probability of default can be used in different ways to help improve portfolio performance; there is not necessarily a need to set an explicit threshold on default probabilities or to declare that a bond will or will not default. What we have established here is that for any choice of weight ratio, there is still the ability to control sensitivity by adjusting the threshold. This allows us to choose a weight ratio setting that gives us a reasonable estimate of default probability.

Does the inclusion of equity-related factors improve our ability to identify default events in advance? Perhaps not. In Panel D, we report the results obtained using just 2 of our 5 factors, the Normalized OAS to represent the cross-sectional component and VIX to represent systematic risk. Using this model with the same 2% threshold as used for the full 5-factor model in Panel C, we find that at this pure classification task, the OAS-based model achieves performance as good as, or even better than, the full 5-factor model. However, all of the default risk that is reflected in OAS has already priced in by the market. As a result, as we shall see in the next section, the usefulness of this model in portfolio construction is rather limited.

Fully Out-of-Sample Projection of Default Probabilities

In the above analysis, we used a single division of the dataset into a training set and a testing set. The model was fitted just once to the data in the testing set, and the resulting parameters were used on the entire testing set. This is a typical setup for model exploration, and indeed we used this approach to compare different possible combinations of variables. However, this does not really correspond to how a model would be implemented in practice. If used in real life, to estimate forward-looking default probabilities as of a given point in time, we would want to fit our model to all data available as of that time. Therefore, for the remaining analysis in this article, we use a growing window procedure in which the model fit is revisited each month using all data available up to that point[18]. This model is then used to compute default probabilities for the coming six months, which can then be evaluated against subsequently realized defaults or used in backtests of portfolio construction strategies.

Model Performance as an Estimator of Default Probability

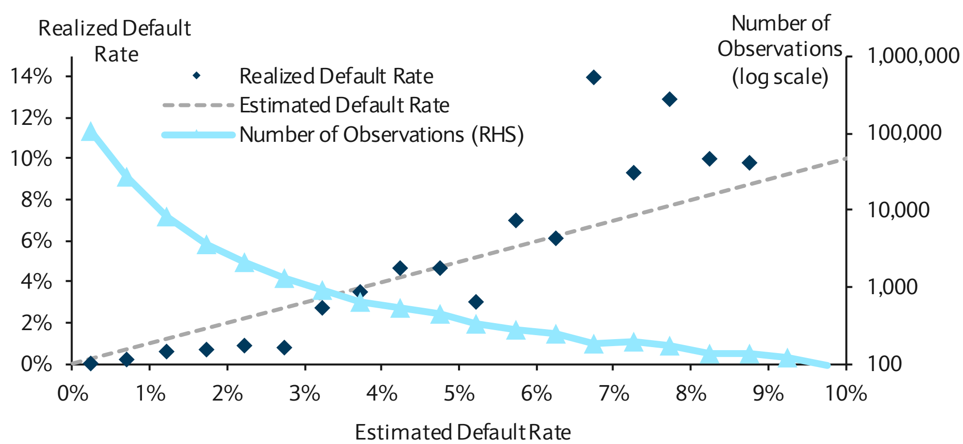
As discussed above, there is no way to test the accuracy of a single projection of a bond's default probability at a given point in time. However, in aggregate, we can measure the default experience of a large group of bonds with similar predicted default probabilities. We carried out this test as follows.

[18] Since the required data for model calibration include input/output pairs comprised of a bond's 5-factor exposure vector and the subsequently realized 6-month default experience, this requirement imposes a 6-month delay. For example, to calibrate the model as of December 31, 2018, we would first fit to a dataset in which the most recent data included would be observations pairing bond characteristics as of June 30, 2018 with a flag indicating whether or not they defaulted in the last six months of that year. This model would then be used to project default probabilities for all bonds in our dataset based on their characteristics as of December 31.

First, we calculated default probabilities for all bonds each month as described above. Then, we divided our observations into buckets defined by small ranges of projected default probability. We counted the numbers of overall observations in each cell as well as the numbers of those that ended up defaulting during the next six months; the ratio of these two counts is the realized default rate for the bucket. We then plot the realized default rates of each bucket against the median projected default rates; ideally, we would like to see these follow the diagonal line for which the two are equal. Figure 25 shows the results using a weight ratio of 1. We find that the projected default probabilities agree quite well with the subsequently realized default rates, slightly overstating the default probabilities for levels under 3% (which comprise the overwhelming majority of observations), and slightly understating them at the high end. When we repeated this analysis using higher levels of weight ratio, we found the realized default rates far below the projected ones. Based on this analysis, we have chosen to use the calibration with Weight Ratio = 1 for the remainder of the article.

FIGURE 25

Realized vs. Estimated 6M Forward Default Rates, January 2004 – January 2019



Source: Barclays Research

Portfolio Construction and Performance

It stands to reason that if we can reduce the rate of realized defaults in a portfolio by incorporating default prediction in the portfolio construction process, performance should be improved. However, this may not be the case if the risk of default is already properly priced in by the market. Specifically, we know that lower-rated bonds tend to experience higher default rates, and we have already shown that OAS is predictive of default as well. Even a successful reduction in default rates may not help performance if it is accompanied by too great a reduction in portfolio yield and spread. Therefore, to test the incorporation of our default predictors into high yield portfolio construction, we proceed as follows.

Controlling for Quality, Sector and Duration

We first partition our high yield bond universe into a coarse grid on three dimensions: we use three quality buckets based on whole-letter index credit ratings (BB, B, and CCC-C), three sector buckets (Industrials, Financials and Utilities), and two duration buckets (short and long, defined as OASD <= 5 years and OASD > 5 years, respectively). Each month, we find the percentage, by market weight, of our eligible bond universe that falls into each of the 18 bins of this 3x3x2 partition, and impose this market structure on all of our portfolios. The application of the default prediction signal is used to select which bonds should be used to fill in each cell of the partition.

Bond Selection

To rank the bonds available within each cell in a given month, we first estimate their default probabilities using all data available up to that date, as described above. We then rank the bonds in each cell from Q1 (lowest signal) to Q5 (highest signal), and then form either an equally-weighted (EW) or market-value-weighted (MW) portfolio of all the bonds in each quintile. We then combine the individual market cell portfolios from each quintile using the overall market allocations on this partition to get a set of five index-matched portfolios that are ranked differently by our model.

We rank the bonds into quintiles using two different approaches:

1. rank by default probability alone
2. rank by a signal equal to the ratio of spread to default probability.

In our first approach, we simply rank bonds within each market cell by their projected probability of default. Q1 consists of the bonds with the highest probability of default, and Q5 the lowest. We track a number of statistics for each portfolio formed in this way: key characteristics include overall portfolio spread (OAS) and duration (OASD); key measures of portfolio performance are the total return in the subsequent month and the realized default experience in the next six months[19]. In the next month, the whole procedure is repeated – the model is calibrated, default probabilities are calculated, and a new set of portfolios is constructed – and another month of performance is measured. We can then produce a time series of results, and summarize these over a given time period to evaluate portfolio performance. We have explored two versions of the strategy: one in which equal weights are assigned to each bond in the quantile portfolio, and one that uses market weights[20]. The long-term performance of this strategy, using equally-weighted portfolios within each quintile, is shown in Figure 26.

FIGURE 26

Performance of Equal-Weighted Quantile Portfolios Ranked by Default Probability (PD), January 2000 – July 2019

	Index	Q1 (worst)	Q2	Q3	Q4	Q5 (best)	Q5 - Index	Q5 - Q1
OAS	4.97	8.34	5.47	4.61	4.11	3.82	-1.14	-4.52
OASD	4.54	4.64	4.63	4.56	4.50	4.40	-0.14	-0.25
Signal (OAS/PD)	92.1	5.0	8.0	11.9	29.6	411.7	319.6	406.7
PD (6m, Proj.)	1.11%	4.26%	1.16%	0.63%	0.40%	0.21%	-0.89%	-4.05%
Default (6m, Actual)	0.86%	3.96%	1.08%	0.55%	0.22%	0.06%	-0.80%	-3.90%
Total Ret. (%/mo)	0.60	0.15	0.57	0.70	0.81	0.91	0.31	0.76
Tot. Ret. Vol. (%/mo)	2.61	4.57	2.91	2.26	1.95	1.82	1.39	3.60
Sharpe Ratio / IR	0.61	0.01	0.51	0.86	1.17	1.46	0.77	0.73

Note: 5-factor model, weight 1, full HY index, EW portfolios

Source: Barclays Research

As could have been expected, the bonds with the lowest default probabilities are also those with the lowest spreads. As a result, both the long-only and the long-short strategies based

[19] Note that in the methodology described here, where each portfolio is rebalanced monthly, the six-month default experience is not directly tied to portfolio performance; it is included to enable us to measure the success of the model at predicting default out of sample (the task it was designed for). The monthly total returns, which are the measure used to evaluate portfolio performance, played no role in model calibration.

[20] Typically, when constructing portfolios with relatively small numbers of bonds, equally-weighted portfolios should give better risk-adjusted performance by reducing concentration risk. We have therefore chosen to focus mostly on the results obtained for this case. The performance of market-weighted portfolios was largely similar, as we will see in Figure 29. We will use the market-weighted portfolios for our default screening strategy, which tracks the index more closely.

on minimizing default probability are handicapped by a large spread disadvantage: the Q5 portfolio, on average, carries a spread of 114bp less than the index and 452bp less than the Q1 portfolio. Despite that, it manages to outperform handsomely in both cases: by 31bp/month, for an IR of 0.77, in the long-only case, and by 76bp/month for the long/short strategy. Note that the Q5 portfolio that minimizes default probability also delivers a total return volatility substantially lower than that of the index. We also see that as we go from the bonds deemed most likely to default (Q1) to those deemed least likely (Q5), we see a steady increase in Sharpe ratio.

In our second approach, rather than simply minimizing default probability, we seek to maximize a ranking signal defined as the ratio of spread to default probability:

Signal = OAS / Probability of Default

The logic of this signal is clear. A high signal means that according to our model, the market is over-estimating default risk; these bonds, with high spread per unit of default probability, should provide the best value[21]. We rank the bonds into quintiles within each market cell by this signal, and then combine the individual market cell portfolios as before to match the index sector-quality-duration allocation.

FIGURE 27

Performance of Index-Allocation Equal-Weighted Quantile Portfolios Ranked by Spread/PD Signal, January 2000 – July 2019

	Index	Q1 (worst)	Q2	Q3	Q4	Q5 (best)	Q5 - Index	Q5 - Q1
OAS	4.97	7.01	5.34	4.79	4.54	4.62	-0.35	-2.39
OASD	4.54	4.49	4.52	4.52	4.58	4.61	0.07	0.12
Signal (OAS/PD)	92.1	4.4	7.5	11.6	28.5	419.8	327.7	415.4
PD (6m, Proj.)	1.11%	4.00%	1.24%	0.69%	0.43%	0.24%	-0.86%	-3.76%
Default (6m, Actual)	0.86%	3.62%	1.18%	0.53%	0.30%	0.15%	-0.72%	-3.48%
Total Ret. (%/mo)	0.60	-0.04	0.47	0.69	0.86	1.16	0.56	1.20
Tot. Ret. Vol. (%/mo)	2.61	3.96	2.83	2.35	2.13	2.13	1.24	2.86
Sharpe Ratio / IR	0.61	-0.15	0.40	0.81	1.16	1.65	1.57	1.45

Note: 5-factor model, weight 1, full HY index, EW portfolios
Source: Barclays Research

In Figure 27, we show the full-period performance of the strategy for equal-weighted quintile portfolios. We find a clear increase in average performance as we move from the lowest-ranked (-0.04% per month) to the highest-ranked quintile (1.16% per month); realized default rates are also substantially lower for the higher-ranked quintiles. At the right-hand side of the chart, we summarize the performance of two relative portfolio strategies: the long-only performance of the Q5 portfolio relative to the index, and the performance of a long-short strategy that goes long the Q5 portfolio and short the Q1 portfolio. The long-only Q5 portfolio outperforms the index by 56bp/month, with a volatility of 124bp/month, for an information ratio of 1.57 (before transaction costs); the long-short strategy achieves a return of 120bp/month, but with higher volatility, for an information ratio of 1.45. Once again, we see a clear and consistent increase in Sharpe ratio, even more pronounced than before, as we move from Q1 to Q5.

[21] This signal is closely related to the SPiDER signal, the ratio of spread to Debt/Equity ratio, proposed by Ben Dor & Guan. SPiDER has been shown to be predictive of performance for IG and non-distressed HY. For details see A. Ben Dor & J. Guan, *SPiDER (Spread Per Unit of Debt to Earnings Ratio) – A New Measure of Value in Credit Markets*, Barclays Research, 16 June 2016.).

Performance Over Different Time Periods

Default risk is not a constant in the market; it tends to come in waves, becoming more acute in times of economic crisis. It is therefore very important to check that the observed performance of our strategy is consistent throughout the study period and not confined to one or two specific episodes. In this section, we focus on the performance of the strategy based on the ranking by our OAS/PD signal.

Figure 28 breaks down the key performance metrics of the long-only and long-short strategies described above into three sub-periods. The earliest period (2000-2007) includes the dot-com crisis of 2001-2002 but ends prior to the onset of the Global Financial Crisis (GFC); the middle period (2008-2010) is relatively short, comprising the lead-up to the GFC and the post-crisis recovery; and the last period (Jan. 2011 – July 2019) represents the relatively benign environment of the past several years.

We find that the strategy delivered solid outperformance in all three sub-periods. While the magnitude of the outperformance, as well as the associated risk, varied substantially by period, the information ratios were consistently above 1.4. Interestingly, the period in which our strategy experienced the largest volatility (and delivered the largest outperformance) was not that of the GFC, but the earliest period, which included the dot-com crisis. This is consistent with an earlier chart (Figure 2) that showed the peak in realized defaults occurred in 2001-2002. In the most recent period, returns were more subdued. For the long-only strategy of buying the bonds in the top quintile to match the index, the TEV was just 55bp/month. The resulting outperformance of 31bp/month on average was substantially lower than in the other periods, but the resulting information ratio was the highest of all, at 1.97.

FIGURE 28

Strategy performance, Equal-Weighted Portfolios, in different sub-periods, 2000 - 2019

	Long-Only Strategy (Q5 - Index)			Long-Short Strategy (Q5 - Q1)		
Period	Tot. Ret. (%/mo)	Ret. Vol. (%/mo)	Information Ratio	Tot. Ret. (%/mo)	Ret. Vol. (%/mo)	Information Ratio
2000-2019	0.56	1.24	1.57	1.20	2.86	1.45
2000-2007	0.81	1.59	1.76	1.73	3.62	1.65
2008-2010	0.62	1.49	1.43	1.23	2.63	1.62
2011-2019	0.31	0.55	1.97	0.69	1.92	1.25

Note: 5-factor model, weight 1, full HY index, EW portfolios, ranked by OAS/PD Signal
Source: Barclays Research

FIGURE 29

Strategy performance of Market-Weighted portfolios in different sub-periods, 2000 - 2019

	Long-Only Strategy (Q5 - Index)			Long-Short Strategy (Q5 - Q1)		
Period	Tot. Ret. (%/mo)	Ret. Vol. (%/mo)	Information Ratio	Tot. Ret. (%/mo)	Ret. Vol. (%/mo)	Information Ratio
2000-2019	0.49	1.16	1.47	1.11	2.94	1.31
2000-2007	0.72	1.48	1.69	1.63	3.82	1.48
2008-2010	0.46	1.37	1.16	1.05	2.86	1.27
2011-2019	0.29	0.55	1.82	0.64	1.68	1.32

Note: 5-factor model, weight 1, full HY index, MW portfolios, ranked by OAS/PD Signal
Source: Barclays Research

Figure 29 presents the corresponding set of results for the strategies based on market-weighted portfolios within each market cell. The performance tends to be slightly worse than that shown in Figure 28 for the strategies based on equal-weighted portfolios, but the variations in performance by time period seen in the two cases follow a similar pattern.

One question we had in designing this study was when to start constructing portfolios and reporting performance. Our dataset begins in January 1998, and to train the model we need to observe six months of subsequent default experience for each observation. Thus, using our growing-window approach to model estimation, the portfolios constructed for January 2000 were built on a model that was calibrated to just 18 months of data. We thus considered the possibility of waiting until January 2004 to start performance measurement. This would have the added benefit of including all of the valuable experience from the dot-com crisis into our model's calibration right from the start – but we would lose out on the chance to measure how the strategy performed during that event. In the end, we chose to include the strategies' full performance history since 2000 in most of our charts, along with a performance breakdown by period. However, to illustrate how a later start date would influence the results, Figure 30 presents the strategy performance since January 2004.

FIGURE 30

Strategy performance in different sub-periods, 2004 - 2019

	Long-Only Strategy (Q5 - Index)			Long-Short Strategy (Q5 - Q1)		
Period	Tot. Ret. (%/mo)	Ret. Vol. (%/mo)	Information Ratio	Tot. Ret. (%/mo)	Ret. Vol. (%/mo)	Information Ratio
2000-2019	0.56	1.24	1.57	1.20	2.86	1.45
2004-2019	0.35	0.80	1.51	0.74	1.89	1.35
2004-2010	0.40	1.03	1.34	0.79	1.87	1.46
2011-2019	0.31	0.55	1.97	0.69	1.92	1.25

Note: 5-factor model, weight 1, full HY Index, EW portfolios, Ranked by OAS/PD Signal, excluding earliest period
Results including the earlier period as well are shown in first row for reference
Source: Barclays Research

The information ratios for the overall time period are little changed: for the long-only strategy, the IR since 2004 is 1.51, down slightly from 1.57 since 2000. Interestingly, though, the breakdown of performance by time period in Figure 30 presents a slightly different picture than the one above. In Figure 28, the outperformance of 31bp/month in the most recent period seemed low by comparison to the earlier, more volatile periods, which both had significantly higher returns and volatility. In Figure 30, the amount of outperformance appears somewhat more stable over time, with the improvement in IR being mainly about the decrease in tracking error volatility.

Focus on Distressed Credits

The dependence of default probability on the various factors that we have used as predictors is highly non-linear; furthermore, for bonds far from default, the rarity of default events makes it difficult to carry out the calibration of the model. Therefore, for investors with a specific interest in distressed credits, it could make sense to calibrate the model, and measure its performance, using a more limited dataset of only the most distressed bonds.

For this purpose, we define the "distressed" universe as the set of bonds with OAS greater than 1.5 times the average market-weighted OAS of our eligible HY bond universe, and we calibrate our model each month based on the prior default experience observed within this portion of the market. The resulting model for default probability can be different from the one estimated using the full set of available HY bonds. A snapshot of the model coefficients from the two model calibrations as of July 2019 is shown in Figure 31.

FIGURE 31

Default model factor coefficients based on calibration to entire HY universe or to distressed bonds only, January 2000 – July 2019

Factor Name	All HY	Distressed Only
Intercept	-7.22	-5.61
Normalized OAS	0.56	0.36
Normalized Equity Volatility	0.41	0.26
Short Term Leverage Ratio	3.25	2.84
Equity 6M Momentum	-2.24	-1.55
VIX	5.67	5.13

Note: 5-factor model, weight 1. All coefficients are found to be highly significant.
Source: Barclays Research

It is somewhat difficult to interpret the factor coefficients, given that the default probabilities depend on them in a nonlinear way and that the factors are scaled very differently. However, there are several things that stand out when we compare the coefficients from the two calibrations. First, the less negative value for the intercept corresponds to a significantly higher base-case probability of default if all other factors are zero[22]; this makes sense given the higher overall incidence of default in this universe. Accordingly, the adjustments due to the other factors are mostly reduced. However, the coefficient for short-term leverage is reduced much less than the other issuer-specific factors, indicating that this factor is given greater importance in the distressed-only calibration.

The model's performance at forming portfolios of distressed bonds is shown in the next two figures. Once again we see that the different ranking approaches produce outperformance in different ways. When ranking strictly by PD, as shown in Figure 32, the long-only strategy outperformed by 0.90% per month with an IR of 0.99. When ranking by our signal of spread per unit of default risk, as shown in Figure 33, the long-only strategy outperformed by 1.19% per month with an IR of 1.38.

FIGURE 32

Performance of Equal-Weighted Quintile Portfolios of Distressed Bonds Ranked by Default Probability (PD), January 2000 – July 2019

	Index	Q1 (worst)	Q2	Q3	Q4	Q5 (best)	Q5 - Index	Q5 - Q1
OAS	12.24	20.21	14.27	12.06	10.70	9.81	-2.43	-10.40
OASD	4.19	3.87	4.15	4.25	4.23	4.17	-0.02	0.30
Signal (OAS/PD)	11.6	1.5	2.1	3.0	5.0	38.2	26.6	36.7
PD (6m, Proj.)	6.99%	19.58%	8.58%	5.91%	4.20%	2.55%	-4.44%	-17.03%
Default (6m, Actual)	5.46%	19.77%	7.51%	4.74%	2.49%	1.60%	-3.86%	-18.16%
Total Ret. (%/mo)	0.59	-0.64	0.30	0.56	1.06	1.49	0.90	2.13
Tot. Ret. Vol. (%/mo)	6.57	8.79	7.84	7.11	5.83	4.94	3.14	5.63
Sharpe Ratio / IR	0.24	-0.30	0.07	0.21	0.54	0.94	0.99	1.31

Note: 5-factor model, weight 1, distressed HY bonds (OAS > 1.5% of index average), EW portfolios, ranked by PD
Source: Barclays Research

[22] Going back to the formulas that define our model, we find that the base case probability of default, if all other factors are zero, would be approximately e^{β_0}. This base case default probability for the distressed-only case comes to 0.36%, five times larger than the 0.07% obtained for the full HY index calibration.

FIGURE 33

Performance of Equal-Weighted Quintile Portfolios of Distressed Bonds Ranked by Spread/PD Signal, January 2000 – July 2019

	Index	Q1 (worst)	Q2	Q3	Q4	Q5 (best)	Q5 - Index	Q5 - Q1
OAS	12.24	16.30	14.15	13.05	12.17	11.41	-0.83	-4.89
OASD	4.19	4.13	4.18	4.15	4.14	4.03	-0.15	-0.10
Signal (OAS/PD)	11.6	1.4	2.2	3.0	5.1	39.1	27.6	37.7
PD (6m, Proj.)	7.0%	17.6%	9.0%	6.4%	4.5%	2.9%	-4.1%	-14.7%
Default (6m, Actual)	5.5%	17.9%	7.6%	4.4%	3.2%	2.4%	-3.1%	-15.5%
Total Ret. (%/mo)	0.59	-0.70	0.21	0.36	1.24	1.79	1.19	2.49
Tot. Ret. Vol. (%/mo)	6.57	7.97	7.69	7.32	6.49	5.44	3.00	4.82
Sharpe Ratio / IR	0.24	-0.36	0.03	0.10	0.59	1.05	1.38	1.79

Note: 5-factor model, weight 1, distressed HY bonds (OAS > 1.5% of index average), EW portfolios, ranked by OAS/PD
Source: Barclays Research

Importance of Individual Factors to the Model

We have shown that our model is successful on two levels. First, it is able to generate a fairly accurate projection of default probability on a six-month horizon. Second, and perhaps more importantly, these default probabilities are not already fully priced in the market; portfolios formed based on these projections have shown steady outperformance.

One important question that we need to investigate is the source of this outperformance. Of the five factors used by our model to predict default, does one of them play a dominant role in generating portfolio outperformance? In particular, we know from earlier research that momentum signals from past equity returns can be predictive of bond returns for those issuers; our team has built a dedicated strategy around this theme[23]. Does our strategy outperform by selecting bonds that are less likely to default, or is this just another implementation of a cross-asset momentum strategy?

To address this issue, we use different versions of our model in which we drop some of the factors one at a time. Recall that our model uses five factors: one systematic factor, the VIX level, represents the overall level of risk in the marketplace, and then four more factors that are normalized or de-meaned to provide more useful issuer-specific indicators. These four are: short-term leverage, equity volatility, equity momentum, and bond OAS. We will specifically address the net effect of the latter two of these factors by dropping one or both of them from our model. In Figure 34 we compare the performance of our main 5-factor model with a 4-factor model (VIX, short term leverage, equity volatility, equity momentum) and a 3-factor model (VIX, short term leverage, equity volatility) when applying all of them to the entire HY universe. We also include a 2-factor model based only on OAS and VIX.

[23] See Polbennikov, S. and A. Desclée, *Equity Momentum in Credit (EMC)*, Barclays Research, 18 August 2017.

FIGURE 34

Performance Summary for Default Model Using Only Some of the Factors, Full HY Universe, 2000-2019

		Q5 (best) - Ranked by Signal				Q5 (best) - Ranked by PD			
Model	**Index**	**Mixed 5-Factor**	**Equity 4-Factor**	**Equity 3-Factor**	**Bond 2-Factor**	**Mixed 5-Factor**	**Equity 4-Factor**	**Equity 3-Factor**	**Bond 2-Factor**
Normalized OAS		✓			✓	✓			✓
VIX		✓	✓	✓	✓	✓	✓	✓	✓
Short Term Leverage		✓	✓	✓		✓	✓	✓	
Normalized Equity Vol		✓	✓	✓		✓	✓	✓	
6-Month Equity Momentum		✓	✓			✓	✓		
OAS (%)	4.97	4.62	5.07	7.03	6.11	3.82	4.20	4.06	2.89
OASD	4.54	4.61	4.61	4.68	4.75	4.40	4.47	4.45	4.16
PD (6m, Projected)	1.11%	0.24%	0.22%	0.94%	1.18%	0.21%	0.19%	0.71%	0.74%
Realized 6m Default Rate	0.86%	0.15%	0.39%	1.40%	1.00%	0.06%	0.13%	0.21%	0.13%
Total Return (% / month)	0.60	1.16	1.19	0.82	0.73	0.91	1.03	0.70	0.41
Total Ret. Vol. (% / month)	2.61	2.13	2.25	3.48	3.54	1.82	1.94	1.81	1.50
Outperformance (%/month)		0.56	0.59	0.22	0.13	0.31	0.43	0.10	-0.19
Tracking Err. Vol. (% / month)		1.24	1.18	1.43	1.29	1.39	1.32	1.25	1.52
Information Ratio		1.57	1.72	0.54	0.36	0.77	1.13	0.27	-0.42

Note: EW portfolios, various models, weight 1, 2000-2019, Full HY Index

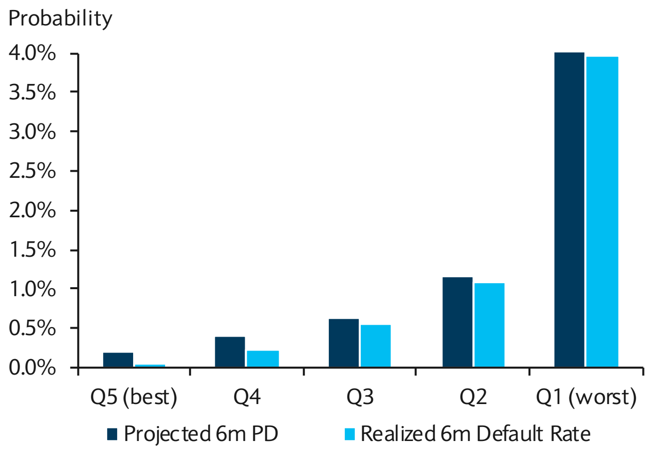
Source: Barclays Research

As we move from the 5-factor to the 4-factor model, we find that the omission of the bond OAS does not degrade model performance – in fact, the 4-factor model outperformed the 5-factor model in total return (although the realized subsequent default rate was doubled). However, if we move down to the 3-factor model, we find that model performance is hurt significantly by removing the momentum factor. Not only do total returns drop when this factor is removed, but the subsequently realized default rates in the top quintile rise substantially. This confirms that the effect of the momentum factor is not just capturing a directional effect on bond prices but that it has a material effect on the accuracy of default estimation. When we look at the 2-factor model based only on OAS and VIX, we find that performance degrades even further. This makes sense; it is hard to evaluate the trade-off between OAS and PD when the estimate of PD is itself based on OAS.

On the right side of the figure, performance is shown for the best quantile when ranked by the lowest predicted probability of default from each model. Here the results are even more striking. The 4-factor model including equity momentum but not OAS again achieves the best performance, but by a greater margin. Furthermore, in this test we find that if we use OAS alone to choose the set of bonds with the lowest probability of default, we underperform the index. The model succeeds in choosing bonds with lower subsequent default rates than the index; but the carry disadvantage it picks up in the process (the average spread in this case is 289bp, more than 200bp less than that of the index) proves to be insurmountable.

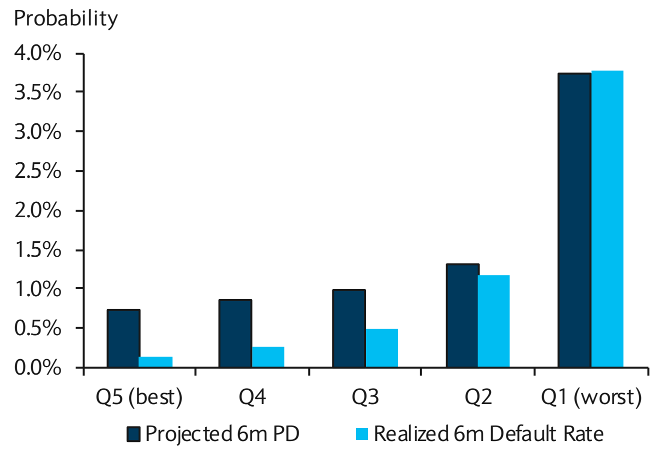
One curious effect that can be seen in the rightmost column of Figure 34 is that for the 2-factor model, the projected probability of default seems to be much higher than the subsequently realized default rate. This is surprising, because even if OAS-based prediction hurts performance, our classification tests lead us to believe that this model should give the most accurate estimates of default probability. To investigate further, we compare the projected probability of default against the subsequently realized across our five quantiles ranked by PD. These are plotted in Figure 35 for the full 5-factor model, and in Figure 36 for the 2-factor model.

FIGURE 35
Projected and Realized Default Rates, 5-Factor PD Model



Source: Barclays Research

FIGURE 36
Projected and Realized Default Rates, 2-Factor PD Model



Source: Barclays Research

We find that the 5-factor model produces accurate predictions of subsequent default rates across the full spectrum from highest to lowest risk. The OAS-based model seems to perform quite well at estimating the default rates in the most risky quintile, and succeeds in partitioning the bonds into progressively lower rates of realized default rates, but is not as good at determining how much lower the probability of default is in the less risky quintiles.

In Figure 37 we repeat the model comparison, applying these four models to the distressed segment of the HY bond universe. The results here are even more drastic than in the previous case. Removal of the equity momentum factor leads to a sharp decrease in strategy performance, especially for the ranking based on our Spread/PD signal. In the absence of the momentum signal, this strategy selects high-spread bonds much more aggressively. Its average spread is pushed out to over 1800bp, and the subsequently realized six-month default rate increases dramatically as well. This strategy still outperforms the market-weighted average return of all distressed bonds, but just barely. Our 2-factor model based on OAS also fares quite poorly, just barely outperforming the index.

FIGURE 37

Performance Summary for Default Model Using Only Some of the Factors, Distressed Bonds Only, 2000-2019

		Q5 (best) - Ranked by Signal				Q5 (best) - Ranked by PD			
Model	**Index**	**Mixed 5-Factor**	**Equity 4-Factor**	**Equity 3-Factor**	**Bond 2-Factor**	**Mixed 5-Factor**	**Equity 4-Factor**	**Equity 3-Factor**	**Bond 2-Factor**
Normalized OAS		✓			✓	✓			✓
VIX		✓	✓	✓	✓	✓	✓	✓	✓
Short Term Leverage		✓	✓	✓		✓	✓	✓	
Normalized Equity Vol		✓	✓	✓		✓	✓	✓	
6-Month Equity Momentum		✓	✓			✓	✓		
OAS (%)	12.24	11.41	14.46	18.42	12.51	9.81	11.21	11.34	8.49
OASD	4.19	4.03	3.91	3.89	4.19	4.17	4.04	4.12	4.30
PD (6m, Projected)	6.99%	2.86%	3.80%	7.02%	7.08%	2.55%	3.31%	5.78%	5.18%
Realized 6m Default Rate	5.46%	2.35%	4.40%	8.92%	5.29%	1.60%	2.44%	2.74%	2.38%
Total Return (% / month)	0.59	1.79	1.78	0.63	0.63	1.49	1.69	1.04	0.82
Total Ret. Vol. (% / month)	6.57	5.44	6.29	8.18	7.06	4.94	5.30	5.74	4.95
Outperformance (%/month)		1.19	1.19	0.04	0.04	0.90	1.10	0.45	0.23
Tracking Err. Vol. (% / month)		3.00	3.01	3.72	2.15	3.14	3.11	3.02	2.56
Information Ratio		1.38	1.37	0.04	0.06	0.99	1.23	0.52	0.31

Note: EW portfolios, various models, weight 1, 2000-2019, Distressed Bonds Only
Source: Barclays Research

When ranking purely by default probability, in contrast, the best-ranked quintile continues to outperform even with the 3-factor model, albeit by less; and the realized default rate does not seem to suffer. Here, giving up the equity momentum factor does reduce strategy returns, but does not seem to have reduced the model's ability to predict default. Equity momentum seems to be a very important contributor to model performance, but even the strategies based on the 3-factor strategy that excludes equity momentum can deliver significant outperformance relative to the index in most cases. On this distressed dataset, selecting the least risky quintile by OAS using the 2-factor model does at least manage to produce modest outperformance relative to the index. Despite giving up 375bp of spread relative to the index, the achieved reduction in default rates by more than half is able to compensate and outperform the index by 23bp/month. Nevertheless, our other models achieve strikingly better performance.

The results in this section seem to point to two divergent conclusions regarding the usefulness of spread at predicting default. In terms of pure default prediction, it clearly helps. The subsequently realized default rates on the portfolios formed using the 5-factor model are substantially lower in every case than the corresponding portfolios from the 4-factor model that excludes the OAS factor. However, because it is already fully reflected in bond prices, the information gleaned from OAS does not improve portfolio performance. Despite the higher subsequent default rates, the portfolios produced with the 4-factor model tend to outperform the full model in risk-adjusted terms. Furthermore, portfolios produced using the 2-factor model based only on OAS and VIX deliver substantially worse performance.

Default Screening: Excluding the Most Risky Bonds

Up to this point, all of the strategy variations that we have explored have represented quite active strategies. Even in the long-only portfolios, the attempt to outperform the index had us selecting only one fifth of the bonds in the index each month. However, even investors who prefer to track their index more closely have an interest in avoiding defaults wherever possible. For such investors, another application of default probabilities might be to screen out the bonds deemed the worst default risks, and form index-neutral portfolios from those that remain. For this application, we use our market-weighted quintile portfolios to form broad default-screened portfolios.

Within each sector-quality-duration cell, we exclude the bonds ranked in the bottom quintile Q1, and form a market-weighted portfolio of all the bonds in quintiles Q2-Q5. The portfolios formed in this way represent a form of enhanced indexing, or smart beta portfolios, that provide modest but steady outperformance of the index with reasonable TEV. The performance of these default-screened portfolios are shown in Figure 38, for strategies based on rankings by either pure PD or Spread/PD, and for either the full HY universe or distressed bonds only. For example, the screening by our Spread/PD signal on the full HY universe delivers an average outperformance of 12bp/month with a TEV of 56bp/month, for an information ratio of 1.04.

FIGURE 38

Performance of Screened Portfolios: Market-Weighted Portfolios of Bonds Excluding the Worst-Ranked Quintile, 2000-2019

	All HY Bonds			Distressed Bonds Only		
	Index	Screened by PD	Screened by Signal	Index	Screened by PD	Screened by Signal
Total Return (%/month)	0.60	0.72	0.77	0.59	0.81	0.86
Total Ret. Vol. (%/month)	2.61	2.20	2.32	6.57	6.30	6.37
Sharpe Ratio	0.61	0.90	0.93	0.24	0.37	0.39
Outperf. vs. Index (%/month)		0.12	0.17		0.22	0.27
Tracking Err. Vol. (%/month)		0.68	0.56		0.66	0.80
Information Ratio		0.60	1.04		1.16	1.18

Note: Full 5-factor model, weight 1, MW portfolios, 2000-2019
Source: Barclays Research

Conclusion

We have constructed a model for estimating the six-month default probability of HY bonds, using a combination of inputs from credit and equity markets. We have demonstrated that while debt markets contain information – from both credit rating agencies and market pricing – from which reasonably accurate projections can be made of the probability of impending default, such projections can be improved by incorporating indicators of corporate health from equity markets and accounting data where available. Furthermore, we have shown that our combined model can be used in several different ways to help improve performance in high yield portfolios.

In the context of the pure binary classification task of predicting which bonds will default over the next six months and which will survive, our model was able to correctly identify better than 94% of defaulting bonds and 94% of surviving bonds in an out-of-sample test. (Either of these performance measures could be improved at the expense of the other; we tuned the model to balance the two.) This use of the model could be relevant to portfolio managers looking to set up an initial screen to exclude the bonds most likely to default from the universe from which they select bonds for the portfolio.

For our backtests of portfolio performance, we utilized a stratified sampling approach to assemble portfolios of bonds that match index exposures on a sector-quality-duration grid but differ in terms of their model rankings. Two flavors of portfolios were investigated – those that rank bonds strictly by their probability of default and form portfolios that minimize default risk; and those that rank by the ratio of spread to default probability, to form portfolios that are paid the greatest compensation per unit of default risk. Both flavors were found to generate outperformance, but those based on the ratio-based signal gave consistently better results, in terms of both raw and risk-adjusted performance.

Our performance backtests, in each flavor, were based on a ranking into five quintiles by the selected signal. For the most part, we looked at performance of active portfolios: long-only portfolios of Q5 bonds (those from the best-ranked quintile, equal-weighted within each market cell) versus the benchmark[24], and long-short portfolios of Q5 bonds verus Q1 bonds (the worst-ranked quintile). Using the ratio-based signal, over the full period of the study, from January 2000 through July 2019, the long-only portfolios outperformed the benchmark by 56bp/month, with TEV of 124bp/month, for an information ratio of 1.57 before transaction costs. The long-short portfolios achieved higher average outperformance (120bp/month) but took more risk (286bp/month), achieving an information ratio of 1.45.

We tested the model using different subsets of our five factors to measure the role played by each in generating strategy performance. We found that not only was equity momentum a strong contributor to strategy returns, but it also helped to improve estimates of default probability. However, a 2-factor model built primarily on bond OAS produced divergent results: it outperformed our full 5-factor model in a threshold-based classification test, but portfolios built using this model substantially underperformed our full model. Even just removing the OAS factor from the model improved strategy performance. The reason is clear: the information about default probability that can be gleaned from OAS, though it may be accurate, has already been fully priced in, so it offers no trading advantage.

We also investigated a more passive screening strategy, in which the portfolio is comprised of all available bonds excluding the worst-ranked Q1 portfolio, on a market-weighted basis. This approach, which had a much lower TEV of 56bp/month relative to the benchmark, outperformed the benchmark by an average of 17bp/month, for an IR of 1.04.

We repeated all of these tests for a universe formed from the most distressed portion of the HY bond universe. Results of these tests tended to show qualitatively similar results in terms of information ratios, with higher levels of both risk and return.

We also broke down the results by time period. We found that in the most recent period, from January 2011 through July 2019, the monthly strategy performance was slightly lower than in earlier periods (marked by the dot-com crisis and the GFC), but volatility was substantially lower, resulting in an even higher information ratio of 1.97 for the long-only strategy on the full HY universe.

Topics for additional research remain. We have so far restricted ourselves to projection of default probabilities on a six-month horizon. The projection of default probabilities on a longer horizon would not only require the assignment of different weights to our selected input variables, but would likely justify the incorporation of additional variables to the model. Second, we have calculated performance before transaction costs. This means that for the most part, the strategies we have illustrated do not represent a practical implementation

[24] The performance benchmark in each case was a market-weighted average of all the bonds in the eligible universe, not the full HY index.

(with the possible exception of the relatively passive default screening strategy). Further work might be called for to measure the impact of transaction costs on strategy performance and to explore the performance of turnover-constrained implementations. Finally, we have restricted ourselves to the public portion of the high yield universe, for which equity market data and fundamentals are readily available. Additional research may be warranted to explore alternative sources of information for private companies. Nevertheless, we have clearly demonstrated that our model shows great promise for constructing timely and accurate projections of impending default, and that these projections have the potential for significant improvements in portfolio performance.

Appendix: Modeling Default Probability with Logistic Regression

A data-driven approach to modeling realized default probabilities is to use a classifier which categorizes bonds into a group that will default within the specified time-horizon, and a group that will not. This is a binary classification, and a probability of default[25] can be inferred from this classification by quantifying the probability that the bond is in either category, typically by calculating an appropriate distance from the classification threshold. In this paper we focus on probability of defaulting within a six month time horizon. This real-world probability is not a quantity that can be directly observed from the market. What can be observed, however, is the bond default state six months later, which we denote by D. Let us set D to be

$$D = \begin{cases} 1, & \text{if default occured} \\ 0, & \text{if default did not occur} \end{cases}$$

The variable D corresponds to a realized binary event – either default occurred in the specified timeframe or it did not. However, what we are after is the probability that this binary event will occur in the future, conditional on some information given by explanatory variables X. That is, we are interested in estimating the probability $PD = Prob[D = 1 \mid X]$. One way to estimate PD given D and X is to use the logistic regression approach, which says that the probability of default is a sigmoidal function yielding values between zero and one, i.e.

$$PD = \text{Prob}[D = 1 \mid X] = \frac{\exp(\beta \cdot X)}{1 + \exp(\beta \cdot X)}$$

Here $X = (1, X_1, X_2, \ldots, X_N)$ are regression variables assumed to be known quantities, and $\beta = (\beta_0, \beta_1, \ldots, \beta_N)$ are coefficients that need to be estimated[26]. When evaluating different models, the dataset is typically split into two separate samples: a training set on which coefficients are estimated, and a validation set that is used to measure out-of-sample performance.[27]

Due to the nonlinearity in the sigmoid function, the coefficients need to be estimated by maximizing the likelihood function. The likelihood function is essentially the joint probability density function for the binomial default variable D, viewed as a function of β and is given by

$$L(\beta|D) = \prod_{i=1}^{L} {\pi_i}^{D_i} (1 - \pi_i)^{1-D_i}$$

where π_i is the conditional probability, $\pi_i = \frac{\exp(\beta \cdot X)}{1+\exp(\beta \cdot X)}$. The optimal coefficients are given by solving the optimization problem

$$\hat{\beta} = \arg\max L(\beta|D)$$

In practice, it is more efficient to maximize the logarithm of the likelihood function, which is given by

[25] It is worth noting that the default probabilities estimated using this approach differ from those using models that back out default probabilities from asset prices. In price-based models, the equations used for this estimation typically rely on an assumption of risk-neutrality, in which the price is assumed to be set to a mathematically fair level for an investor who is neither risk-seeking nor risk-averse. However, since real-world investors are typically risk-averse, an additional step is needed to adjust these risk-neutral probabilities to real-world probabilities. The modeling approach used here, because it is calibrated not to asset prices but to default events themselves, directly calculates real-world default probabilities without requiring this adjustment.

[26] Note that the augmented variable vector X contains the constant 1 so that β_0 corresponds to the intercept.

[27] To make maximal use of available data, machine learning often uses the k-fold cross-validation technique, in which the dataset is randomly split into a training and testing sample multiple times, with the results averaged. We have not reported any such results in this report.

$$\ln L(\beta|D) = \sum_{\{D_i=1\}} \ln(\pi_i) + \sum_{\{D_i=0\}} \ln(1-\pi_i)$$

Since the logarithm is monotonic, the maximum of the likelihood function and log-likelihood function are equal, i.e.

$$\hat{\beta} = \arg\max L(\beta|D) = \arg\max \ln L(\beta|D)$$

Let us denote by $\hat{\beta}$ the resulting coefficients estimated by maximum likelihood on the training set. We can then obtain an estimate of the probability of default of any bond in the validation set through

$$\widehat{PD} = \frac{\exp(\hat{\beta} \cdot X)}{1 + \exp(\hat{\beta} \cdot X)}$$

Choosing the Right Penalties: Balanced Weights

For rare events datasets such at the one we are considering, estimating coefficients and measuring performance using the Accuracy Ratio may lead to misleading conclusions regarding model performance. To see why this is the case, consider for instance the two hypothetical models that were presented in Figure 22 above.

We would like to have estimators which produce Confusion Matrices like Model B rather than Model A, and performance metrics which would rate the performance of Model B better than Model A. To do this we introduce a Weighted Maximum-Likelihood Estimator (WMLE) and Weighted Accuracy Ratio (WAR) which takes into account the relative rarity of default events and the relative difficulty in predicting them.

The WMLE weights the two terms in the likelihood function differently. Let ω_1 represent the importance of correctly predicting default events, and ω_0 the importance of correctly predicting non-defaults.[28]

The *weighted* log-likelihood function is then given by

$$\ln L_\omega(\beta|D) = \omega_1 \sum_{\{D_i=1\}} \ln(\pi_i) + \omega_0 \sum_{\{D_i=0\}} \ln(1-\pi_i)$$

The first term rewards high projected default probabilities for default events; the second rewards low probabilities for non-defaults. Clearly then, if $\omega_1 > \omega_0$, each default has a larger effect on the log-likelihood function than each survival. This can be used to balance out for the fact that defaults are rare events, and there are many more survivals than defaults in the dataset. In this approach, the model coefficients are estimated by maximizing the weighted log-likelihood function via

$$\widehat{\beta_\omega} = \arg\max \ln L_\omega(\beta|D)$$

Given $\widehat{\beta_\omega}$ the probability of default can then be projected as

$$\widehat{PD_\omega} = \frac{\exp(\widehat{\beta_\omega} \cdot X)}{1 + \exp(\widehat{\beta_\omega} \cdot X)}$$

[28] The ratio of the two weights, ω_1/ω_0, is the weight ratio discussed in the body of the report. Typically, the two weights are chosen such that they sum to one and have the desired ratio. In some cases, practitioners have set the weights according to the percentage of default events in the data sample.

References

Ben Dor, A. & Xu, J., "An Empirical Analysis of the Difference between Public and Private Issuers of High Yield Bonds", Quantitative Portfolio Strategy, Barclays Research, March 25, 2015.

Black, F. and Scholes, M., "The Pricing of Options and Corporate Liabilities", Journal of Political Economy, **81** (3): 637-54, 1973.

D. Dwyer, Z. Li, S. Qu, H. Russell, & J. Zhang, "CDS-implied EDF Credit Measures and Fair-value Spreads" Moody's Analytics, March 11, 2010.

Dastidar, S., and B. Phelps, "Credit Spread Decomposition: Decomposing Bond-Level Credit OAS into Default and Liquidity Components", Quantitative Portfolio Strategy, Barclays Research, July 8, 2010.

Jarrow, R. and Turnbull, S. M, "Pricing Derivatives on Financial Securities Subject to Credit Risk", Journal of Finance, **50** (1): 53-85, 1995.

Preclaw, R., "Don't Count Them Out", Credit Research, Barclays Research, Sept 16, 2016.

King, G., & Zeng, L., "Logistic Regression in Rare Events Data", Political Analysis, **9** (2): 137-163, 2001.

Merton, R., "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", Journal of Finance, **29** (2): pp. 449-70, 1974.

Powers, D., "Evaluation: From Precision, Recall and F-Score to ROC, Informedness, Markedness & Correlation", Journal of Machine Learning Technologies, **2** (1): 37-63, 2011.

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