A Note on Forecasting Aggregate Recovery Rates with Macroeconomic Variables

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Abstract

We provide an ex-ante forecasting model for aggregate recovery rates. Summarizing the literature on recovery rates, there is a variety of factors considered to have influence on recovery rates of loans and bonds. In empirical works there has been strong evidence that recoveries in recessions are much lower than during phases of economic expansion. Following Altman et al. we include the business cycle and macroeconomic variables in order to forecast aggregate recovery rates of the next year. As main input the model uses the CBOE market volatility index that provides very good results in ex ante forecasts in the US bond market.

Keywords: Business Cycle, Recovery Rates, Multiple Regression, CBOE Volatility Index

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1 Introduction

Until the end of the 1990s research on recovery rates was rather limited. While on modeling default risk of bonds or loans there was a great variety of models, the other main component of credit risk, recovery rates or loss given default (LGD) was more or less neglected. One reason for this may be that average recovery rates of bonds or loans have experienced lower variation than default rates. In a study by Altman et al. (3) the average recovery rate was about 40% through the years with a standard deviation of 27.7% while average default rates ranged from $0,16\%$ in 1981 to over 10 percent in 1990 and 1991 for the US high yield market. However, in the last five years there has been an increasing amount of research on recovery rate estimation. In the new Basel capital accord (Basel II) one of the major input variables in the internal rating based (IRB) approach is the recovery rate of a loan (5). Especially the advanced IRB approach of Basel II leaves a bank quite a high amount of flexibility to determine the recovery rates for a loan. This could be considered as a motivation for a bank use the more advanced IRB approach and provide an own sophisticated model for LGDs.

Summarizing the literature on recovery rates, there is a variety of factors considered to have influence on recovery rates of loans and bonds. For a review on different approaches to recovery rate modeling we refer to Trück et al. (25). Next to factors like priority in the capital structure, presence and quality of collateral or industry, it is widely accepted that the business cycle and macroeconomic factors play a decisive role in measuring LGD. This was confirmed by studies of Carey (6), Schürmann (22) or Altman et al. (3). However, many of the surveys conducted in the literature investigated the connection between default and recovery rates for the same year. The models were not particularly designed for the issue of forecasting recovery rates but rather for illustrating the link between aggregate default and recovery rates.

In this paper we will follow another philosophy and provide an ex ante approach to forecasting yearly average recovery rates using information about the business cycle and macroeconomic variables. Section 2 gives an introduction to changes of average yearly recovery rates through time and business cycle effects. Special focus is set on the work by Sironi et al. (23) and Altman et al. (2). Section 3 describes the entering variables and its assumed influence on one-year ahead recovery rates. In the fourth section a multiple regression model for aggregate yearly recovery rates is developed. We provide empirical results on the multiple regression model in forecasting Moody's issuer weighted aggregate recovery rates. Section 5 concludes.

2 Recovery Rates and Business Cycle Effects

In empirical works there has been strong evidence that recoveries depend on the state of the business cycle. Carey (6), concentrating on private debt portfolios found that especially for risky loans recessions have an enormous impact on the distribution of recovery rates. According to his findings this is especially true for the tails of the loss distribution. While for investment grade loans the cyclical effect is rather small, he found that loss rates for subinvestment grade loans during a recession are more than 50% higher than during an expansion of the economy. Figure 1 illustrates the variation of aggregate recovery rates through time based on Moody's issuer weighted recovery rates for corporate loans from 1982-2003.

Hu and Perraudin (16) investigated recoveries and aggregate default rates through the cycle and found that correlations in Unites States are between -0.2 and -0.3 - the higher numbers were reached when only the tails as the more decisive part of the distribution for risk management were considered. These results were also confirmed by Altman et al. (2) who found a high negative correlation between recovery rates and aggregate default rates. Finally, Schürmann (22) provides clear evidence on the different shape of the probability densities of recoveries across the business cycle, investigating Moody's data from 1970 to 2003. His findings for the changes in recovery rates during recession and expansion periods are displayed in table 2.

It is obvious that recessions bring with them many more instances of worse

Figure 1: Issuer Weighted Recovery Rates for Corporate Loans (1982-2003), Source: Moody's KMV

	Mean	Std. Dev.	25%	50%	75%
Recessions	32.07	26.86	10.00	25.00	48.50
Expansions	41.39	26.98	19.50	36.00	62.50
Whole Sample	39.91	27.17	18.00	34.50	61.37

Table 1: Recoveries across the business cycle for all issuers (Moody's, 1970-2003)

	Mean	Std. Dev.	25%	50%	75%
Bank Loans	63.10	21.83	47.50	65.50	81.50
Bonds	49.52	26.56	28.00	44.75	72.00
Bonds excl. ETCs	53.31	28.31	28.00	54.38	79.75

Table 2: Recoveries for Senior Secured Loans and Bonds across the business cycle (Moody's, 1970-2003)

recoveries: the average recovery rate and the mean recovery rate is about 10% lower during recessions than during expansions. Further, Schürmann (22) finds that during expansions recovery values are more evenly distributed. Most of the published research treats recoveries of bonds rather than loans. Of course, the main reason for this fact is that recovery rates for loans are hardly available. Since banks are expected to monitor the evolving financial health of the obligor in their loan portfolio, one would expect to have higher recovery rates for loans, if all other factors (industry, business cycle, etc.) being equal. This assumption should be reinforced by the fact that loans usually are more senior in the capital structure. In Schürmann (22) this assumption is confirmed by an empirical investigation. The results for his analysis using Moody's data for Senior Secured Debt on recovery rates by instrument type are displayed in table 2.

Altman et al. (2) provide an extensive study on correlations between yearly average recovery rates and probabilities of default (PDs). They examine historic bankruptcy data for evidence of correlation between the recovery rate and the PD. At the time Altman et al. published their report many major credit-VaR-models still based on the assumption of independence between PDs ad LGDs. Therefore, Altman et al. provided empirical evidence on the correlation between these two figures and showed the impact of this correlation on credit Value-at-Risk. Therefore, they compared three scenarios with deterministic recovery rates, stochastic recovery rates independent of the probability of default and stochastic recovery rates correlated with the probability of default by running Monte Carlo simulations. The results of the simulation were unambiguous. Expected losses, VaR and standard errors were approximately equal for the scenarios with deterministic recovery rates and independence between the risk factors. However, they were about 30 percent higher for the scenario with correlated defaults. Therefore, VaR models assuming independence between the probability of default and loss given default clearly underestimate the expected credit loss. The authors further showed that recovery rates are driven by demand and supply on the market for distressed bonds. They performed univariate and multiple least square regressions determining the recovery rate and the log of the recovery rate using United States macroeconomic and microeconomic indicators.

In their study they find that taking the logarithm of bond default rates as exogenous variable explains about 60 percent of the variation of the logarithm of bond recovery rates. Additionally, also macroeconomic factors are able to explain some of the variation of recovery rates. But unfortunately, the best of the five macroeconomic factors was still worse in explaining the variation in the recovery rate than the worst of the six bond market variables.

In the multiple regression case, the results are improved to values of R^2 of approximately 90%, which can be considered to be extraordinarily high. Also the signs of the coefficients in the regression were as intuitively predicted by the assumed economic relationship between the variable and average yearly recovery rates. Thus, Altman et al. show a significant negative correlation between the number of defaults as well as the probability of default and recovery rates. However, their model is not very useful for forecasting future recovery rates which is of major interest for a risk management framework.

In an update of their first model, Altman, Brady, Resti and Sironi (3) also perform ex-ante recovery rate estimation. For this purpose they use recovery rate predictions of Moody's for the global speculative grade issuer default rate for the upcoming year. The model yields an R-square of 0,39 when implementing it in a multiple regression model what is considered a remarkable result for aggregate forecasting recovery rates. Based on these results in the sequel we will develop a multiple regression model to forecast aggregate yearly recovery rates in the US bond market using macroeconomic variables, credit spreads and a stock market volatility index.

3 Entering Variables

In this section we will describe the variables entering our regression models for ex-ante recovery rate forecasts. On the one hand the regression follows the work of Altman et al. (2), (3). We also use cyclical macroeconomic variables, historic market prices of bonds, indices derived from market prices and leading financial indicators. On the other hand we provide an approach especially designed for estimating future recovery rates based on these macroeconomic data only. Therefore, we will leave out the default rate of the same year as exogenous variable. However, in our ex ante model prior year's default rates will be considered to forecast recovery rates of the next year.

Unless otherwise stated all the data used is from the US bond markets as historical data for the European market is still hard to find. The regressand has been the value weighted recovery rate provided from Moody's KMV for defaulted US corporate bonds, which has been chosen, because it can be considered to be really close to a recovery rate index. Figure 2 shows the high variation of value weighted recovery rates through the years 1982-2003. In the introduction we already took a first glance at issuer weighted recovery rates - we find that aggregate issuer and value weighted recovery show very similar behavior.

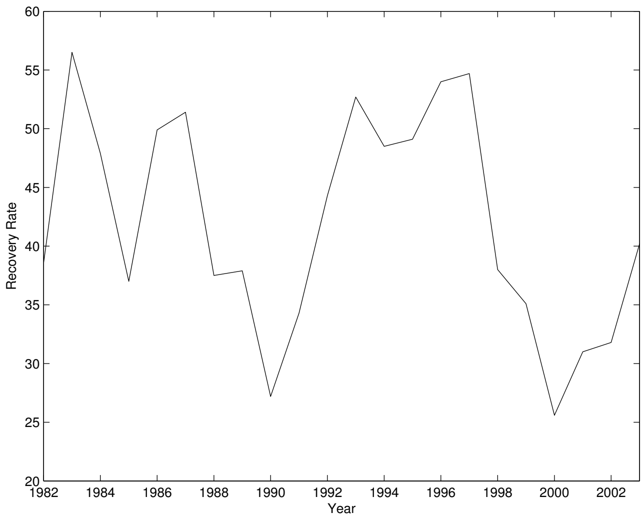

Figure 2: Value Weighted Recovery Rates for Corporate Loans (1982-2003), Source: Moody's KMV

Variable	Notation	Expected Sign
annual value weighted bond recovery rate	$AVRR_{t-1}$	+
annual issuer weighted bond recovery rate	$AIRR_{t-1}$	+
annual default rate	ADR_{t-1}	-
annual US high yield default rate	$HYDR_{t-1}$	-
weekly spreads on investment grade bonds	AAS, AS, etc.	+
gross supply of high yield loans	$GSHY_{t-1}$	-
gross supply of investment grade bonds	GSI_{t-1}	-
gross supply of fixed rate bonds	$GSFR_{t-1}$	-
net supply of fixed rate bonds	$NSFR_{t-1}$	-
net supply of fixed rate bonds	$NSFR_{t-1}$	-
national purchasing manager index	$NOMI_{t-1}$	-
CBOE volatility index	VIX	-

Table 3: Selection of tested variables for ex ante recovery rate regression models.

The exact recovery rate is difficult to calculate because of extra-regular after-default payments and the uncertainty regarding the departure from bankruptcy or liquidation. Thus, Moody's defines the market prices of distressed bonds 30 days after the default event divided by the par-value as a proxy for the recovery rate. It should be pointed out that the issuer weighted recovery rate is in some part a more artificial measure, as large and small companies defaulting are assigned the same weight. This is regardless of the different economic damage (credit loss) their default inflicts on an average investor's portfolio.

Table 3 gives an excerpt of the considered variables. In addition to the variables dispayed there, further macroeconomic variables like GDP, working output per hour etc. were tested. We point out that in our regression model stock market returns were not included. In Altman et al. (2) correlations between stock market index returns like S&P 500 and recovery rates could not support significant explanatory power for this variable.

In the sequel we will emphasize some of the considered variables like credit losses, credit spreads etc. according to their anticipated effect on average yearly recovery rates.

The default rate of speculative grade issued bonds is assumed as a major input variable for the regression model. Defaults in the non-investment grade sector should determine the future stance of high yield bond investors towards buying speculative grade bonds and especially as well as towards holding distressed bonds. If investment losses on speculative bond portfolios rise in percentage terms, we should assume that a higher risk premium will be demanded also influencing non-investment grade credit spreads. Furthermore, investors might be willing to sell distressed bonds at a lower rate and be less inclined to invest in funds buying distressed bonds.

Assuming capital markets to be at least approximately efficient, market prices of bonds are supposed to include good estimates on future credit risk. The class of intensity based credit risk models more or less is based on this assumption and often credit spreads are used to adjust historical migration matrices to market prices, e.g. (18). Hence, we included credit spreads of bonds as an explaining variable also for future recovery rates. The knowledge of informed investors priced in market spreads should reflect the current expectations about future default rates adequately. The credit spread data was derived from the difference between US treasury yields from US bond yields for different maturities.

According to Altman et al. (2), the total gross and net amount of fixed coupon bonds issued in the market affects the total amount of outstanding debt. As a consequence it should also influence the supply demand balance of distressed bonds as a major driver of recovery rates. As nearly all defaults happen from speculative credit rating, the supply of high yield bonds of companies with a low credit standing could materially affect the amount of distressed bonds. A further effect could be observed in the 1980s, when high yield bonds were very popular and not as critically evaluated by investors as before. This led to a burst of low quality high yield bonds at the end of the

1980s in the USA and to a substantial drop in recovery rate values.

Another economic indicator stems from the institute of supply management. As a classical macroeconomic variable the monthly national purchasing manager index was used. The index for the manufacturing sector is based on surveys at regional purchasing managers across the USA. At the stock market it is regarded as one of the most significant early predictors of future economic trends.

The last regressor variable considered in the model is the volatility index (VIX) of the Chicago Board of Options Exchange (CBOE). In 1993, the CBOE introduced the most widely recognized index for stock market volatility calculated on the basis of the implied volatility of index options on the S&P 500. The underlying computation methodology for the VIX has changed on September 22, 2003 and we will use the values derived from the new pricing model. The index is based on the CBOE index options on the S&P 500 with similar expiration characteristics. It uses a modern volatility trader standard formula giving as result the volatility of a synthetic S&P 500 option exactly at the money with a maturity of 30 calendar days. The CBOE introduced several derivative products basing on the VIX in March 2004. For the exact calculation of the index we refer to the documentation that can be found under *http://www.cboe.com/micro/vix/vixwhite.pdf.*

We point out that as a general rule the volatility rises when the stock markets turn bearish, as stock prices historically tended to fall faster than they climbed. A possible interpretation is that up to a certain degree the nervousness of the option market participants is reflected in the implied volatility of the index. The VIX is often referred to as "the investor fear gauge", following Whaley (27).

Data for the VIX is available since 1990 on a daily basis. For our regression model we use a moving average of different length between 30 days and one year. The best results are obtained using a six-month moving average of the VIX. The smoothed time series with a six-month moving average compared to the original time series is displayed in figure 3.

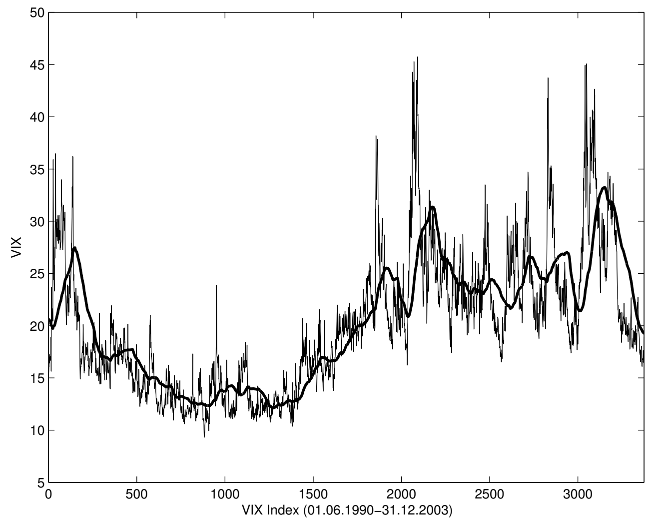

Figure 3: CBOE Market Volatility Index, six-month moving average and original time series, 01.01.1990-31.12.2003

4 A Multiple Regression Model for Recovery Rate Forecasting

4.1 Univariate Regression Results

Starting with an univariate regression model we test a variety of variables and their ability to provide information on future recovery rates. Data on issuer weighted and value weighted recovery rates were available for a time period from 1982 to 2003. Unfortunately some of the considered exogenous variables were available from 1990 only. Hence, the model is estimated for recovery rates from 1991-2003. For annually updated variables the values in year $t-1$ are used for the estimation of year t aggregate recovery rate. If monthly, weekly or even daily data is available moving average techniques are used to determine the forecasting power of the considered variable. Table 4 provides a summary on the most significant variables for the univariate regression.

Due to the outstanding results of the CBOE volatility index we will give

Variable	R^2	β_0	β_1
$AVRR_{t-1}$	0.475	14.12	0.672
$AIRR_{t-1}$	0.391	13.17	0.729
ADR_{t-1}	0.301	50.35	-4.78
$HYDR_{t-1}$	0.426	51.08	-2.306
AAS	0.57	38.88	0.755
$GSHY$	0.755	56.49	-0.083
GSI	0.330	58.28	-0.0379
$GSFR$	0.433	52.24	-0.0429
VIX	**0.812**	78.96	-1.929

Table 4: Results for univariate ex ante regression.

a brief explanation on the choice of the moving average window for the index. The variable is available on a daily basis back until 1990. It exhibits high volatility with daily jumps of over 10 percent not being unusual. Therefore a moving average technique for the regressor is used to be applicable to an annual regressand like the average yearly recovery rate. An interesting result is that the actual prognostic power is the highest when looking at the values at a time of about 0.5 years after the start of the recovery rate's predecessor year. Low recovery rates in the ongoing year were historically anticipated by high volatilities in stock options in the prior year. This is consistent with the idea that high volatility mirrors the nervousness of investors about future events and that often a high level of nervousness anticipates a period of economic weakness. The value of R^2 was 0.812 when looking at equity market volatilities half a year after $t-1$ using a moving average of a six month period.

4.2 Results for the Multiple Regression

After testing the variables in an univariate model we conduct a multiple regression analysis. Due to the fact that only 13 data points for the average recovery rate could be used for estimation we imposed some constraints on the estimated model in order to prevent overfitting. We allow for a maximum number of three regressors in the estimated model. Composite indices like the products or other functions of two regressors are not considered. Further for daily available data like VIX or observed credit spreads, the minimum averaging period is one month, in order to smooth the curves and prevent short-term fluctuations to impact annual figures too much.

The gross supply of high yield bonds is available as an annual figure since 1991. Since this was the variable in the univariate model giving the second best fit, we perform ex ante regression for average yearly recovery rates starting in 1991 and 1992. Furthermore it is tested, whether using the VIX averaged over one year instead of 6 months yields better results when mixing it with other regressors. We find that the results for regression models starting in 1991 were best using a model with two variables using the 6-month averaged VIX and 1 year moving average AA+ spread. We obtain values of $R^2 = 0.853$ for ex ante regression. The exact regression parameters and test results can be found in table 5 . When calculating the values for the regression of the 1992-2003 recovery rates the VIX remains the most significant factor. Using supply of high yield bonds, the second best univariate linear regressor and additional the AA+ credit spreads we obtain an $R^2 = 0.854$. Testing also multiple models with more than three variables some models are able to improve the R^2 values to a level of $R^2 > 0.9$, however only when 6 regressors are used for only 13 regressand data-points. Due to overfitting risk for the model, these results were excluded. For all models with the restrictions mentioned earlier in this section not including the VIX variable, R^2 remains below 0.80.

4.3 Recovery Rates for Individual Rating Classes

It should be pointed out that the estimates on recovery rates obtained by this method are one-year forecasts based on global recovery data from Moody's. However, there is also an influence of the rating of a company before the

	β_0	β_1	β_2	R^2
Coefficient	74.88	-1.756	0.169	0.853
Std. Errors	(5.360)	(-1.756)	(0.116)	
t statistic	13.97	-6.715	1.456	

Table 5: Coefficients for multiple ex ante regression with variables VIX (β_1) and AAS (β_2).

	1 year	2 year
Aaa	n.a.	n.a.
Aa	95.4	62.1
A	51.3	47.1
Baa	43.3	42.3
Ba	37.3	40.3
B	35.9	35.0
C	28.4	22.4
Investment Grade	46.2	44.5
Speculative Grade	34.6	33.9
All Issuers	35.7	35.4

Table 6: Moody's Senior Unsecured Issuer-Weighted Mean Recovery Rates for ratings one year and two years prior to default.

company defaults. The influence was illustrated e.g. in an empirical study by Varma et al (26). In table 6 average recovery rates for the different rating classes are denoted for a time horizon one year and two years ahead of default. The results are based on an extensive study by the rating agency Moody's covering the years 1982-2003.

It should be noted that the 95.4 recovery rate from the Aa rating class cannot be considered as a reliable estimate. It seems as if this estimate stems from a very low number of defaults, maybe even a single default. A better estimate for Aa rated companies would probably rather be the recovery rates two years prior to default. Also for the Aaa rated issues, there was not a single default to observe one or two years prior to default. A possible estimator for the individual rating class recovery rate $R\hat{R}_{i,t}$ based on the aggregate recovery rate forecast $R\hat{R}_t$ could be:

$$R\hat{R}_{i,t} = R\hat{R}_t \cdot \frac{R\bar{R}_i}{R\bar{R}} \tag{4.1}$$

with $R\bar{R}_i$ and $R\bar{R}$ denoting the average recovery rates in rating class i and the overall average recovery rate through the considered time period. Of course, other adjustment methods are possible. If more information about seniority grade of the issue is available also such data should be included. For further influence on individual recovery rates of a loan, see Gupton and Stein (13), (14).

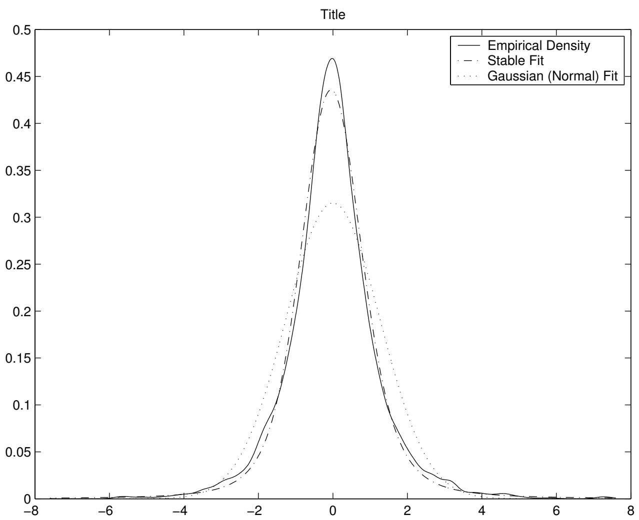

Figure 4: Fit of α-Stable and Gaussian Distribution to Returns of VIX

4.4 Simulation of Risk Factors

For forecasting and simulating future recovery rates it is necessary to have a correct simulation model for the model variables. Considering the entering variables we also investigate whether the assumption of normally distributed returns for the variables are justified or whether phenomena like heavy tails and excess kurtosis can be observed also for the volatility index. For various applications of the alpha-stable distribution we refer to Rachev and Mittnik (21). Figure 4 illustrates stable and Gaussian fit to the volatility index for the period from 01.01.1990-31.12.2003. We find that returns of the variable VIX exhibit heavy tails, high kurtosis and obtain a significantly better fit to the index. For applications like CDO pricing where also simulation of future recovery rates may play an important role this issue should not be neglected.

5 Conclusions and Future Work

In this paper we developed a multiple regression model based on macroeconomic variables that can be used for aggregate recovery rate ex-ante forecasting. Following Altman et al. (2) we suggested the business cycle and macroeconomic factors to play an important role for LGD values. As main input the model used the cyclical variable of CBOE market volatility index that provided surprisingly good results in ex ante forecasts of yearly average recovery rates in the US bond market. Forecasting Moody's issuer weighted 1992-2003 recovery rates amodel with the additional variable if investment grade AA+ credit spreads we obtained $R^2 = 0.854$. Due to the considered time horizon of only 13 years we propose to reestimate the model regularly when more data is available. Since in the suggested model only aggregate yearly recovery rates were estimated, we also suggested a simple procedure for recovery rate adjustment for individual rating classes. We point out that the good forecasting results suggest the capability of macroeconomic variables to indicate future aggregate recovery rates. However more research on this topic will be necessary in the future.

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