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An Empirical Examination of the Power of Equity Returns vs. EDFs™ for Corporate Default Prediction

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Summary

In this paper we study the effectiveness of using equity returns for corporate default prediction. Specifically, we analyze whether using equity return information alone can yield similar performance to EDFs in default prediction. . We find that the answer is no. Key results from our study are as follows.

» EDFs exhibit superior default predictive power to 6-month cumulative equity returns over a one year horizon, with the accuracy ratio of the former 27 percentage points higher than that of the latter. Shorter equity return windows lead to even larger differences in default prediction power.

» For 97% of the firms analyzed in our study, equity returns underperform EDFs by large margins as default risk indicators, sometimes even providing signals opposite to realized default rates. It is only for the 3% of the worst performing firms – where financial distress is most obvious – that equity returns exhibit comparable prediction power to EDFs.

» EDFs consistently outperform equity returns as default risk signals over time. The cohort accuracy ratios of EDFs are also much more stable than that of equity returns, ranging between 80% and 90%, while those of equity returns were between 24% and 83%.

» There is a weak relationship between equity returns and default risk. Both EDFs and realized default rates show a "smirk"-shaped relationship to equity returns. In addition, there is wide variation in EDFs among stocks with similar past equity returns, suggesting that EDFs and equity returns contain directionally different information.

» When firms with high EDFs and high equity returns are compared with those with low EDFs and low equity returns (i.e., EDFs and equity returns provide distinctly opposite default warning signals), the realized default rate of the former group is 16 times higher than that of the latter group, suggesting EDFs are a much more accurate predictor of default.

» When the one-year distance to default, or DD1 (a monotonic transformation of EDFs), is pitted against equity returns in a regression setting, the coefficient estimate of DD1 is of the expected sign and is statistically significant, while equity returns provide no additional default prediction power in the presence of DD1.

1 I would like to thank David Munves, Jing Zhang, and Ozge Gokbayrak for their helpful comments and suggestions at various stages of the study. I am particularly indebted to David Hamilton, from whom I have received numerous inputs from methodology to editorial comments

Table of Contents

Introduction

Equity prices are one of the major inputs to Moody's Analytics' Expected Default Frequency (EDF^{TM}) credit measures. The model underlying EDFs is built on Merton's (1974) insight that corporate equities can be viewed as call options on corporate assets. By exploiting the option-like relationship between equity prices and asset values, one can infer a firm's (unobservable) asset value from its equity price.[2] In conjunction with the estimate of the firm's asset volatility and its capital structure, one can estimate the firm's Distance to Default (DD), which is, loosely speaking, the number of standard deviations a firm's asset value is away from its default point. By calibrating DD to historical default experience, the model produces estimates of probabilities of default, called EDFs, for over 30,000 public firms worldwide.

Since their introduction some 20 years ago, EDFs have gained broad recognition among financial institutions, corporations and academia as powerful predictors of default.[3] Despite the widespread understanding and use of structural credit risk models in general and EDFs in particular, many risk professionals still ask whether, since EDFs are derived from equity prices, one can forecast corporate defaults by simply observing changes in equity prices. A more pertinent question arises among EDF users: do EDFs provide *additional* default-related information beyond what is already contained in equity prices?

Anecdotal evidence suggests that equity prices typically decline precipitously prior to default, thereby sending signals of financial stress to markets. One is tempted to construct the following rule in forecasting defaults: the probability of default is higher for companies whose shares perform badly relative to their peers. Putting it differently, there is assumed to be a negative relationship between firms' past stock performance and their default rates. We have seen versions of this forecasting rule actually implemented in many clients' credit risk management systems. Despite the approach's popularity, two important questions remain unanswered: Is there a theoretical justification for this hypothesis? And even if the hypothesis is theoretically justified, does it hold empirically?

In this study, we argue that the practice of predicting corporate defaults using equity performance lacks a sound theoretical foundation, and it has only weak empirical support. Even if equity performance by itself has some statistical power in default prediction, our hypothesis is that it will not work as well as a credit risk measure derived from a structural model, such as EDFs. We provide theoretical reasons in this study why equity performance alone does not give you a powerful default risk ranking tool—namely, the failure to incorporate capital structure information into default risk assessments. In addition, we show that this hypothesis is well supported by empirical evidence. Not only does equity performance have weaker power than EDFs in default prediction, it provides no marginal explanatory power to corporate defaults beyond EDFs in a regression setting.

In the academic credit risk literature, equity information has long been used as a covariate for single-name default prediction. Altman (1968) uses the ratio of market value of equity to book value of debt to construct his Z-score. Shumway (2001) uses one-year trailing market-adjusted equity returns as a predictor of default in duration analysis of probability of default. More recently, equity returns are found to be a useful covariate in multi-period default prediction by Duffie, Saita, and Wang (2007). However, it is not clear from these studies whether in a simple one-period "static" model equity returns contain directionally similar default-relevant information to EDFs, and whether equity returns adds marginal explanatory power to default prediction beyond EDFs.

In this paper, equity performance is measured by *n*-month cumulative equity returns. We compare the default prediction power of this measure with that of public firm EDFs. This measure of equity performance was chosen as a credit scoring instrument because 1) returns are public information, readily available to all market participants, 2) this measure is easily constructed and is appealing to a wide range of market

2 Moody's Analytics' approach is based on the Vasicek-Kealhofer model, a significant advancement of the standard Black-Scholes-Merton model. See Kealhofer (2003a, 2003b) and Bohn and Stein (2008) for more information on the model.

3 Here and elsewhere we use the term default "prediction" advisedly. In the literature on credit risk, default prediction is refers to an estimate of statistical default likelihood. We use this terminology in our study, but make clear the meaning of the term to readers less familiar with its use in the credit risk literature.

practitioners, and 3) low cumulative equity returns are typically the results of consecutive declines in equity prices, which are commonly interpreted as signals of financial distress and hence higher likelihood of default. As noted above, the common conjecture is that low equity returns over an extended period of time are associated with high default risk, and *vice versa*. Therefore, we would expect to observe a negative relationship between *n*-month cumulative stock returns and the probability of default.

We should make one point clear at this juncture. Since we are purely interested in the *power* of a credit measure in identifying defaulters from non-defaulters (in a way to made precise later), we simply measure the rank orderings of firm-level default risk the credit measures provide.[4] This means that the proper calibration of EDF *levels* is not evaluated in our study, although it is critical to many applications in credit risk management. So we are studying one aspect of EDFs without fully measuring their capabilities.[5]

The paper is organized as follows.

» We discuss the theoretical differences between equity returns and EDFs for the purpose of seeking theoretical guidance for our subsequent empirical analysis.

» We outline the research objectives and describe the datasets used in the study.

» We compare the default predictive power of EDFs versus equity returns for various samples and equity return windows. In this section we compute the power (i.e., power curve accuracy ratios) for both pooled samples and on a cohort-to-cohort basis. The idea is to compare not only the overall power of the two credit measures, but also the time series of their power performance.

» We then investigate whether equity returns and EDFs provide consistent rank orderings of firms' default risk. We conduct both one-dimensional sorts and two-dimensional sorts on the two credit measures to examine whether the information content of the two credit measures is directionally similar. This helps us understand the disparity in their default prediction power.

» We follow the portfolio analysis with formal logit-type regressions to pit EDFs against equity returns. In particular, we want to test whether equity returns provide additional predictive power of default in the presence of EDFs and vice versa.

» The conclusion

Equity Returns versus Structural Default Risk Models

In this section we address the conceptual linkage between equity prices and default risk in a general structural model setting. The discussion in this section applies not only to Moody's Analytics' public firm EDF™ model, but also to the class of structural models in general. In fact, we can replace the word PD with EDF in subsequent discussions and the relevant statements are all valid. In particular, we compare default-relevant information incorporated in equity returns, essentially a transformation of equity prices, to those incorporated in probabilities of default that are outputs of structural models. By analyzing the informational content of the two credit measures, we seek guidance from finance theory on how equity returns are related to default risk and why other inputs to structural models of PD calculations transform equity price information to default risk assessments that are more informative than those conveyed by simple equity returns.

From equity prices to the probability of default: the theoretical link

To many credit market practitioners accustomed to the idea of using yields and spreads to measure risk and returns, the notion of inferring the probability of default on a firm's liabilities from its stock price may sound esoteric. Liabilities and equities are two distinct classes of claims on a firm's assets, with their priorities well-defined in the event of default. Beyond the observation that firms in financial distress frequently see their stock prices decline, what other default-relevant information can one extract from its stock performance?

4 Indeed, it is not at all clear how one would map equity returns to probabilities of default.

5 Public firms EDFs have been regularly and rigorously validated by Moody's Analytics. See Korablev and Qu (2009) for the most recent results.

The answer lies in the contractual feature of limited liabilities borne by a company's shareholders: the maximum loss to shareholders in the event of company default is the value of its shares. That is, if the firm's total asset value drops below that of its liabilities, any loss beyond the value of the equity will be borne by the debtholders.

The relationship between the value of a firm's assets and liabilities in the event of default is illustrated in **Figure 1** below. Given a firm's current asset value A_0, its projected growth rate μ, and the rate of variation in asset value σ, the distribution of the firm's market asset value T periods later can be plotted as shown. The firm will continue to operate only if its market asset value is greater than the value of its liabilities due at time T, X_T, which is termed the default point. If the firm's asset value drops below the default point, it is in default.

Conceptually, there are three key inputs to calculation of the probability of default (PD) in the structural approach: 1) expected market asset value, 2) asset volatility, and 3) default point. From the graph it is straightforward to see that 1) the higher the expected market asset value, with everything else being kept constant, the lower the PD; 2) the larger the asset volatility (translated into a wider asset value distribution), the higher the PD; 3) the higher the default point, the higher the PD. If a firm's asset value and asset volatility were readily observable, we would not need its equity value to calculate the PD. The task of assessing the PD would be much easier, since the third input, a firm's liability information, is regularly released to the public (at least for public firms).

In reality, the market value of a firm's assets and its asset volatility are not observable. The best one can do is to infer a firm's asset value and volatility from its equity value. A key insight provided by Merton (1974) is that a firm's equity can be viewed as a call option on its assets by the virtue of shareholders' limited liability (that is, if the value of assets falls below that of liabilities, the shareholders have no further liability towards the firm). Therefore, the unobserved asset values and volatilities can be estimated based on observable variables of equity values and equity volatilities, via the well-established option-pricing framework.[6]

Once all three key inputs are estimated, distance to default (DD) is calculated as the difference between the expected asset value and the default point, scaled by the volatility of asset values over the forecasting horizon. To convert DD, which is measured in standard deviations, to expected default probabilities, the structural approach often relies on a distributional assumption imposed on future asset value. However, Moody's EDF model does not impose a parametric distributional assumption on asset values. Instead, it relies on historical default experiences to map DD to EDFs.

Why do firms' capital structures matter?

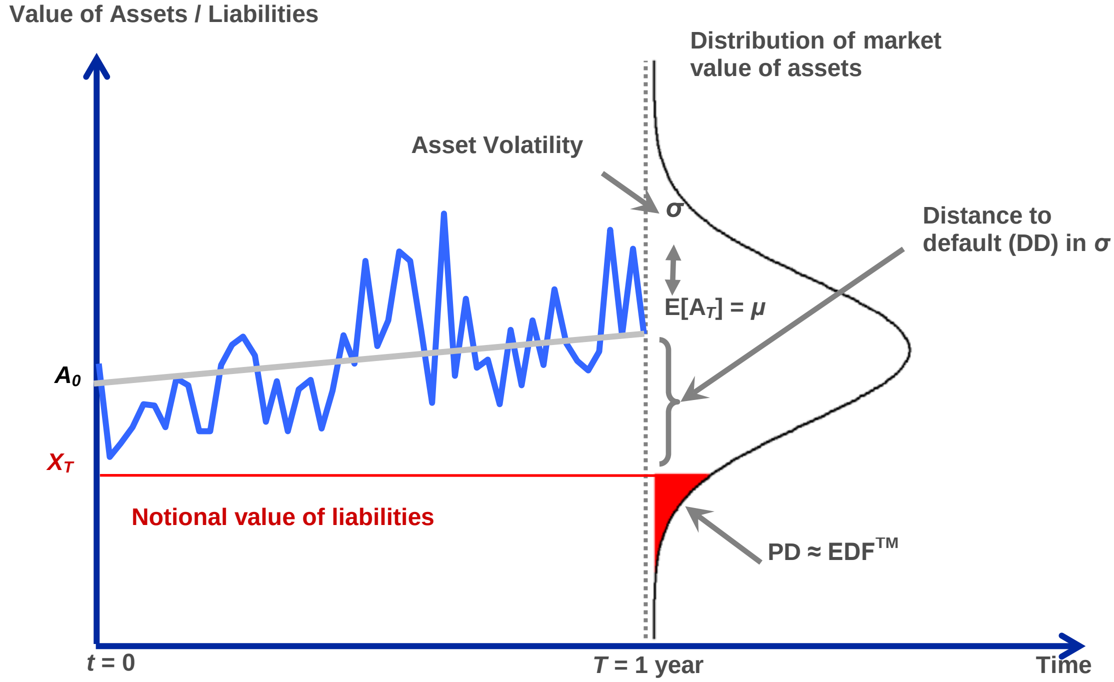
By describing the process of PD estimation in structural models, we highlight the key piece of information that is incorporated into structural credit risk models but missing in equity prices: firms' capital structures. Firms with similar equity performance and market equity risk may have very different PD estimates because their capital structures vary considerably.

There are at least two channels through which capital structure impacts a firm's PD. First, leverage directly affects the default point, with higher leverage implying a higher default point. Second, leverage affects a firm's PD through its impact on the firm's asset volatility. Leverage magnifies a firm's business risk, i.e., a firm with higher leverage will exhibit greater equity volatility than an otherwise identical firm with lower leverage. When we reverse the process to infer firm asset volatility from equity volatility, a firm with higher leverage will have *lower* asset volatility than a firm with identical equity volatility but lower leverage. So for a given equity value and equity volatility, asset volatility is inversely related to leverage.

The two channels through which leverage impacts PD have offsetting effects. Through the default point channel, high leverage implies high PD. But through the volatility channel, high leverage implies low asset volatility, and hence, low PD.

6 The EDF model uses proprietary technology to estimate firms' asset values and asset volatilities based on histories of their equity values. Its methodology is described in greater details in Crosbie and Bohn (2003).

Figure 1 - Default Process in Structural Credit Risk Models



Capital structure not only impacts PD by itself, it also affects how changes in equity values are translated into PD. Drops in equity prices reduce a firm's DD and raise its PD if other inputs to PD calculation are kept constant. However, even in hypothetical situations where all PD drivers except equity prices remain constant, large decline in equity prices does not translate into increases in PD levels at a similar rate. This is because the impact of equity price swings is often dampened by the "deleveraging" effect of a firm's capital structure noted above. It is also possible that a firm's PD persistently stays at an elevated level, even with small contemporaneous equity price changes. This is because the firm is already very default risky as determined by other PD inputs, such as capital structure. So small absolute changes in equity values will not change much the firm's default risk assessment by structural models. This line of reasoning implies that changes in equity values may be weakly correlated with PD.

Equity market information is not translated into default risk rank ordering in a monotonic fashion

In sum, capital structure impacts a firm's PD not only because it contains the debt load information, but also because it interacts with other inputs of structural models. As a result, equity market information is not translated into default risk rank ordering in a monotonic fashion. So the task of quantifying (or at a minimum, rank ordering) default risk from equity market information requires incorporation of firms' capital structure. Doing so is a nontrivial exercise, of course.

Equity returns and default risk: where does theory stand?

The foregoing section discusses, at an intuitive level, why information on firms' capital structures is critical in transforming equity prices into proper default risk assessments. In the absence of capital structure information, are there sound theoretical reasons that equity returns can provide useful stand-alone credit measures? The answer is unfortunately no. The reason is that the decomposition of realized equity returns, used for constructing equity performance-based credit measures, consists of two components: an expected returns component, commensurate with firms' equity risk, and an excess returns component, due to informational surprises pertaining to a firm.

Strong equity performance is potentially a reflection of high default risk

We argue that the two components work in opposite directions in translating default risk into realized equity returns. The first component, expected equity return, is *positively* related to a firm's equity risk. This tenet underlies almost all financial theories. The firm's likelihood of default is arguably one source of its equity risk.[7] So if we ignore the information surprise component to realized returns, strong equity performance is potentially a reflection of high default risk. By contrast, the second component, return surprises, is expected to be *negatively* related to default risk. Positive earnings news will generally reduce a firm's default likelihood, and at the same time causes its stock price to react positively to the news. In situations where the second component dominates, equity performance is negatively related to default risk, which is the hypothesis underlying the conventional wisdom associated with equity performance-based credit measures. However, when the first component of realized returns dominates, the conventional wisdom breaks down—low realized returns are simply a reflection of low risk, including default risk, associated with the stocks.

In practice, it is very difficult to determine empirically how much of realized equity returns is attributable to default risk and how much is attributable to return surprises.[8] So equity performance is, at best, a noisy signal of firms' default risk. And in some occasions, it will produce misleading signals, depending on which of the two return components dominates realized returns. Our empirical analysis later validates this point.

In summary, we should not expect equity performance alone to provide a proper rank ordering of default risk. By contrast, business risk is properly accounted for in structural credit risk models after the complex effect of capital structure on a firm's probability of default is fully incorporated. Thus, at a theoretical level, EDFs should have a superior power to equity performance in forecasting defaults.

Before concluding the section, we discuss briefly another informational difference between equity returns and EDFs. EDFs use a firm's equity level, volatility and capital structure at a given point of time to produce estimates of default likelihood. These data points are just a snapshot of firms' default risk. In contrast, *n*-month cumulative equity returns incorporate a longer window of information in rank ordering default risk. Thus, the information content of equity performance-based credit measures is not a subset of that of EDFs, even though the latter contains additional dimensions of information beyond equity prices.

Data and Methodology

The equity performance of a firm is measured by its trailing 6-month cumulative stock return

For the majority of the analysis in this study, the equity performance of a firm is measured by its trailing 6-month cumulative stock return. To be included in the sample at a given point of time, say, the end of December 2004, a firm needs to have stock returns in the past six months, as well as a one-year EDF observation on the last trading date of December 2004. We then collect default information on the firm over the subsequent 12 months, in this case from January 2005 to December 2005. This matched sample allows us to compare the predictive power of 6-month equity returns and one-year EDFs. Because we are simply interested in whether equity returns can properly rank order default risk, no transformation of equity returns to PDs is needed to compare them with EDFs.

There is a certain degree of arbitrariness in selecting the length of the return window. Two considerations impacted the choice: the strength of default warning signals and the number of observations that made it through the data filter. Shorter windows allow more firms to be included in a given cohort, but they capture weaker momentum in equity movements, and hence provide less effective default warning signals provided that equity returns are a legitimate credit scoring instrument. Longer windows capture stronger momentum in equity price movement but induce potentially larger survivorship biases. We chose a 6-month return window to strike an appropriate balance between the two considerations.[9]

When 6-month windows are used to construct equity performance-based credit measures, the sample period for the study is restricted to the time between October 2001 and July 2009. The last cohort is formed

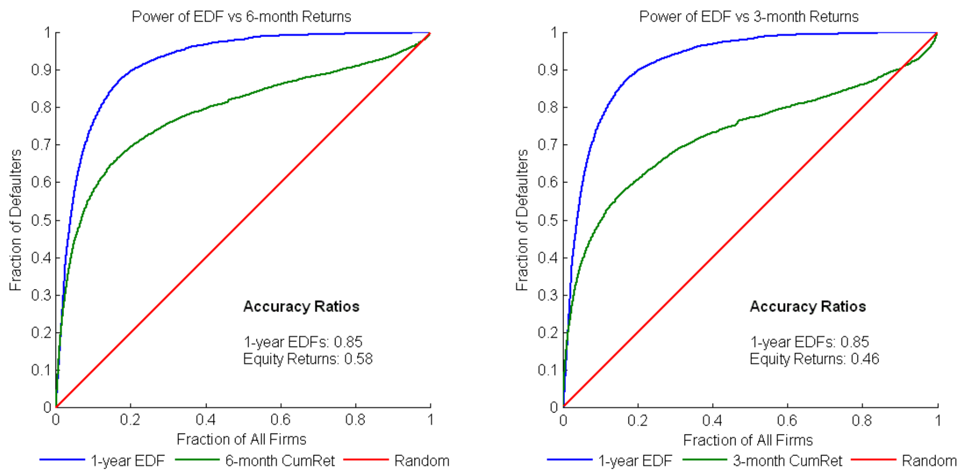
7 There is an ongoing discussion of whether a firm's default risk is priced in its equity returns in academic research. See, for example, Vassalou and Xing (2004).

8 There is hardly any agreement in academic literature on how to identify the expected return component from the return surprise component, as evidenced by dozens of papers produced each year surrounding the controversy. Separating default risk from informational surprises in return generating processes would be even more difficult.

9 We also tried other return windows such as 3 months and 12 months. The results are qualitatively very similar. We discuss these results where relevant but do not completely report the results separately.

at the end of July 2008, so defaults in the subsequent 12 months can be observed. As we increase the length of return windows, we lose a few months of matched observations at the beginning of the sample period and hence have fewer cohorts at our disposal. We also exclude financial firms, as well as corporates with sales less than $30 million, from the sample of North American firms. For European firms, the sample is restricted to corporates with sales equal to or greater than €30 million.[10] There are in total 6,016 unique firms with 714 default events included in the sample.

Figure 2 - CAP Curves of EDFs and Equity Returns for North American Corporates



Default Prediction Power of EDFs vs. Equity Returns

We begin our empirical analysis with an investigation of the predictive power of equity returns in forecasting 12-month horizon defaults, and compare their power with those of EDFs. We plot the Cumulative Accuracy Profile (CAP) curves of each scoring system and calculate the associated Accuracy Ratios (ARs). (The methodology for plotting CAPs and the interpretation of ARs are discussed in the sidebar.) The CAP curves of trailing 6-month equity returns and one-year EDFs for North American coporates are plotted in the left panel of **Figure 2.**

The left panel of **Figure 2** shows that both EDFs and equity returns exhibit default prediction power for the base sample of the study: the CAP curves of both credit measures stay above the 45 degree line throughout the risk spectrum. To our knowledge, this is the first time the predictive power of equity returns has been empirically examined. The result suggests that the conventional wisdom of associating high default risk with poor equity performance is somewhat supported by empirical evidence.

10 The rationale behind this data exclusion is that the restricted sample is known to be less sensitive to data outliers.

The economic advantage of adopting EDFs over equity returns in default prediction is too obvious to be overlooked

However, the power of the two credit measures differs by a large amount. The accuracy ratio of EDFs is 85%, whereas the AR of 6-month equity returns is only 58%. To put the 27 percentage point difference in perspective, Stein and Jordao (2003) show that a five percentage point difference in AR leads to significant economic benefits of adopting a stronger default prediction model instead of a weaker one. The economic advantage of adopting EDFs over equity returns in default prediction is too obvious to be overlooked.

The CAP curves also help us identify the segment of the risk spectrum where the performance difference is most significant. For EDFs, the entities are arranged in the x-axis in the order of from highest EDFs on the left to lowest EDFs on the right; for 6-month equity returns, the entities are arranged in the order of from worst stock performance on the left to best stock performance on the right. We can see in **Figure 2** that the CAP curves of the two credit scoring systems almost coincide with each other at the riskiest portion of both rating systems. They begin to diverge at the coordinate of roughly (0.03,0.35), suggesting that to avoid 35 percent of defaulters, one can either exclude 3 percent of all entities with highest EDFs, or equivalently, 3 percent of all entities with worst 6 month stock performance. This is not surprising, since the worst stock performers likely experience extreme financial distress. The sign of distress is so obvious that structural models like the one behind EDFs cannot extract default-relevant information that is more precise than what is already reflected in stock markets.

A Primer on the Cumulative Accuracy Profile (CAP) and Accuracy Ratio (AR)

The rank ordering power of a credit scoring instrument is measured graphically by the Cumulative Accuracy Profile (CAP) and its summary statistic, the Accuracy Ratio (AR).

In plotting a credit measure's CAP curve, one sorts all entities (both defaulters and nondefaulters) of a portfolio from the most risky (e.g. highest EDF) to the least risky (lowest EDF) and represents the cumulative percentage of the sorted entities on the x-axis. The y-axis of the CAP curves is constructed similarly to the x-axis, but the sample is restricted to firms that default within a given horizon, typically one year, subsequent to cohort formation. Each point on the CAP curve of a credit measure answers the question, "How many firms in a portfolio of credits does one have to exclude to avoid a certain percentage of defaulters?" Certainly, the smaller the number is, the more powerful the rating system is in identifying defaulters from non-defaulter, and the steeper the CAP curve.

A random model has no power in separating defaulters from non-defaulters and, as a result, its CAP curve follows a 45 degree line through the unit square. By contrast, a perfect model will have its CAP curve rise immediately to the unit level on the y-axis and stay flat to the top right corner of the unit box.[11] Any model with a CAP curve staying above the 45 degree line will have some predictive power in default forecasting. The closer is its CAP curve to that of a perfect model, the more powerful the model is.

To summarize the power performance of a credit scoring system, one computes the area under its CAP curve but above the 45 degree line and divide it by the corresponding area for the perfect model. This ratio is termed the Accuracy Ratio (AR), which, in essence, measures how close a rating system is to being perfect (in terms of rank ordering). Like a correlation statistic (which is very similar to AR), the accuracy ratio ranges from 0 to 1. The closer it is to 1, the more discriminatory power the associated credit scoring system offers. Also, a credit scoring system with a higher AR than another does not necessarily mean that the former is uniformly more powerful than the latter in default prediction. Two CAP curves may cross each other and yet have very different accuracy ratios. In this case, the credit scoring system with higher accuracy ratio outperforms the other on an overall basis, but may under-perform the latter for a certain portion of the risk spectrum.

11 Strictly speaking, the CAP curve of a perfect model is slightly to the right of the top left corner of the unit box to account for the fact that all defaulters within the entire population are successfully identified to be those with lowest credit ratings.

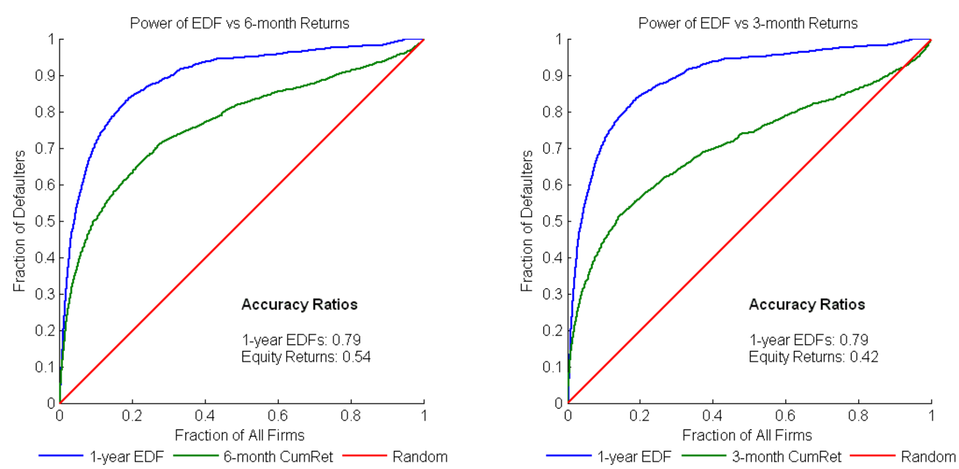
The performance differential is economically as well as statistically important

However, as we began to examine stocks with better past performance, it becomes more likely that equity returns provide the wrong rank ordering of default risk, i.e., firms with relatively good past stock performance default in the subsequent 12 months. Or conversely, firms with relatively poor past stock performance continue to operate without defaulting in the next 12 months. To put this another way, the CAP curves indicate that the superior performance of EDFs does not come from identification of obvious defaulters; rather its performance advantage is for entities whose default risk is not readily reflected in its stock performance. Credit risk managers are primarily concerned with identifying the likely defaulters in this intermediate quality range, rather than the obvious cases, so the performance differential is economically as well as statistically important.

Note also that the CAP curve of 6-month equity returns becomes linear or slightly convex-shaped for the best-performing stocks (i.e., in the top right portion of the curve). A convex CAP curve suggests that superior equity returns are followed by *higher* default rates, which is contrary to the conventional wisdom of using stock performance for default prediction. We present more evidence of this "anomaly" in subsequent analysis.

To test the robustness of the results, we plot the CAP curves of one-year EDFs versus those for 3-month cumulative equity returns and calculate their accuracy ratios, as shown on the right panel of **Figure 2**.[12] We also conduct the same analysis for large European corporate firms.[13] Their CAPs curves and corresponding ARs are displayed in **Figure 3**. The superior performance EDFs is evident in both samples, as well as for both equity return windows. A couple of additional observations are worth mentioning. First, as we reduce the window size for cumulative return calculation from 6 months to 3 months, the power differential between EDFs and equity returns measured by accuracy ratios increases. For example, for the North American corporates sample, the difference in accuracy ratio goes up from 27 percentage points (85% versus 58%) to 39 percentage points (85% versus 46%). One explanation for this is that longer return windows incorporate longer return history, and therefore allows a stronger momentum effect to be captured by return-based credit signals. Second, there is higher degree of convexity in the top portion of 3-month equity return CAP curves for both North American and European samples than what is observed for 6-month equity return CAP curves. This suggests that shorter equity return windows may send a very misleading early warning signal for stocks with very good performance: better past performance may be followed by relatively higher default rate, albeit the overall level of default risk for these entities is very low.

Figure 3 - CAP Curves of EDFs vs. Equity Returns for European Corporates



12 We end up with a sample of 6,115 firms and 723 defaults, when 3-month equity returns and one-year EDFs are used as data filtering criteria.

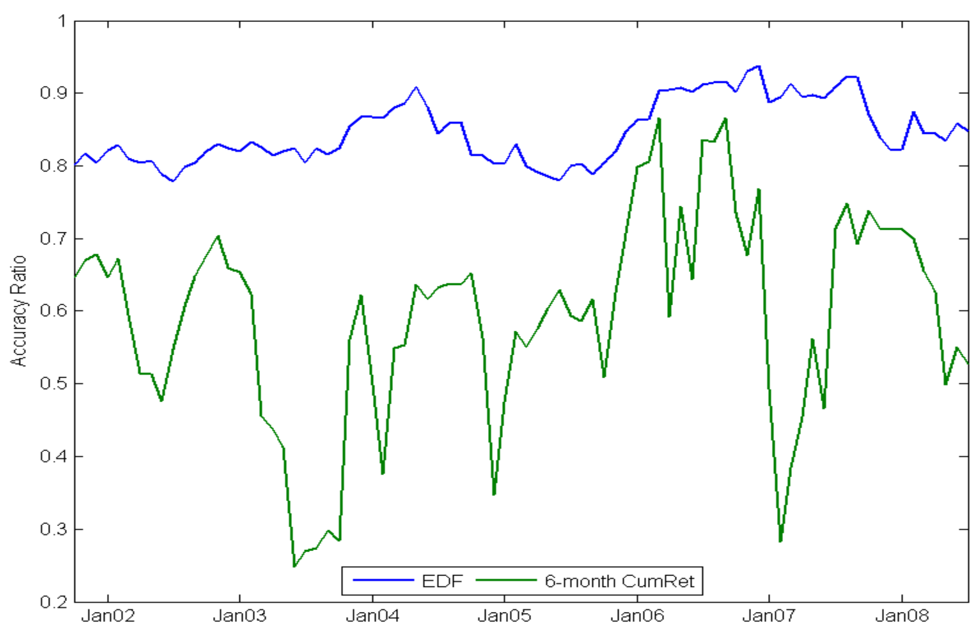
13 The European sample for the comparison of 1-year EDF and 6-month equity returns consists of 6,291 firms and 306 defaults; the European sample for the comparison of 1-year EDF and 3-month equity returns consists of 6,462 firms and 315 defaults. We also increase the length of return window to 12 months for both North American and European corporates. The advantage of EDF over equity returns in default prediction power is still very significant. However, longer return windows introduce a larger survivorship bias in favor of equity returns since firms with shorter return windows but high EDFs prior to default are excluded from the sample.

The time series of EDF accuracy ratios stay consistently above its equity return counterpart, indicating superior default prediction power by EDFs throughout the sample period

Poor stability of equity return performance

In addition to the overall power of a credit scoring system, credit risk managers are also interested in the stability of its performance over time. To this end, we calculate the ARs of the two credit scoring systems, EDFs and 6-month equity returns, cohort-by-cohort for the North American sample and plot their time series in **Figure 4**. A couple of observations are in order. First, the time series of EDF accuracy ratios stay consistently above its equity return counterpart, indicating superior default prediction power by EDFs throughout the sample period. Second, the variation in accuracy ratios of EDFs over time is much smaller than that of equity returns. The EDF ARs stay within the band of 80 to 90 percent most of time. In contrast, the ARs of 6-month equity returns fluctuate wildly over time, dropping below 30 percent on a few cohorts and spiking up to more than 80 percent occasionally. The two observations combined suggest that EDFs not only outperform equity returns consistently in default prediction they are also a more reliable early warning signal.

Figure 4 - Time Series of Accuracy Ratios of EDFs and Equity Returns, North American Corporates



Why Do Equity Returns Underperform EDFs in Default Prediction?

The above analysis shows that both EDFs and equity performance exhibit predictive power for corporate defaults. But the CAP curves and ARs do not reveal the functional form of the relations between equity returns, EDFs and default risk. As a result, the source of underperformance by equity returns in default prediction is largely unknown. In this section we take a limited step in understanding the source of power differential between the two credit measures by exploring if either credit measure is monotonically related to default risk, and if the two credit measures are monotonically related to each other.

As a first step in this direction we investigate whether equity returns and EDFs generate monotonic rank ordering of default rates by forming portfolios on the two credit measures separately. This is a crude test of whether each credit measure by itself is monotonically related to default risk, a desirable feature of a powerful credit measure.[14] In addition, we examine whether the two credit measures generate consistent portfolio rank ordering between themselves. A consistent rank ordering between the two credit scoring systems implies that default-related information incorporated in the two systems is at least directionally

14 We note that a monotonic relationship between a credit measure and default rate implies that the credit measure has default predictive power, but the reverse is not necessarily true. For this reason, a powerful credit measure is not necessarily useful in practice, as is the case of equity returns.

identical. However, it does not preclude the possibility that one rating system is still more powerful than the other because its rank ordering of default risk at finer portfolio levels might be better aligned with actual default experience. On the other hand, if the rank orderings produced by the two systems are *not* lined up with each other, then one credit scoring system must have incorporated additional dimensions of default-related information.

In the first part of this section, we show empirically that EDFs contain additional dimensions of information that is directionally dissimilar to equity returns. This is consistent with the earlier arguments that EDFs take into account firms' capital structures and business risk in addition to their equity values. The informational dissimilarity between the two credit warning systems prompts us to further sort firms in two dimensions, i.e., according to their equity returns and their EDFs. The two-dimensional sort enables us to identify which dimension is better aligned with actual default rates.

Do equity returns line up with EDFs?

To test the hypothesis of a negative relationship between stock performance and default rates, we sort the base sample of large North American corporate firms into 10 equal-sized portfolios based on their trailing 6-month cumulative returns, ranked from the lowest to the highest at the end of each month. We then calculate the average 6-month returns,[15] mean EDFs, median EDFs, as well as the realized default rate for each portfolio. The time series averages of portfolio statistics are reported in **Figure 5**.

Figure 5 - Portfolios Sorted on 6-Month Stock Returns

PORTFOLIO	AVG RET	MEAN EDF	MEDIAN EDF	DEFAULT RATE	#FIRMS
Lowest Ret	-0.51	14.50	11.33	9.24	393
2	-0.26	5.16	2.04	2.07	394
3	-0.15	3.18	0.80	1.10	394
4	-0.07	2.25	0.42	0.66	394
5	-0.01	1.85	0.28	0.51	394
6	0.06	1.68	0.24	0.40	394
7	0.13	1.56	0.22	0.41	394
8	0.21	1.66	0.26	0.39	394
9	0.36	2.09	0.38	0.51	394
Highest Ret	0.87	3.81	0.92	0.77	394

Equity returns are of limited value in default risk assessment

By construction, the average of 6-month equity returns (the sorting variable) increases from -51% for the lowest return portfolio to 87% of the highest return portfolio. The hypothesized negative relation between equity performance and default rate only holds for stocks with poor performance. After portfolio 6 the default rate becomes flat, and even rises slightly as 6-month equity returns continue to increase. The time series averages of mean and median EDFs exhibit a similar pattern to realized default rates in their relations to past stock performance. This "smirk"-shaped relationship suggests that equity returns are of limited value in default risk assessment, and that their default predictive power is strongest for firms with very poor equity performance, i.e., when entities' distress is most obvious in the stock market. This observation is consistent with what we learned from the CAP curve derived from equity returns. Furthermore, for strong stock performers, the tendency of default rates, as well as EDFs, to increase with equity returns is consistent with convex-shaped CAP curves at the top end of the plots.[16]

Figure 5 shows that both EDFs and default rates are smirk-shaped, when rank ordered based on 6-month equity returns. But the result does not address directly whether EDFs properly rank order actual default rates. To this end, we sort entities in the base sample by EDFs on a cohort-by-cohort basis and construct a table similar to **Figure 5**. The average 6-month equity returns and default rates for these EDF-based portfolios are reported in **Figure 6**.

15 Six-month cumulative equity returns are winsorized at 1 percent and 99 percent levels.

16 It is also worth noting that median EDFs are lower than their mean EDF counterparts for all return sorted portfolios. This is consistent with right-skewed default probability distributions.

Figure 6 - Portfolios Sorted on Mean EDFs

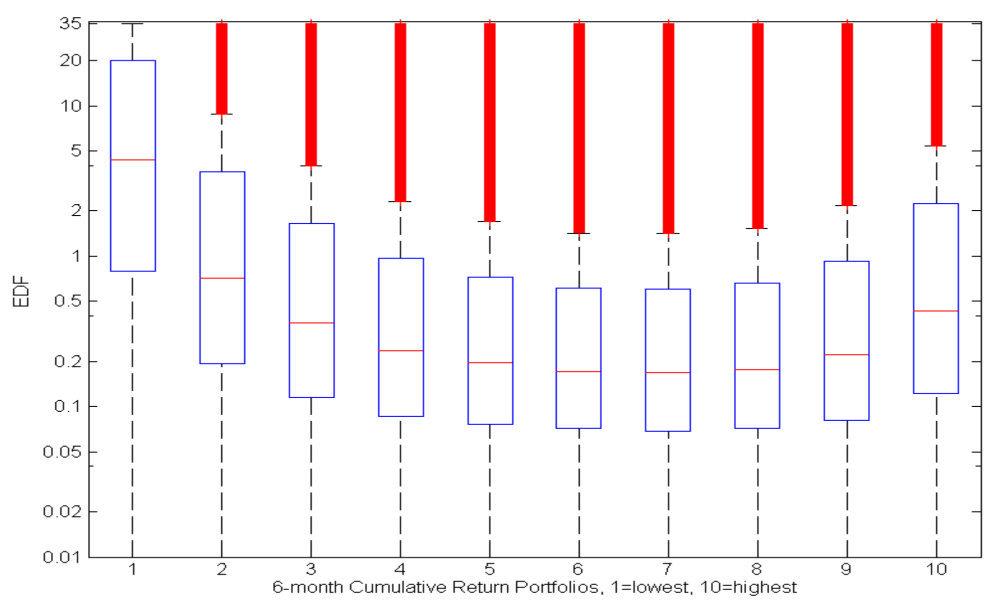
PORTFOLIO	MEAN EDF	MEAN RETURN	DEFAULT RATE	#FIRMS
Highest EDF	23.19	-0.19	12.99	397
2	8.07	0.02	2.97	391
3	3.22	0.06	0.96	394
4	1.48	0.09	0.55	394
5	0.76	0.10	0.33	394
6	0.41	0.11	0.12	394
7	0.24	0.11	0.10	394
8	0.14	0.11	0.04	394
9	0.09	0.11	0.04	394
Lowest EDF	0.04	0.10	0.01	393

Figure 6 shows that realized default rates decline monotonically as EDF levels go down, suggesting that EDFs provide proper rank ordering of firms' default risk. Improvement in average 6-month equity returns prior to cohort formation accompanies significant drops in EDFs only up to portfolio 4. After that, equity returns are fairly flat, while default risk measured by EDFs continues to fall. Again, this is consistent with our earlier observation that equity returns and default risk are not monotonically related.

In addition to the relationships between average *levels* of EDFs and firms' past stock returns, we are also interested in how *distributions* of EDFs vary with past equity returns. The EDF distribution for each equity return-sorted portfolio is plotted in Figure 7. The box for each portfolio represents the inter-quartile range of its EDF distribution, with the red bar inside the box representing the median of the distribution. The red "whiskers" represent data outliers beyond the 99th percentile of the distribution. In a typical distribution, the whiskers are scattered red + signs. But in the graph, there are so many outliers that they cluster together to create the appearance of a red bar. The vertical axis of the plot is in log scale, which suggests caution in interpreting the graphs on a purely visual basis.

A couple of observations on Figure 7 are in order: first, the sizes of boxes are not directly comparable across portfolios. Distributions with identical box size on a log scale may have very different degree of dispersions on a linear scale, depending on the position of the box. And secondly, what appear to be symmetric distributions on a log scale are actually highly right skewed when placed on a linear scale.

Figure 7 - EDF Distributions for North American Corporates Sorted on 6-Month Cumulative Returns



The medians of the EDF distributions decline initially with past equity returns for poor performing stocks. As the stock performance improves, the rate of decline slows down; after portfolio 7, the median EDF shows a tendency to increase with past equity returns. This is consistent with the observation drawn from **Figure 5**.

In addition, **Figure 7** shows that EDF distributions are widely dispersed and right skewed. This shows that firms with similar stock performance exhibit very different EDFs. Note, too, that the degree of dispersion of EDF distributions shows a similar smirk-shaped pattern to the medians of distributions in their relationships to past equity returns. Because the y-axis is on a log scale, the inter-quartile ranges of the distributions with higher median EDFs are much larger than that for those with smaller medians of equal size box. This means that the divergence of default risk as measured by EDFs is most acute among stocks with extreme past performances (i.e., those in portfolios 1, 2 and 10). Second, also due to the log-scaled y-axis, the EDF distributions of all portfolios are skewed to the right based on a linear scale. Moreover, because EDFs are capped at 35 percent, the EDF distributions of all portfolios are truncated to the right. The truncation to portfolio 1 is most obvious because the upper limit of its inter-quartile range almost reaches the 35 percent EDF cap. For portfolios 2-10, the right tails of their EDF distributions are so fat that outliers cluster together to form red bars.

Overall we learn from this box plot that EDFs and stock returns may differ substantially for a large subset of stocks. This reinforces the early observation that EDFs incorporate additional dimension of default-related information than what is already contained in equity returns.

Sources of superior default predictive power by EDFs

Both power analysis (i.e., CAP curves and ARs) and one-dimensional portfolio analysis suggest that EDFs and equity returns incorporate directionally dissimilar default-related information. So a logical next step is to disaggregate their contributions to default prediction by sorting the universe of firms on both variables. The two-dimensional sort is done in two steps: 1) at the end of each month, we sort the universe of firms into 5 equal sized portfolios based on their trailing 6-month cumulative stock returns; 2) within each return quintile portfolio we further sort the firms into 5 equal sized portfolios based on their end-of-month EDFs. In this way, we end up with a 5X5 matrix. We then calculate average values of each sorting variable, the realized default rate over the subsequent 12 months, and the total number of observations for each of the 25 portfolios, on a cohort by cohort basis. Time series averages of the portfolio statistics are reported in **Figure 8**. In these 5X5 matrices, cumulative equity returns increase (hence default risk, in equity returns' view, declines) from top to bottom for each column; EDFs increase from left to right for each row. The top right (bottom left) cells of the matrices represent firms deemed most (least) default risky by both credit scoring systems. However, the cells at top left and bottom right corners contain firms whose default risk are viewed very differently by EDFs and equity returns. In particular, the top left cell contains firms that are deemed most default risky from the perspective of equity returns but least default risky as measured by EDFs, whereas the views of default risk for the bottom right cell from the two systems are just the opposite.

Figure 8 - Two Dimension Portfolios Sorted on 6-Month Stock Returns and EDFs

PORTFOLIO	LOW EDF	2	3	4	HI EDF	LOW EDF	2	3	4	HI EDF
	A. Average 6-Month Returns					B. Average One-Year EDFs				
Low Ret	-0.28	-0.30	-0.33	-0.38	-0.47	0.30	1.17	3.22	8.60	24.57
2	-0.09	-0.10	-0.11	-0.11	-0.11	0.07	0.21	0.51	1.47	9.28
3	0.03	0.03	0.03	0.03	0.03	0.05	0.12	0.25	0.72	6.52
4	0.17	0.17	0.17	0.17	0.17	0.05	0.11	0.24	0.67	6.11
Hi Ret	0.49	0.55	0.61	0.64	0.72	0.08	0.22	0.56	1.61	9.74
	C. Average Realized Default Rates (%)					D. Average Number of Firms				
Low Ret	0.16	0.74	1.50	4.97	17.46	153	153	153	151	155
2	0.02	0.13	0.20	0.59	3.18	153	153	153	153	154
3	0.00	0.06	0.09	0.31	1.73	153	153	153	153	154
4	0.02	0.04	0.08	0.19	1.64	153	153	153	153	154
Hi Ret	0.01	0.09	0.20	0.29	2.59	153	153	153	153	154

We first examine the variation of the sorting variables across rows and columns. By construction, the average values of sorting variables are monotonically increasing in the direction they are sorted. Specifically, average equity returns increase from top to bottom for each column (Panel A) and average EDFs increase from left to right for each row (Panel B). What makes this two-dimension sort more interesting is to examine how the values of sorting variables behave across the other sorting dimension.

For stocks with the best past performances, average equity returns increase with EDFs

By examining the behavior of average equity returns across the EDF dimension (i.e., variation across columns for each row in Panel A of Figure 8), we find that the linkage between equity returns and EDFs is very weak for most stocks. Stocks with the poorest 6-month performance see their average equity performance decline with increases in EDFs, indicating that equity returns and EDFs provide similar rank ordering of default risk for this set of firms. For stocks with moderate 6-month performance, i.e. portfolios 2 to 4, equity returns vary little with EDFs, suggesting that equity returns provide little discriminating power even though EDFs can be very different. Interestingly, for stocks with the best past performances, average equity returns *increase* with EDFs. This is the opposite of the conventional wisdom using equity returns as a credit scoring instrument, but consistent with the S-shaped, convex CAP curve observed for equity returns.

By studying the pattern in EDF change for each column in Panel B of Figure 8, we observe that EDFs tend to have a smirk-shaped relationship with past equity returns. The same pattern is observed for one-dimensional portfolios sorted only on 6-month equity returns. Thus, both the one-dimensional and the two-dimensional sorts suggest that information incorporated in EDFs and equity returns is not directionally aligned. Furthermore, there is a substantial amount of variation in EDFs within each equity return portfolio. For example, average EDFs for the poorest performing stocks range from 30 basis points to 24.59% and average EDFs for the best performing stocks range from 8 basis points to 9.76%. If we assume that EDFs reflect true default risk, this means that firms with similar equity performances have very different levels of default risk. The conclusion reconfirms our early observation that EDFs incorporate information beyond what is already contained in firm's equity performance.

Realized default rates in the 5X5 portfolios

The variation of sorting variables across rows and columns describes dissimilarity in informational content between the two credit scoring instruments. To address which of the two instruments is a better tool for default prediction, we examine the realized default rates for each of the 5X5 portfolios.

Differences in EDFs are much better predictors of default risk differentials than differences in past stock performance

The variation in realized default rates in the two-dimension sort (Panel C of Figure 8) is very similar to what is observed for EDFs. First, realized default rates increase monotonically with EDFs for each return portfolio. The differences in realized default rates between the lowest EDF and the highest EDF portfolios are substantial, and are of similar magnitude to the differences in EDFs themselves (compare Panel C to Panel B). For example, average default rates increase from 16 (1) bp to 17.42% (2.62%) for the poorest (best) performing stock portfolio.[17] Second, the realized default rate also has a smirk-shaped relationship with equity returns, similar to that between EDFs and equity returns. Observant readers may notice that there is significant variation in realized default rates among firms with highest EDFs, suggesting that equity returns may contain default-related information not captured by EDFs. However, the pattern, as well as the magnitude, of variation is closely matched by these firms' EDFs, as shown in Panel B. Overall, differences in EDFs are much better predictors of default risk differentials than differences in past stock performance.

It is illuminating to compare the default rates of firms whose default risk is assessed very differently by equity return signals and by EDFs. At the top left corner of the 5X5 matrices are firms deemed of high default risk by equity return signals but very low default risk by EDFs; at the bottom right corner of the 5X5 matrices, the opposite is true. The realized default rate for the bottom right portfolio is 2.62%, whereas the default rate for the top left portfolio is only 16 bp, i.e., 16 times smaller than the former. The two corner portfolios highlight the superiority of EDFs to pure equity return-based default warning signals.

Regression Analysis

Methodology

By analyzing default occurrences and their relationships with EDFs and equity returns at the portfolio level, we collect substantial evidence that EDFs outperform equity returns in default risk prediction. To verify this assertion with statistical rigor, we need to carry out regression-type analyses where EDFs and equity returns are pitted head-to-head against each other. To this end, we employ logit regression of the following specification

$$P(y_{it}=1)=\Lambda(x_{it}\beta+e_{it}),\quad t=1,2,\cdots,T_i, i=1,2,\cdots,N, \qquad (1)$$

where $y_{it}=1$ when default occurs within 12 months subsequent to cohort formation at time *t* for issuer *i*, Λ (z) is the logistic function $\Lambda(z)=1/(1+\exp(-z))$, and x_{it} captures the covariates (independent variables, in regression terms) for the logit regression.

In this study we consider only two covariates to be included in the logit regression: one-year distance to default (DD1) and 6-month cumulative equity returns. One-year EDFs are a monotonic transformation of DD1, but unlike DD1, they are capped from below at 1 basis point and from above at 35 percent. Using DD1 in place of EDFs as a covariate eliminates the problem of data censoring and therefore yields the same partial effect on conditional default probability as if unconstrained EDFs had been used as a covariate.

Readers may question whether the model is properly specified by using at most two covariates on the right hand side of the regression equation. After all, there is a large body of research where a multitude of market and accounting variables are shown to be significant in default prediction. The answer to the question is two-fold.

First, the purpose of this analysis is not to find an exhaustive list of variables from which a best combination is identified for default prediction. Instead, the goal is more limited: we want to test 1) whether DD1 and equity returns predict default in the direction consistent with earlier portfolio evidence and 2) whether DD1 subsumes the power of equity returns in default prediction and vice versa.

Second, in Merton-style structural models (including the EDF model), distance to default (DD) supposedly captures all default-relevant information, and hence all other variables are expected to have zero

17 Higher average EDFs than realized default rates for the same portfolio may be caused by 1) hidden defaults, defaults that are not collected into default database, and 2) skewed default distribution which means mean default is higher than what is most likely observed over a certain period.

contribution to default prediction in the presence of DD. Of course, whether this assertion holds in practice is subject to empirical investigation.[18]

Since a time series of default flags along with their covariates are observed for each issuer, we are dealing with time-series cross-sectional data, also called panel data or longitudinal data. In this setting, a pooled logit regression approach, in which the error terms e_{it} are assumed to be conditionally independent across both firms and over time, is not appropriate. It is reasonable to expect nonzero serial correlation in the error terms between time series observations of a given firm. One way to deal with "intra-class" serial correlation is to decompose the error term e_{it} into two components

$$e_{it} = u_i + v_{it} \qquad (2)$$

where u_i captures the unobserved firm-specific heterogeneity that may raise or reduce the overall level of a firm's probability of default but are not included in x_{it}, and v_{it} denotes the "true" noise that are conditionally independent both across firms and over time. Note that this approach further lessens the need to include other covariates in the regression, as the firm-specific error term will absorb any additional variance (which, again, we are not specifically concerned with in this paper).

Given the presence of unobserved firm-specific effects, there are generally two approaches to estimation of *β*, fixed effects (FE) estimation and random effects (RE) estimation. The key distinction between the two approaches is whether the unobserved effect u_i is assumed to be independent of the covariates x_{it} for all *t*.[19] Under the RE approach to panel logit regression, it is assumed that $u_i \mid x \sim N(0, \sigma_u^2)$, so that u_i and x_i are independent. This means, in the context of a default prediction model, that firm-specific characteristics that may affect the level of a firm's PD but which are not included in x_i are uncorrelated with x_{it} for all *t*. This assumption is reasonable when DD1 is included in x_i, since DD1 is a sufficient statistic to default probability in structural models. However, when equity returns are the sole covariate of the logit regression, variables excluded from x_{it} are likely to be correlated with x_i (e.g. accounting ratios are likely correlated with equity returns).[20] In the absence of other covariates, RE estimation would not be an appropriate approach in this case. By contrast, FE estimation allows the unobserved effect to be arbitrarily correlated with variables included in x_i. So FE estimation is a suitable approach when equity returns are the sole regressor of the panel logit regression.[21]

We estimate five models using DD1 and equity returns as regressors: fixed and random effects models using equity returns and DD1 alone (respectively); a pooled logit model on both covariates; a generalized estimating equations (GEE model) with the same regression specification as the pooled logit model but robust standard errors; and a random effects model that includes both DD1 and equity returns. The last regression deserves the most attention as it provides that answer to the question we are trying to answer in this section.

18 Some contradicting evidence has been documented by researchers using their versions of Merton-type structural models. Hillegeist, Keating, Cram, and Lundstedt (2004) show in a discrete duration model that their version of distance to default does not entirely explain variation in default probabilities across firms. Campbell, Hilscher, and Szilagyi (2005) also find that distance to default does not produce a sufficient statistic for the probability of default in the presence of market leverage and volatility information, among other covariates.

19 Traditionally, random effects are distinguished from fixed effects estimation by the fact the unobserved firm-specific heterogeneity term is treated as a random intercept in RE approach, whereas in FE approach, it is explicitly estimated as a firm-specific parameter. In this study, we adopt a modern view of the distinction: The firm-specific heterogeneity term is treated as a random variable sampled from the population along with other covariates. What distinguishes the two estimation methods is essentially the correlation assumption between the unobserved effect and the covariates. See Wooldridge (2001).

20 A large body of financial research in the field of asset pricing is concentrated on the task of searching for risk variables (or proxies of them) which can be used to predict/explain variations in equity returns. A partial list of these studies can easily exceed dozens of pages. In this default prediction study, it is quite logical to believe that these risk variables may help increase default prediction power of equity returns and at the same time are highly correlated with equity returns,

21 The FE estimation to panel logit model is also called conditional logit model since the number of default observations for each issuer is conditioned out in forming the joint likelihood function.

Results of the logit regressions

For each of the five logit regression models we report the coefficient estimate of a covariate as its impact on the odds ratio of default versus no-default in the first row of a given cell in **Figure 9**. The standard deviation of the coefficient is reported on the second row of the figure, and its *z*-statistic on the third row. The coefficient should be interpreted as change (in multiplicative terms) in the odds ratio of default versus no-default for a unit change in the given covariate. Since DD1 and equity returns are recorded in different units, comparing the size of their coefficients makes little sense. However, the size of their *z*-values does provide an indication of how important a role a covariate plays in default prediction. It is also noted that since the reported coefficients in odds ratio form are just exponential transformation of the original coefficients, a value of 1 in exponential form is translated to zero value in its original form, implying zero impact of the covariate on the odds ratio of default versus no-default. Similarly, a value of less (more) than one of a covariate's coefficient in exponential form implies that there is a negative (positive) relation between the covariate and the odds of default versus no-default.

Figure 9 - Logit Regression Coefficients (in Odds Ratios), Std Dev and *z*-Statistics

MODEL NO.	ESTIMATION METHOD	DD1	EQUITY RETURNS
1	RE on DD1	.26	
		.005	
		-65.68	
2	FE on Return		.66
			.257
			-10.64
3	Pooled logit on DD1, Return	.35	.79
		.005	.023
		-80.02	-8.08
4	GEE on DD1, Return	.35	.79
		.056	.302
		-18.86	-0.76
5	RE on DD1, Return	.26	.99
		.005	.006
		-65.03	-1.49

We first run univariate panel logit regressions of default dummy on DD1 and equity returns, respectively. The purpose of these regressions is to examine whether the two covariates working alone provide default signals that are consistent with our intuitions. In Model 1 of **Figure 9** where DD1 is the sole covariate, the RE approach to estimation is reasonable per our earlier discussion. In Model 2 where equity returns are used as the sole covariate, the FE estimation is more appropriate. In both models firm-specific heterogeneity is explicitly incorporated into the error term e_{it} . The coefficient estimates of both models are less than one in odds ratio terms, conforming to our intuition about their association with the likelihood of default. The signs of the coefficient estimates are also consistent with the portfolio evidence we presented in the previous sections. Furthermore, they are also statistically significant in both univariate logit regressions.

We next run a pooled logit regression on both DD1 and 6-month cumulative equity returns (Model 3 of **Figure 9**). In a pooled logit regression, the error term e_{it} is assumed to be independent both across firms and over time, i.e., firm-specific heterogeneity is ignored. As discussed above, this is not an appropriate model in this context. However, it serves as a benchmark for the ensuing, more elaborate models. The coefficients of both covariates under this estimation approach are less than one and statistically significant, suggesting a negative relationship between both variables and the odds ratio of default. Taken at face value, the result of the pooled logit regression indicates that both covariates contribute to default prediction, and that neither credit measure can subsume the default predictive power of the other. This conclusion appears to be contradictory to the two-dimensional portfolio evidence presented earlier. The contradiction is likely caused by the independence assumption imposed on the composite error e_{it} , which yields an unrealistic implication that the probability of default is uncorrelated across observations made on consecutive months of the same firm.

The Generalized Estimating Equations (GEE) approach provides a flexible framework for estimating population-averaged model. In particular, a logit regression can be viewed as a special case of the GEE approach in which the dependent variable is assumed to be binomially distributed and the link function is of logistic form. When the error structure is assumed to be homoscedastic and serially uncorrelated, the GEE approach is essentially the same as the pooled logit regression. However, one can make inference of the coefficient estimates in the GEE model using Huber-White type robust standard errors. The coefficient estimates under the GEE approach (Model 4 of **Figure 9**) are identical to those of the pooled logit regression (Model 3). But with robust standard error estimates, only the coefficient for DD1 remains statistically significant.

In Model 5, both DD1 and equity returns are included as covariates in the panel logit RE estimation. We argue that this is an appropriate estimation approach because it allows serial correlation in composite errors between repeated observations of the same firm and it is reasonable to assume zero correlation between unobserved firm-specific effects and DD1 in structural credit risk models. Therefore, the estimation results are amenable to proper interpretation. The coefficient for DD1 is less than unity and remains statistically significant, implying a negative relationship between DD1 (and EDFs) and the odds ratio of default. However, the coefficient for equity returns is very close to one, and we cannot reject the null hypothesis by looking at its *z*-statistic that equity returns provides no additional power to default prediction in the presence of DD1. This conclusion is consistent with the two-dimensional portfolio evidence, where the realized default rate monotonically increases with EDFs but exhibits smirk-shaped variation over the dimension of equity returns.

Overall, the RE panel logit regression presents a compelling case that EDFs are superior to equity returns as warning signals of default risk, when the error structure of the logit regression is properly accounted for. Although equity returns exhibit default predictive power when they are used as the sole covariate (consistent with their moderate accuracy ratio), they provide little additional explanatory power in the presence of DD1.

Conclusion

Equity prices are an important input in deriving Moody's public firm EDF™ credit measures. If one has access to a firm's equity price history, does he/she still need a signal derived from a structural credit risk model such as EDFs in assessing the firm's default risk? In light of evidence from this study, the answer is yes, except for the very limited situations where the firm's imminent default risk is readily reflected in its precipitously declining stock prices.

The empirical evidence presented in this paper shows that there is a weak direct link between equity returns and default risk. Unlike EDFs, equity returns do not properly rank order firms' default risk. As expected, very poor stock performance is indicative of high default risk. However, very good stock performance is also, on average, followed by relatively high default rates. As a result, the widely assumed link between low equity performance and high default risk is actually rather weak. In addition, to the extent that EDFs represent the true, unobservable default rates, there is substantial variation in default risk among firms with similar past stock performances. This is true even for subsets of firms whose equity performance, on average, lines up properly with their EDFs. So equity returns may not only provide misleading directions in discriminating defaulters from non-defaulters for firms with moderate to good stock performances, they are also very noisy in the sense that firms with similar stock performances report both very high and very low EDFs.

Not surprisingly, the overall power of default prediction by equity returns is much lower than that by EDFs, as measured by their accuracy ratios. This is not to say that equity returns have no predictive power at all. But their performance is generally inferior to EDFs. Another weakness of using equity returns as default warning signals is that the resulting accuracy ratios exhibit wide swings over time, rendering its default predictive power very unreliable. The superior predictive power of EDFs relative to equity returns is most striking when EDFs and equity returns cast opposite views of firms' default risk. In this situation, the average default rate of firms viewed as most default risky by their EDFs, but least default risky by their equity returns, is 16 times higher than firms located in the opposite end of the risk spectrum, i.e., most risky viewed by equity returns but least risky by EDFs. By pitting EDFs against equity returns in logit-type regressions, we show formally in a statistical sense that equity returns contribute no additional default predictive power in the presence of EDFs.

We argue that the lack of monotonic relationship between equity returns and EDFs (as well as realized default rates) is a manifestation of directionally distinct information incorporated in the two measures. In particular, the derivation of EDFs relies on both the risk assessment of a firm's underlying business and the firm's capital structure, as well as its equity prices. The results of this study provide another demonstration that the first two inputs into EDFs' calculation, i.e., business risk assessment and capital structure, are critical in improving their default predictive power.

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