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Validating the Public EDF™ Model During the Credit Crisis in Asia and Europe

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Abstract

In this paper, we validate the performance of the Moody's Analytics EDF™ (Expected Default Frequency) model during the recent credit crisis. We analyze the model's performance during the past two and a half years, and compare this performance with the model's longer history (2001–2006). We focus on the model's ability to differentiate between good and bad firms, the timeliness of its default prediction, and accuracy of levels for two primary samples: Asian and European non-financial firms. The current credit crisis has elevated default rates in both samples. We measure performance with predictive power, early warning, and level validation. A separate, recent Moody's Analytics study looks at North American non-financial firms as well as global financial firms.

Overall, the EDF model's predictive power is as good as or better than the previous period. The model provides an early warning signal a few years before default occurs; EDF levels were conservative (higher than subsequently realized default rate) before the crisis compared with later-realized default rates, and levels were statistically consistent with later-realized default rates.

We find that EDF credit measures perform consistently well across different time horizons and across regions. Our tests indicate that EDF credit measures provide a very useful measure of credit risk that can be applied throughout the world.

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Overview

In this paper, we present the results of a study validating the performance of Moody's Analytics EDF™ (Expected Default Frequency) credit measures during the recent credit crisis. In this study, we analyze the EDF model performance during the past two and a half years and compare this performance to the model's longer history. We focus on the timeliness of the model's default prediction, its ability to differentiate between good and bad firms, and on accuracy of levels for two primary samples: Asian non-financial firms and European non-financial firms.

Our previous EDF model validation study (2007) covered the period from 2001 through 2006.[1] A recent study conducted in June 2009 looks at EDF model validation for North American non-financial firms and global financial firms during the recent credit crisis.[2] In this study, we extend our review of the model's performance for Asian and European non-financial firms from 2001 through July 2009, a period that saw the most severe global economic downturn in 75 years. Credit analysis becomes more difficult during high default rate periods, but the severity of this credit crisis makes default prediction particularly challenging. Actions by governments in the United States and Western Europe to rescue failing institutions (i.e., financial and automotive sectors) have resulted in several, high-profile credit events that do not typically correspond to default events, but are still important to creditors.[3] In this study, we follow our existing model performance testing methodology.[4] We measure performance with predictive power, early warning, and level validation.

Overall, we find the EDF model's predictive power is comparable to or better than it was during the previous six years. The model provides an early warning signal a few years before default occurs; EDF levels were conservative (i.e., not too low) before the crisis compared with later-realized default rates, and levels were statistically consistent with subsequently realized default rates.

This paper is organized as follows:

- Section 2 presents the results for the EDF model's predictive power for Asian and European non-financial firms.
- Section 3 discusses EDF credit measures as early warning signals for default.
- Section 4 shows the level validation results.
- Section 5 provides concluding remarks.

The Predictive Power of EDF Credit Measures

Default prediction models should be sophisticated enough to prospectively differentiate bad (i.e., genuinely distressed) firms from good firms. In this paper, to test the power of the EDF model we use a well-known approach: the Cumulative Accuracy Profile (CAP). This approach is summarized by a measure known as the Accuracy Ratio (AR).

Typically, the higher the AR, the better the model. In extreme cases, for a totally random model that bears no information on impending defaults, AR=0. For a perfect model, AR=100%.[5]

In this study, to assess the predictive power of the EDF credit measure, we compute Accuracy Ratios separately on the Asian corporate (non-financial) sector and the European corporate (non-financial) sector. For each region, we compare Accuracy Ratios between a sample encompassing 2001–2006 and a sample covering 2001–July 2009. Our findings show that the inclusion of the crisis period did not reduce the predictive power of the EDF credit measure.

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[1] For further details, see Dwyer and Korablev (2007), "Power and Level Validation of Moody's KMV EDF™ Credit Measures in North America, Europe, and Asia."

[2] See Korablev and Qu (2009), "Validating the Public EDF Model Performance During the Recent Crisis."

[3] To our knowledge, companies involved with government bailouts fulfilled all of their contractual obligations. Nevertheless, it seems unlikely that they would have been able to meet these obligations without the bailout loan.

[4] For further details, see Bohn, Arora, and Korablev (2005), and Dwyer and Korablev (2007).

[5] A detailed discussion about Accuracy Profiles, as well as a related approach (Receiver Operating Characteristic [ROC]) can be found in Keenan and Sobehart (2000), and Dwyer and Korablev (2007).

In all tests, we use defaults included in the Moody's Analytics default database, collected and updated daily from numerous printed and online sources worldwide.[6] As a result, Moody's Analytics employs the most extensive public company default database available. Nevertheless, small public companies often disappear without news or record before they default, or they do not publicly disclose missed payments. To reduce the problem of hidden defaults, we restrict the sample to firms with more than $30 million in annual sales.[7]

Asian Non-financial Companies

Asian Corporate Firms

In this section, we calculate one-year horizon Accuracy Ratios using an overlapping cohort methodology. At the start of a cohort, we form a portfolio of all firms for the given universe, tally the defaults and non-defaults over the next 12 months, and calculate the AR for the period. When the time period rolls to the next month, we repeat the calculation for the next 12 months for firms in that cohort, and so on.

Table 1 shows the countries and the number of firms in each country that constituted the Asian module in Moody's Analytics Credit Monitor® and Moody's Analytics CreditEdge® between 2001 and 2009. We exclude the following countries from the validation:[8]

- China, because of government intervention, default definition is not clear.[9]
- Australia and New Zealand, because they belong to the Pacific region.
- Japan, because it has a different economic structure and a "hidden default problem."
- Pakistan and Sri Lanka, because they have a small number of companies.

The remaining countries have the most comprehensive default coverage. These countries are Hong Kong, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, Thailand, and Taiwan. We run validation tests separately for Japan.

[6] We utilize government filings, government agency sources, company announcements, news services, specialized default news sources, as well as sources within financial institutions to ensure, to the greatest extent possible, that we account for all defaults.

[7] Size is measured by total annual sales for non-financial firms. Where the firm's total sales number was not available, we used the book assets value. We used book assets for financial firms. This number was further adjusted for inflation-effect across years by adjusting the numbers to a common denomination by using a "deflation adjustor," calculated internally by Moody's Analytics.

[8] If not stated otherwise.

[9] Including China does not have a significant impact on the model's predictive power. Results are available upon request.

Table 1 Countries in the Asian Database: 2001–2009

Country	Number of Observations (firms)
Australia	919
China	1,873
Hong Kong	780
Indonesia	221
India	1,276
Japan	4,103
Korea	1037
Sri Lanka	21
Malaysia	692
New Zealand	108
Pakistan	97
Philippines	114
Singapore	556
Thailand	364
Taiwan	1,367

To track the solvency of each EDF observation for 12 months, for the 2001–2006 test, we use EDF credit measures between January 2001 and December 2005, and default events between January 2001 and December 2006. Similarly, for the 2001–2009 test, we use EDF credit measures between January 2001 and July 2008, and default events between January 2001 and July 2009.

In Figure 1, the right panel shows the EDF model performance of Asian non-financial firms during 2001–2009, and the left panel presents historical results. During the 2001–2006 period, the EDF credit measure AR is 66%, lower than the 2001–2009 period ratio, 69%. As shown in the figure, for Asian firms, the Accuracy Ratio increased with the addition of the 2007–2009 period. Although problems may arise when comparing accuracy ratios from two different data samples, the addition of two and a half years of data, which includes the recent credit crisis, suggests that the EDF model performed as well as or better than during the past.[10]

[10] As a result of the entry and exit of firms through time, the sample of firms used for the validation changes to some extent.

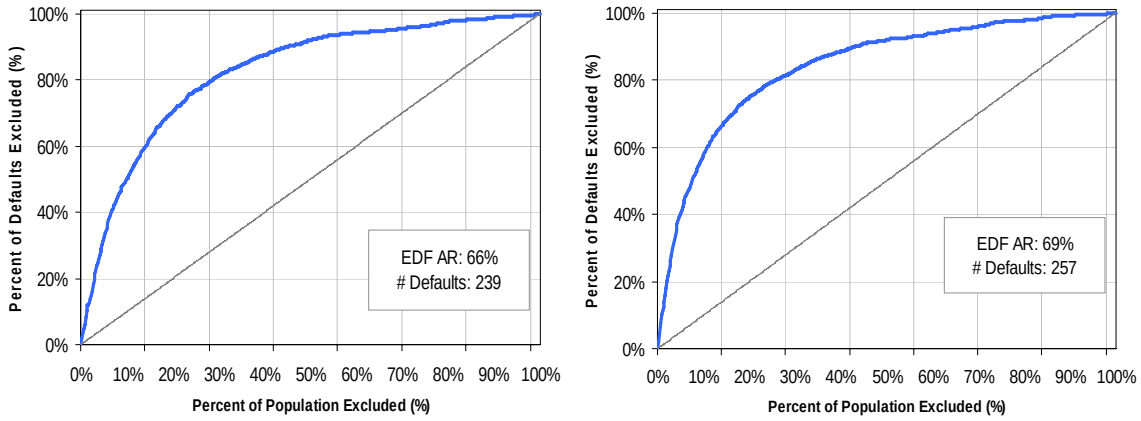

Figure 1 CAP Curves Comparing EDF Credit Measure Historical Performance for Asian Non-financial Firms: 2001–2006 versus 2001–2009

In Figure 2, the right panel shows the EDF model performance of Japanese non-financial firms during 2001–2009, and the left panel presents EDF model performance during 2001–2006. As shown in the figure, for Japanese firms, the performance difference is minimal when comparing the two periods.

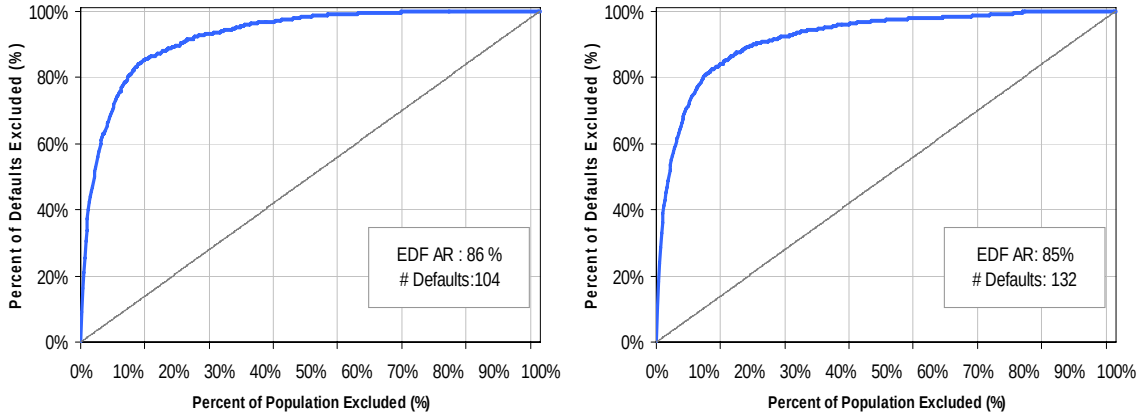

Figure 2 CAP Curves Comparing EDF Credit Measure Historical Performance for Japanese Non-financial Firms: 2001–2006 versus 2001–2009

European Non-financial Companies

In this section, we calculate one-year horizon Accuracy Ratios for European non-financial companies using the same methodology defined above.

Table 2 shows the countries and the number of firms in each country constituting the European module in Moody's Analytics Credit Monitor® and Moody's Analytics CreditEdge® from January 2001–July 2009. As the table shows, Great Britain has the largest number of firm observations in the sample, followed by France and Germany. During 2001-2006, there were 282 unique default events; in 2007, 2008, and 2009, there were 49 defaults.

Table 2 Countries in the European Database: 2001–2009

Country	Number of Observations (firms)
Austria	105
Belgium	130
Switzerland	243
Czech Republic	58
Germany	827
Denmark	150
Spain	163
Finland	149
France	816
Great Britain	1,763
Greece	300
Hungary	37
Ireland	94
Iceland	12
Israel	241
Italy	314
Luxembourg	45
Netherlands	263
Norway	244
Poland	249
Portugal	78
Russia	179
Slovakia	14
Slovenia	12
Sweden	323
Turkey	186

In Figure 3, the right panel shows the EDF model performance for European non-financial firms during 2001–2009, and the left panel presents historical results. During 2001–2006, the EDF credit measure AR is 79%, slightly lower than the 2001–2009 period's 80%. Again, although problems may arise when comparing accuracy ratios from two different data samples, the addition of two and a half years of data, which includes the recent credit crisis, suggests that the EDF model performed as well as before, if not better. This result is more significant given the apparent lack of risk differentiation in the market during 2007–2009, when credit spreads and volatility reached unprecedented levels.

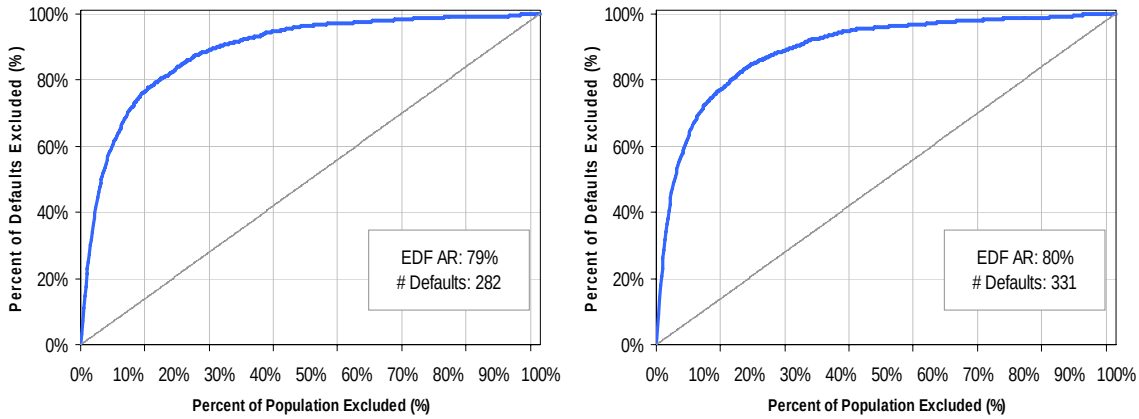

Figure 3 CAP Curves Comparing EDF Credit Measure Historical Performance for European Non-financial Firms: 2001–2006 versus 2001–2009

EDF Credit Measures as Early Warning Signals

To test the timeliness of default prediction as an early warning signal, we create a sample of defaulted firms from January 2007–July 2009. We compute the 25th, 50th, and 75th percentiles of the EDF credit measure for these defaulted firms dating back to December 2001. We also compute the same percentiles for the entire sample, and then plot two sets of percentiles on the same graph. If the EDF credit measure provides early warning signals, we would expect the default sample EDF credit measure distribution to move higher and away from that of the entire population as they approach default dates. This finding is indeed what we observe.

Asian Non-financial Companies

In the Asian non-financial sector, 18 firms defaulted between January 2007 and July 2009.

Figure 4 presents EDF credit measure percentiles for these defaulted firms. The red lines represent the 25th, 50th, and 75th percentiles of EDF credit measures for companies that defaulted between January 2007 and July 2009. The blue lines represent percentiles for the entire sector.

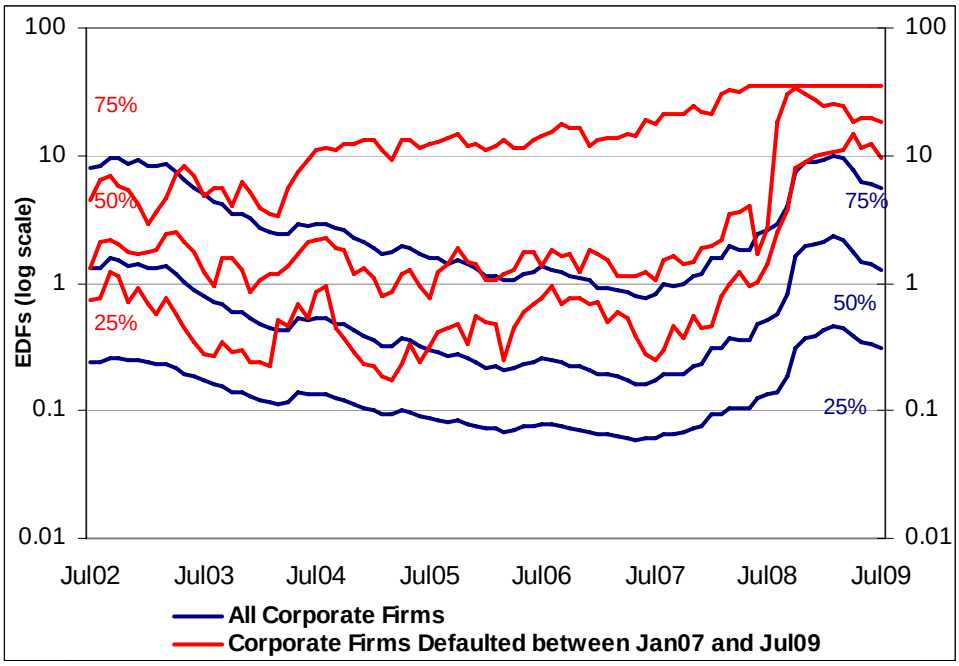

Figure 4 Early Warning and Distribution of EDF Credit Measures for Asian Corporates: 25th, 50th, and 75th percentiles

These two distributions are distinctly different. As shown in Figure 4, beginning in mid-2003, defaulters were riskier than the rest of the sample, and usually had higher EDF credit measures than non-defaulters well before default. As the entire sector improved between the end of 2002 and mid-2007, defaulters began to deteriorate in early 2005. The top 25th percentile of the defaulters' EDF measures began increasing as far back as mid-2004. The speed of the deterioration increased in 2007. Defaults were realized between January 2007 and July 2009, when the entire sector's risk began to increase.

Figure 5 displays information about Japanese non-financial firms. In this figure, we see a pattern similar to that of the rest of Asia. Defaulters had higher EDF credit measures than non-defaulters. In addition, defaulters' EDF credit measures also increased sooner than all firms, well before default. [11]

[11] In 2009, the number of defaulters in the sample remains very small, causing large swings in percentiles (red lines) during the last year of the graph.

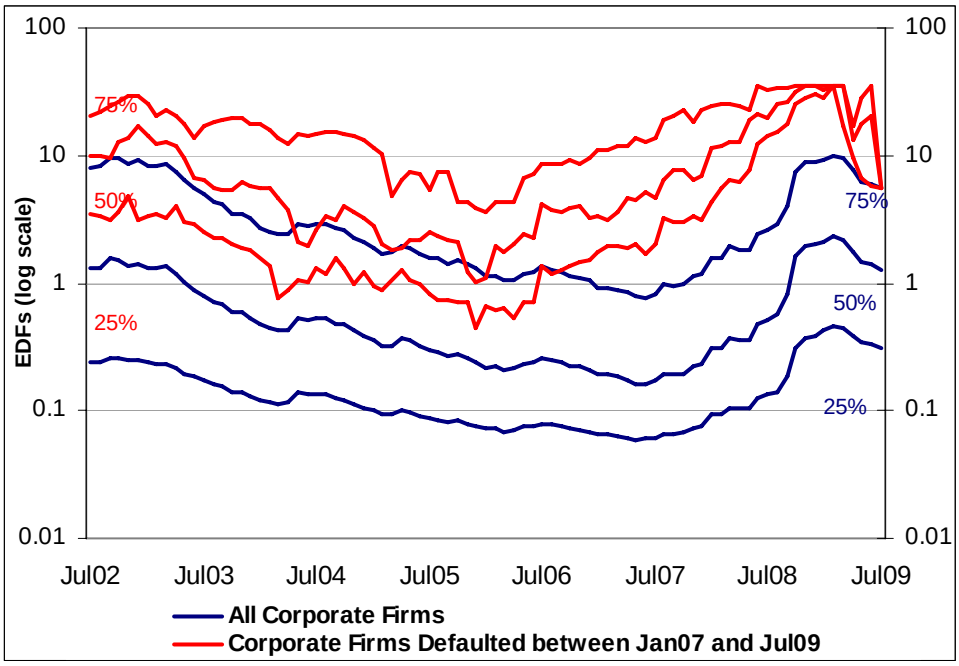

Figure 5 Early Warning and Distributions of EDF Credit Measures for Japanese Non-financial Firms: 25th, 50th, and 75th percentiles

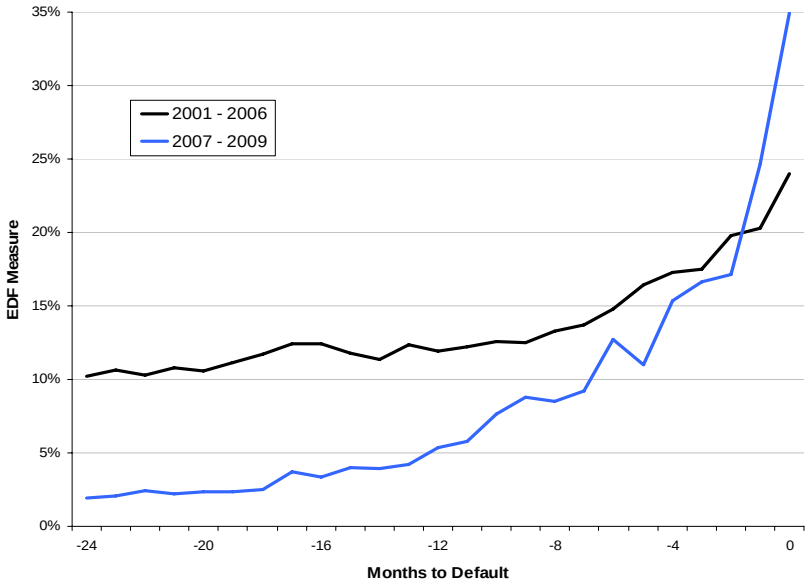

Figure 6 Median EDF Credit Measures for Asian Defaulters

Another way to test the timeliness of default prediction is to measure the number of months before an impending credit event the EDF measure provides a signal of deteriorating credit quality. To test timeliness, we create a sample of defaulted firms, retaining monthly observations from 24 months prior to default, and then compute the median EDF credit measure by months to default. In Figure 6, we overlay and compare the median EDF measures of the two periods (2001–2006 and 2007–2009) for Asian corporate firms. For this analysis, China and Japan are included in the sample to enable a better populated defaulter sample during the 2007–2009 period.

Figure 6 demonstrates that, in the event of default, the early warning performance of EDF credit measures for Asian firms, including the current recession, is similar to historical performance. For both periods, the EDF credit measure is elevated for more than 12 months prior to the credit event and continues increasing steadily. As shown in Figure 6, the median EDF level 24 months prior to default is lower for the 2007–2009 period compared with 2001–2006 period. However, this difference is not surprising given that the two years prior to the crisis, the 2005–2007 period, was a benign period. Additionally, for the 2007–2009 period, the slope of the increase in median EDF level steepens as early as 14 months before the default.

European Non-financial Companies

In the European non-financial sector, 34 firms defaulted between January 2007 and July 2009.

Figure 7 presents EDF credit measure percentiles for these defaulted firms. The red lines represent 25th, 50th, and 75th percentiles of EDF credit measures for companies that defaulted between January 2007 and July 2009. The blue lines represent percentiles for the entire sector.

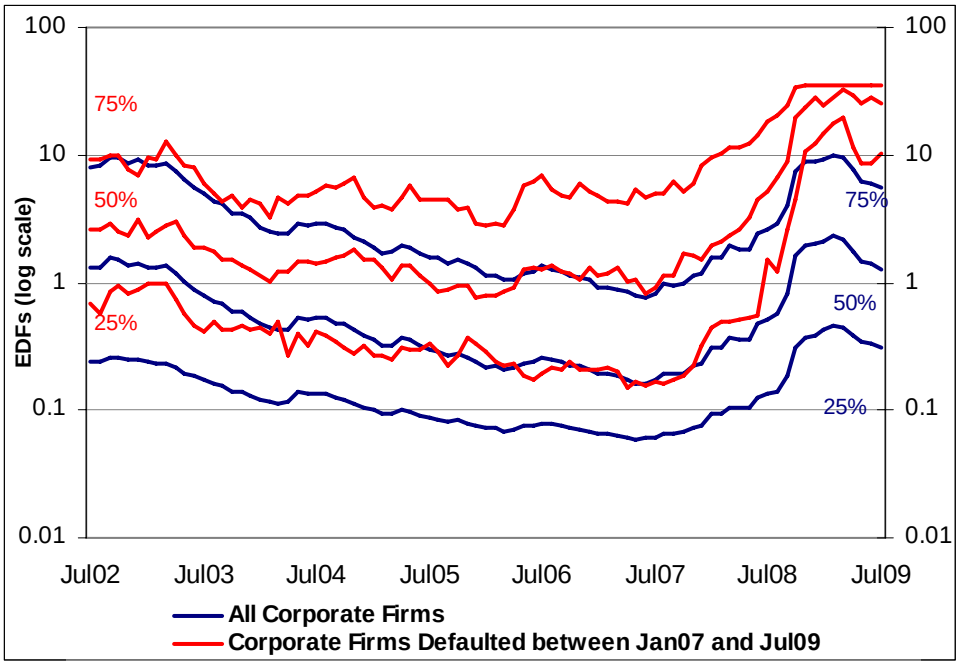

Figure 7 Distributions of EDF Credit Measures for European Corporates: 25th, 50th, and 75th Percentiles

For European non-financial sector, the EDF distributions of defaulters and the entire sector are distinctly different. As shown in Figure 7, during the beginning of the period defaulters were riskier than the rest of the sample, and usually had higher EDF credit measures than non-defaulters well before default. As the entire sector improved between 2002 and 2007, defaulters began to deteriorate in early 2006. The speed of the deterioration increased in early- to mid-2007. Defaults were realized after 2007, when the entire sector's risk began to increase.

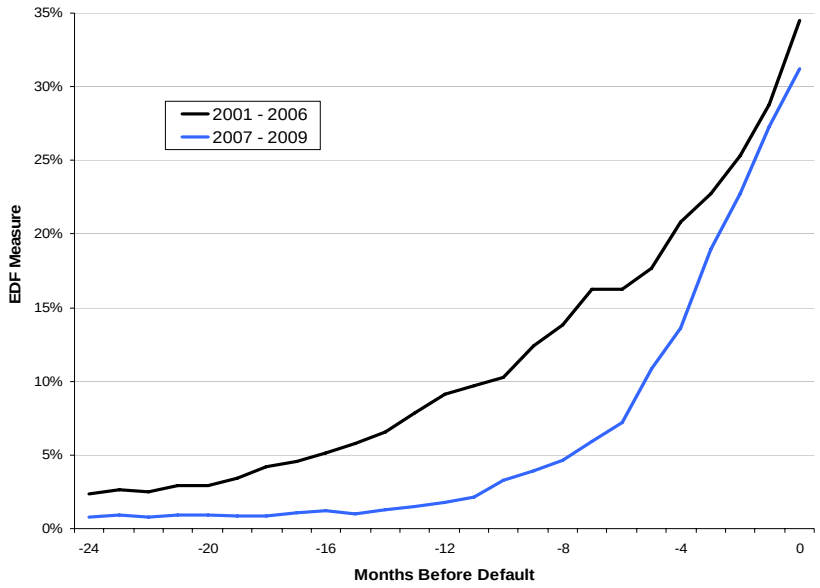

Figure 8 Median EDF Credit Measures for European Defaulters

In Figure 8, we compare the performance of EDF credit measures across time. Specifically, we look at their ability to predict timely default using the median EDF level of defaulters in Europe beginning 24 months before default. For both periods, the EDF credit measure begins rising more than 12 months before the actual default, providing an early warning of credit deterioration.

Level Validation

Level validation measures how well the EDF model's predicted default rates track realized default rates. EDF values have declined consistently since 2002, reaching their lowest levels in mid-2007. The subsequent credit crunch saw a dramatic turn in the credit environment. After observing an unprecedented increase of the EDF credit measure and elevated default rates from 2007 through 2009, we ask the following question: did the EDF model underestimate the risk during benign times? In this section, we provide evidence showing that EDF levels were not too low relative to defaults observed later.

We use the following distinct approaches to assess the EDF levels against observed default rates:

- We group firms by their EDF levels and compare realized default rates for each group. This grouping can be done at any given point in time, and can also be aggregated across time. Either way, we find that the EDF credit measure remains consistently conservative (i.e. high relative to realized defaults).
- Even given the true default probability models, because defaults are random events and companies are correlated, realized default rates can be higher or lower than the predictions from the true model. We simulate defaults using EDF values and asset correlation, and compare the simulated default rate distribution with the observed default rate. We find that we cannot reject the hypothesis that the EDF model is the true default probability model.

Comparing EDF Levels and Realized Default Rates for EDF Groups

Asian Non-financial Companies

We begin by comparing the one-year EDF values with realized default rates for companies grouped by their EDF levels. The one-year EDF credit measure at time t is designed to describe the expected default frequency for the 12 months following time t. If the model is correct, for a group of firms with a given EDF level, the realized default rate from the

group during the following 12 months should be near the average EDF level. If the model underestimates risk, the realized default rate should be higher than the average EDF level.

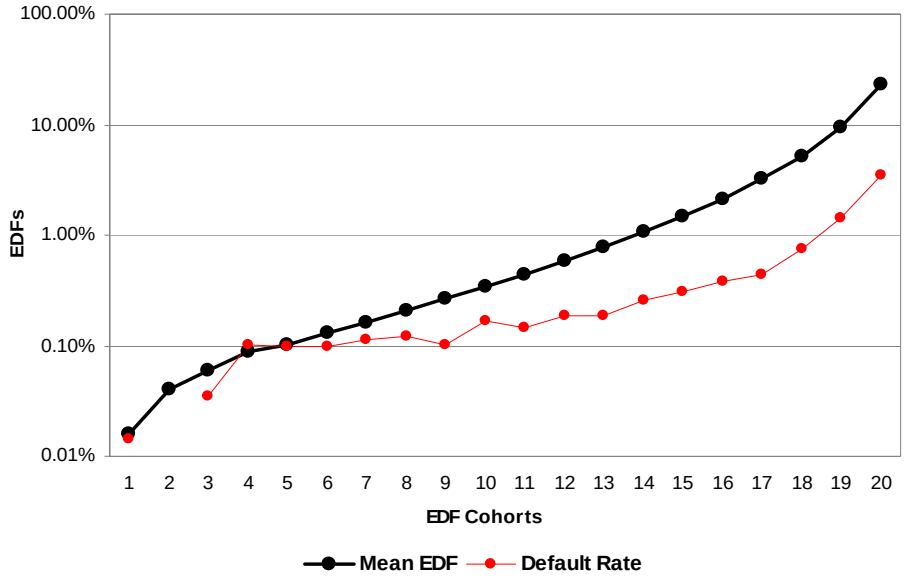

Figure 9 Distribution of Average EDF Levels and Default Rates for Asian Corporates: 2003–2007

Figure 9 provides a comparison for Asian non-financial firms.[12] As shown in the figure, EDF measures have traditionally been consistent with realized default rates for Asian firms. The EDF credit measures are taken between January 2003 and December 2006, while defaults are taken between January 2003 and December 2007, allowing the last EDF credit measure 12 months to default. The panel data is grouped into 20 EDF groups with equal sample sizes (5% of the sample each). Figure 9 indicates that the EDF levels are generally higher than observed default rates, as expected, due to the hidden defaults issue. Group 4, in which default rate exceeds mean EDF value, is a very low EDF group, and the difference is caused by only one default.

The hidden defaults issue refers to the failure of a default data set to capture all economic defaults. This failure can occur for various reasons. For example, when a debt extension occurs, it is difficult for an outsider to know if this is caused by the borrower's inability to pay or by legitimate business need. In other cases, when the loan amount is small, failure to pay is simply written off by the bank, and no public announcement is released. When default data collection relies on public information to identify defaults, many default events may go missing. This is particularly true for smaller firm borrowers that draw little public attention.[13]

Moody's Analytics default data is manually aggregated by a team of specialists utilizing multiple information sources including, but not limited to, bankruptcy newsletters, rating agency debt monitoring publications, news media and news search engines, corporate regulatory filings, internet browsing, and targeted searching. As of July 2009, the database recorded more than 8,000 unique default events for public firms or firms that had been public before default happened. Many of these defaults were collected real-time during the past two decades. Despite being the largest public default database we are aware of, we believe a significant number of defaults occurring outside the universe of North American large non-financial firms were not captured. We calibrate the EDF model with this specific universe to circumvent the hidden default problem, and avoid underestimation of default risk.

[12] To ensure that a reasonable number of defaults during the December 2007 snapshot, China and Japan are also included in the Asian non-financial firm sample.

[13] See Stein and Dwyer (2005), and Dwyer and Qu (2007), for more information about hidden defaults.

The sample underlying Figure 9 constitutes all Asian non-financial firms during 2003–2007. The observed default rates are subject to hidden defaults. This long-term picture provides a benchmark for a more recent snapshot, reported in Figure 10 for December 2007, shortly before defaults increased.

Figure 10 presents the more interesting recent period, December 2007. During this period, EDF levels increased from historic lows, and were followed by the most severe economic turmoil since the Great Depression. In addition, corporate defaults increased. As shown in Figure 10, default rates per EDF rank were properly ordered for the December 2007 period, and the outcome was consistent for the December 2007 cohort. Two relatively low EDF groups had no defaults, while four other relatively low EDF groups had few defaults. Overall, the default rates are generally much lower than average EDF values.

When the two groups with the highest EDF levels have the most defaults, the ratios between average EDF level and default rates are comparable to the long-term average, as shown in Figure 9.

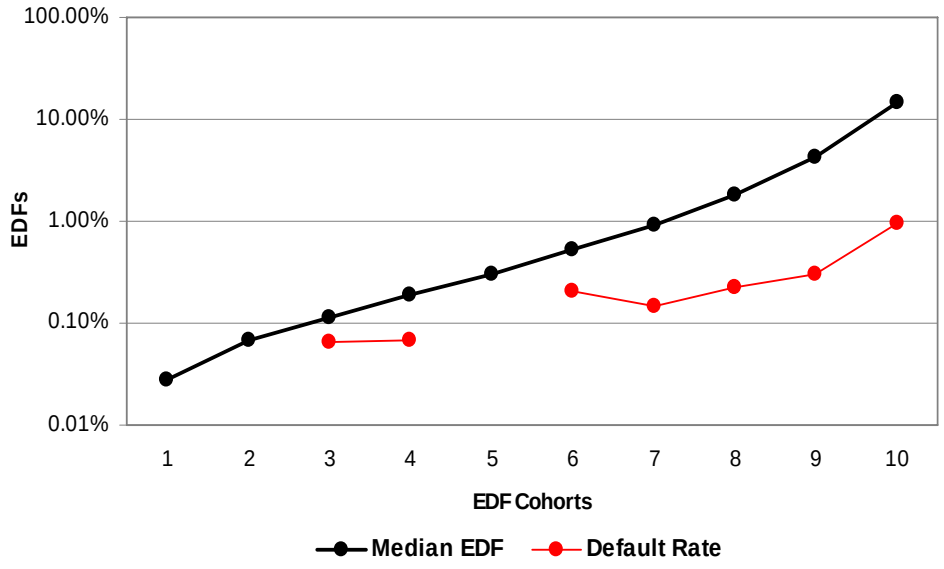

Figure 10 Average EDF Levels and Default Rates for Asian EDF Groups: December 2007

European Non-financial Companies

For European firms, Figure 11 provides a historical average for data during the period of 2003–2007. Figure 12 shows the snapshot on December 2007, comparing average EDF values and their corresponding default rates realized during 2008. Even during the most tumultuous period and within the most turbulent sector, groups with higher EDF levels generally have higher default rates.

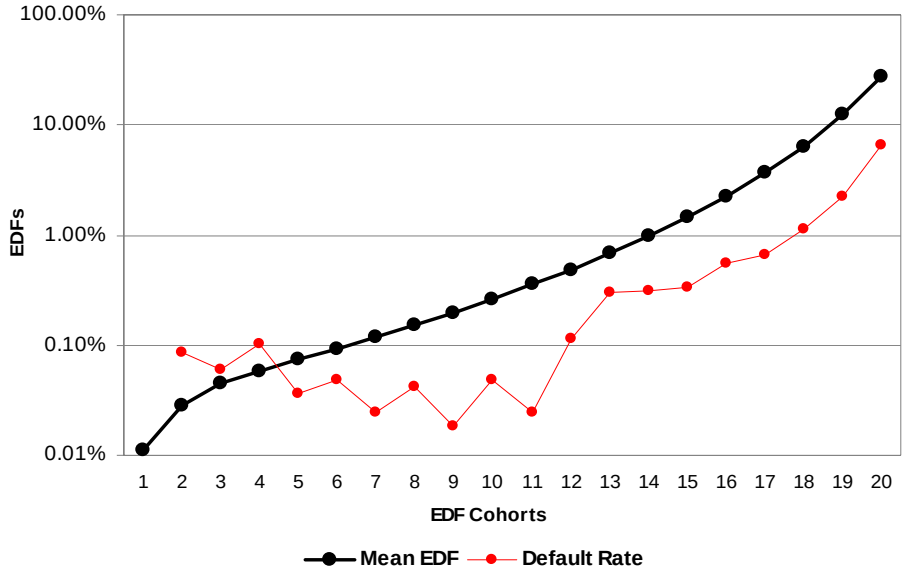

Figure 11 Distributions of Historic Average EDF Credit Measures for European Corporates: 2003–2007

In Figure 11, we see that EDF credit measures are consistent with realized default rates. The exceptions where default rates are higher than average EDF values are driven by only four defaults.

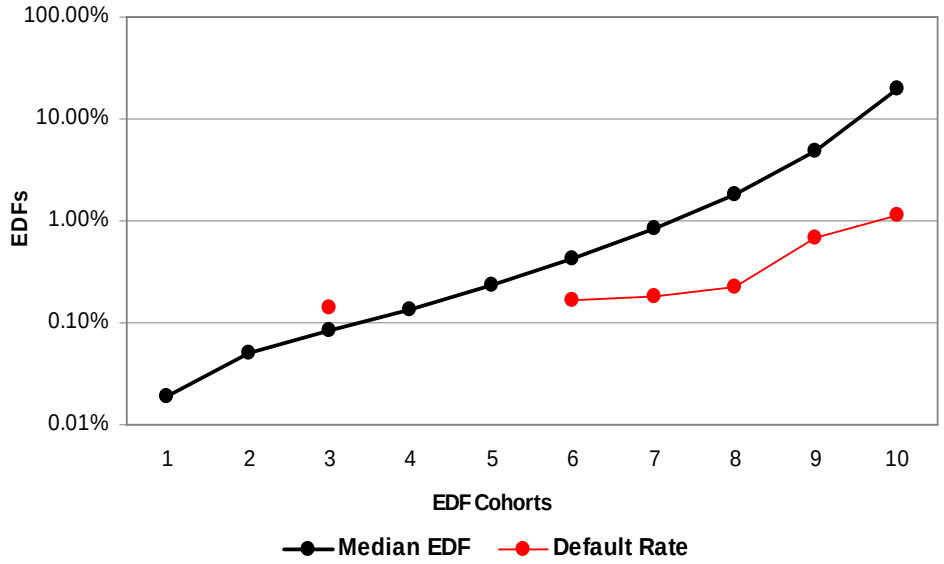

Figure 12 12-month Default Rates by EDF Rank for European Corporates, December 2007

As presented in Figure 12, the 12-month default rate indicates that the default rate has largely remained the same during the most recent recessionary period so far. [14]

[14] There is one default, Belvedere SA, in Group 3, where the default rate exceeds the mean EDF.

Validating EDF Levels with Simulated Levels

In this section, we use a structured approach to test whether we can statistically reject the hypothesis that the EDF model is a true model for default prediction.

EDF credit measures are probability measures, and, for a given portfolio of companies, the model implies a distribution of possible default rates. We test whether the observed default rate is consistent with such a default rate distribution.

We use a simple numerical example to illustrate the nature of the test. Suppose we have 100 independent companies, each with a default probability of 10%. The expected default rate is 10%, and it is possible, but not likely, to have a default rate of less than 5% (the p-value is only 5.75%).[15] When we actually observe a 5% default rate, we would reject, at a 10% confidence interval, the hypothesis that the default probabilities are 10%.

When companies are correlated, the implied default rate distribution is wider, in that the likelihood is higher for the realized default rate deviating from the mean prediction. For example, for two independent firms each with a 50% true default probability, the likelihood of observing no default, a negative deviation from the expectation of 50%, is only 25%. However, if these two firms are perfectly correlated, the likelihood of no default increases to 50%.

Based on the above concepts, Kurbat and Korablev (2002) developed a method that uses realized defaults for testing models of default probabilities. Specifically, they assume firm values are correlated with one common factor, and obtain a default rate distribution by simulating random realizations of a common factor and firm-specific factors. In simulations, each firm's unconditional default probability is kept at the level predicted by the subject probability of default (PD) model. In this study, we use the same approach to test if the observed default rate is consistent with the default rate distribution implied by the EDF credit measures. For each year in the sample, we take EDF values calculated at the beginning of the year, use them to simulate a distribution of default rates, and compare the actual default rate during the year against the resulting distribution. [16] We use a pair-wise asset correlation of 0.25, calibrated using long-term data from the Moody's Analytics Global Correlation Model (GCorr). For each year, we run 1,000 simulations to create a distribution of 1,000 simulated default rates.

Figure 13 presents the results for Asian non-financial firms. To avoid the hidden default issue, we limit our sample to companies with annual sales greater than $300 million. Also, because the EDF credit measures are truncated at 35%, we exclude firms with an EDF level of 35% to avoid underestimation of the default rate distribution. As shown in Figure 13, the realized default rate was lower than the median EDF level during the past nine years, but it remained within the intervals bounded by the 10th and 90th percentiles of the simulations with the exception of 2009. The hidden default issue may explain the low default rates, given that the collection of default data in Asia is more difficult than in the U.S. and Europe, primarily because of language barriers, poor reporting of default events, and government intervention preventing company collapse, which often goes unreported. The overprediction of defaults in 2007, 2008, and 2009 may also reflect market uncertainties regarding the Asian recovery, while Europe and North America experienced recession. In addition, the actual default rate in 2009 does not reflect the year-end levels of 2009, but rather the annualized default rate based on the first seven months.

[15] The likelihood of less then n% default is $\sum_{i=0}^{n} \frac{100!}{i!(100-i)!}(0.1)^{i}(0.9)^{100-i}$.

[16] Since the defaults in 2009 have not been fully observed, the default rate observed up to July 2009 is annualized to calculate the actual default rate in 2009.

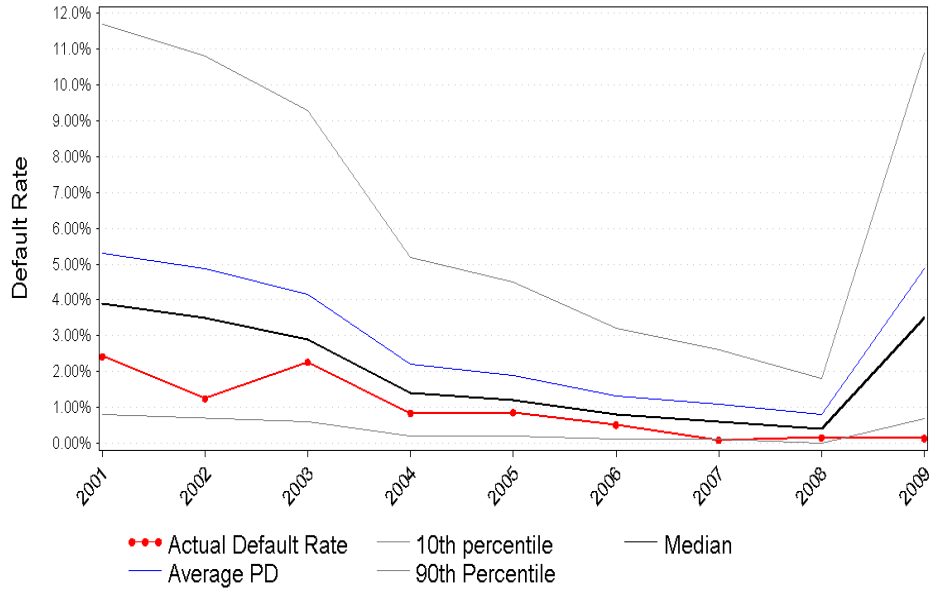

Figure 13 Asian Non-financial Firms (EDF<35% and Book Assets >USD300 million)

Figure 14 illustrates the level validation results for the sample of Japanese firms with size greater than $300 million. As explained above, we exclude firms with an EDF level of 35% to avoid underestimation of the default rate distribution. Because banks and parent companies may extend credit to companies that would otherwise default, the EDF credit measure is higher than the observed default rate in Japan, as expected.

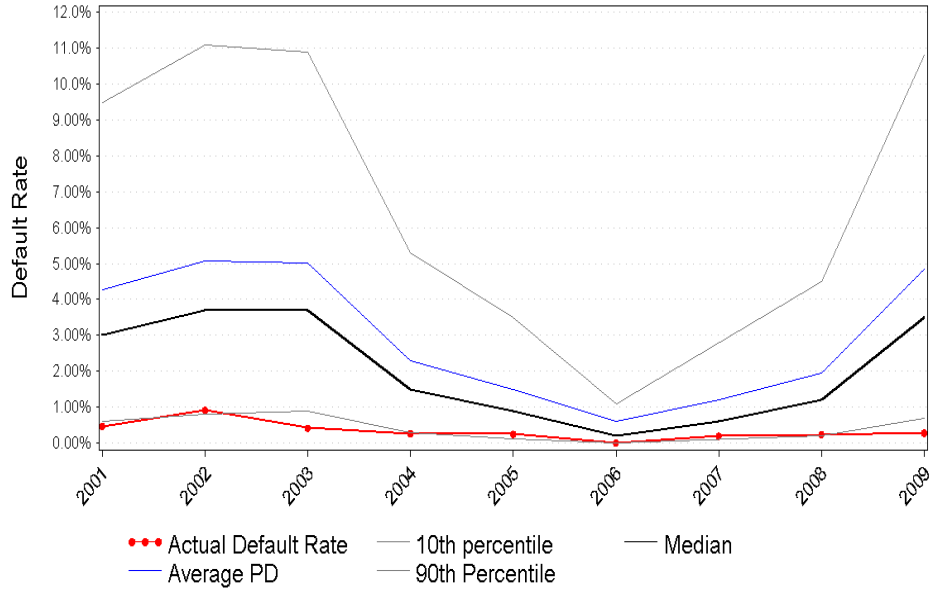

Figure 14 Japanese Non-financial Firms (EDF<35% and Book Assets >USD300 million)

Figure 15 presents the results for European non-financial firms. Following the same procedure, we limit our sample to companies with annual sales greater than $300 million in order to avoid the hidden default issue. Also, because the EDF credit measures are truncated at 35%, we exclude firms with an EDF level of 35% to avoid underestimation of the default rate distribution. We see from the figure that, for most of the past nine years, the predicted default rate of

European corporates tracks the realized default rate well. The overprediction of defaults in 2009 may reflect the uncertainties in the market. Overall, the default rates have remained within the intervals bounded by the 10th and 90th percentiles of the simulations, and we cannot statistically reject the hypothesis that the EDF model is a true model for default prediction.

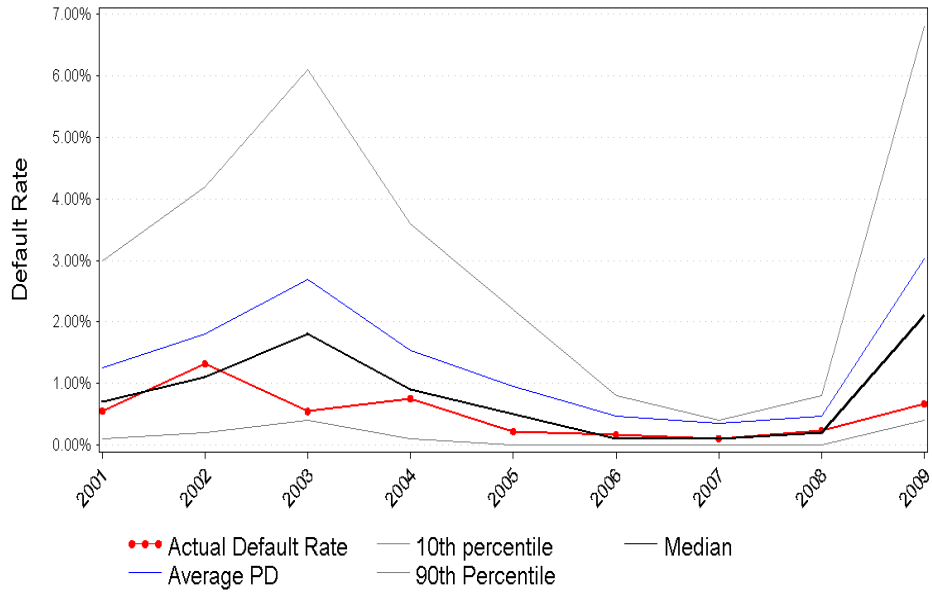

Figure 15 European Non-financial Firms (EDF<35% and Book Assets >USD300 million)

We can conclude from these results that the observed default rates are consistent with EDF model predictions for all years, and across different regions.

Conclusion

In this study, we tested the public EDF model using three major performance measures: accuracy ratios in default prediction, early warning signals, and default risk levels, with attention on the most recent credit crisis.

In accuracy ratio testing, we found that EDF credit measures are as powerful as they have been historically in their ability to discriminate good firms from bad firms over time and across different regions.

We also found that the EDF model provides ample early warning signals. The distribution of EDF levels for defaulters begins to emerge out of the entire population distribution a number of years before defaults occur.

We also showed that the EDF levels are consistently higher than observed default rates, due to the hidden default issue. EDF levels were not low before the crisis, except in a few pockets of the population. Over the long history, the realized default rate for countries with better default coverage lies within the prediction interval, and we cannot reject the hypothesis that the EDF values are true measures of default risk.

Overall, the EDF model's predictive power is as good as or better than the previous ten years, and the model provides an early warning signal more than 12 months before default occurs; EDF levels were conservative (i.e., not too low) before the crisis, compared with later realized default rates, and levels were statistically consistent with later realized default rates.

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