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Macroeconomic Impact on Expected Default Frequency*

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Abstract

We use a vector error correction model to study the long-term relationship between aggregate expected default frequency and the macroeconomic development, i.e. CPI, industry production and short-term interest rate. The model is used to forecast the median expected default frequency of the corporate sector by conditioning on external forecasts of macroeconomic developments. Evaluations of the model show that it yields low forecast errors in terms of RMSE. The estimation results indicate that the interest rate has the strongest impact on expected default frequency among the included macroeconomic variables. The forecasts indicate that EDF will rise gradually over the forecast period.

Keyword: Expected Default Frequency; Macroeconomic Impact; Business cycle; vector error correction model; Financial stability; Financial and real economy interaction.
JEL classification: C32; C52; C53; G21; G33.

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Introduction

Operations of banks are typically dominated by the granting of credit and therefore, credit risk is the largest individual risk in the banking system by far. In recent years, central banks and commercial banks have begun to use models that make it possible to more coherently probe the development of the banks' credit risks on basis of different assumptions and events.

In its stability analysis, the Riksbank uses a portfolio model to assess credit risk in the Swedish banking system. The idea behind this approach is that the resilience of the banks is reflected in the size of the capital buffer they hold in relation to the credit risk measured in their loan portfolios. A portfolio model makes it possible to calculate the probability that loan losses of various sizes may arise in existing portfolios. Information regarding the composition of the portfolio, the probability of default, and recoveries is needed in order to calculate the risk in the loan portfolio. Two measures are usually used to quantify the credit losses the banks may incur. One is a measure of the expected loss that indicates how much a bank can expect to lose in its current credit portfolio. This is calculated by multiplying the likelihood of default by exposure at default (exposure*LGD, where LGD is Loss Given Default). The other is a measure of the size of the losses that can occur in addition to the expected losses and for which the bank must have capital cover (required risk capital). In this way, it is possible to study how changes in the credit quality of the banks' borrowers influence the credit risk in the banks' loan portfolios.

The banks compensate themselves for the expected loss through a risk premium on the price of loans in their regular operations. If there is an increase in the expected loss in the portfolio, this may mean that the bank's costs increase as a result of increased reserve funds. The banks hold a buffer to cover possible loan losses above those expected; let us call this the risk capital requirement. Loan loss distribution makes it possible for banks to calculate the size of this need, given a certain tolerance level. The unexpected loan loss – and thereby the need for risk capital – also affects the prices banks set for their loans since holding capital entails a cost for the banks in the form of a return on investment requirement from the shareholders, and the banks must compensate themselves for this. The amount of capital the bank requires to cover unexpected losses depends on the loan loss distribution. The greater the probability of extreme outcomes, that is to say, the more outcomes that lie far to the right of the distribution, the greater is the need for risk capital.

The above discussion indicates that one of the most important variables for assessing credit risk in banking is the likelihood of default which reflects the borrowers' credit quality. It is quite likely that macroeconomic variables play an important role in determining the direction of the future development of borrowers' credit quality.[1] Linking credit quality to the development of macroeconomic variables makes it possible to undertake scenario analyses where the credit risk for the banks can be appraised on basis of the paths of different macroeconomic development curves. We present a model that creates a link between the assessment of credit risks and macroeconomic appraisals.

Several papers address the empirical relationship between fundamentals and default probabilities among companies. Chan-Lau (2006) offers a survey of this literature where macroeconomic-based models constitute one class of such models. These models study how default probabilities are affected by the state of the economy and can be divided into models that allow for feedback between default probabilities and explanatory economic variables and models that do not. Virolainen (2004) is an example of the latter category while Alves (2006), Pesaran et al. (2006), Castrén et al. (2007) and Jacobson et al. (2005) are time series models that do take feedback effects into account.

Jacobson et al. present an empirical model that consists of a system made up of three blocks. The first is a vector autoregressive (VAR) model for the macroeconomic variables they

[1] See i.e. Jacobson et al. (2005).

consider. They include domestic output, inflation, the nominal interest rate, and the real exchange rate as endogenous variables in the VAR. The foreign macro variables as well as the aggregated default frequency of incorporated firms enter the model exogenously. In the second block, they have a logit model for the default risk at the firm level where the macroeconomic variables as well as various balance-sheet variables enter as regressors. The third block in their empirical model is an attempt at estimating how the balance-sheet variables included in the logit model depend on the macroeconomic variables. Alves (2006), Pesaran et al. (2006), and Castrén et al. (2007) are models that allow for feedback from explanatory economic variables on default probabilities, but not the other way around. They use VAR models for forecasting the development of the macroeconomic variables. These forecasts are then used in a satellite model for credit risk. Unlike Pesaran et al. (2006), and Castrén et al. (2007), Alves (2006) takes into account that the likelihood of defaults and the macroeconomic variables display common trends.

In this paper, we depart from the literature in one important respect. The analysis of the likelihood of defaults in the corporate sector is here done using a forward-looking measure of the likelihood of defaults. One example of a structural credit risk model of this kind is Credit Monitor (Moody's KMV) which offers a theoretically attractive model for calculating the empirical Expected Default Frequency (*EDF*) for individual companies.[2] Forward looking-measurement of the capacity of listed companies to make payments can be calculated using the market value of their assets in relation to the book value of their debts. The market value of equity is a function of the current value of all future cash flows the company can be expected to generate. General economic developments play an important role for the development of company cash flows. Therefore, it is reasonable to assume that *EDF* and the macroeconomic variables display common trends. We study the long-term relationship

[2] This model is based on Merton's approach for the evaluation of credit risk as refined by Vasicek and Kealhofer, which is why it is known as Kealhofer Merton Vasicek (KMV).

between expected default frequencies and macroeconomic development using a Vector Error Correction Model (VECM), i.e. a VAR model that includes an error correction term. The choice of a VECM can be justified by its ability to discern shared trends between series as well as allowing for feedback between default probabilities and explanatory economic variables. Estimates of the coefficients may be improved if the existence of shared trends in series is taken into account. Including shared trends becomes even more important when the model is estimated on high frequency data, which is the case in this paper. A principal feature of cointegrated variables is that their time paths are influenced to the extent that any of these deviate from their long-run relationship. Moreover, the short-run dynamics must be influenced by the deviation from the long-run relationship.

This paper has two objectives. One is to explore whether the development over time of aggregate EDF for listed companies provided by Credit Monitor can be explained by macroeconomic development.[3] The other is to conduct a stress test of aggregate EDF, given unfavourable macroeconomic development.

In section 1, we give an intuitive discussion of the impact of various macroeconomic factors on aggregate EDF. Section 2 presents the database used for the empirical analysis, followed by an empirical time series model for aggregate EDF in section 3. Section 4 contains an evaluation of this model. In section 5, forecasts are given for future default frequency in the corporate sector conditioned on the Riksbank's (the central bank of Sweden) official forecasts of macroeconomic development. In section 6, a stress test is conducted of the expected default frequency of companies. The discussion that follows sums up and concludes the paper.

[3] Aggregate EDF is represented by the monthly median of EDF:s for individual Swedish non-financial companies in Moody's-KMV Credit Monitor.

1. Expected default frequency (EDF) and macroeconomics

Moody's KMV Credit Monitor calculates EDF as a function of distance to default. The premise for Moody's KMV model is that a company becomes bankrupt when the market value of its assets (MV_A) is lower than its default barrier, i.e. the company's debts (D): $MV_A < D$ or $MV_E = MV_A - D < 0$ where MV_E is the market value of the company's equity. The distance to default (DD) is measured in the number of standard deviations, which makes it possible to compare default frequencies between different companies, irrespective of their size.

(1) $$DD = \frac{MV_A - D}{\sigma_A} = \frac{MV_E}{\sigma_A},$$

where σ_A is the volatility (standard deviation) of the market value of the company's assets. The market value of the company's equity is a function of the current value of all future cash flows the company can be expected to generate. General economic developments play an important role for the development of company cash flows. Therefore, it is reasonable to assume that the EDF and the macroeconomic variables display common trends. The existence of common trends is estimated and tested using a Vector Error Correction Model (VECM). We have decided to present the macroeconomic conditions by three different variables: the domestic industrial production index ($INDY$), the domestic consumer price index (CPI), and the nominal domestic three-month rate for treasury bills ($R3M$). On this basis, we estimate the following relationship

(2) $\log(EDF) = \beta_0 + \beta_1 R3M + \beta_2 \log(INDY) + \beta_3 \log(CPI) + u$.

The selection of the macroeconomic variables included in the empirical assessment in this paper is based on Jacobson et al. (2005). They model the macro economy by a set of macroeconomic variables, including aggregate bankruptcy frequency, in a quarterly vector autoregressive model (VAR). Based on work by Lindé (2002), they choose to include the following endogenous variables: the gap in domestic production, domestic inflation, the Riksbank's repo rate and actual exchange rates. The exogenous variables included in their paper are the gap in foreign production, foreign inflation and foreign three-month interest rates. In addition to these macroeconomic variables, Jacobson et al. (2005) also include a measurement of the aggregate proportion of defaults as another exogenous variable in the VAR. This consists of the number of actual defaults in relation to the total number of existing companies.

The model in this paper is deliberately based on a few variables only in order to keep it relatively simple and transparent. This means that operationalising the model in the ongoing analysis does not require any large amount of resources and that the results are not too difficult to interpret either. Moreover, the aim of the model is to provide a platform for scenario analysis to study the effects of major macroeconomic shocks – an analysis that is by nature relatively rough. Moreover, the model in this paper will be used to make conditional forecasts on EDF. This means that we will condition EDF-forecasts on external forecasts on macro variables. The forecasts for these variables are made taking the foreign macroeconomic developments into account. This is one of the reasons why we do not include foreign macroeconomic variables as exogenous variables in the model. Finally, we have opted for including industrial production in the estimates instead of the non-observable production gap since the estimates in this paper are based on monthly data. The estimates indicate that on the whole, there is a one-to-one relationship between changes in the GDP and changes in industrial production.

It is difficult to know a priori what effect each of the macroeconomic variables may have on EDF. From the model specification in the Appendix (see equation A.6), the impact of the macroeconomic variables on EDF is not unambiguously decided and thus, it is ultimately an empirical issue. Nevertheless, it can be argued that the different macro variables should affect the EDF in certain ways. A negative correlation is expected between manufacturing output and EDF because increased output implies higher economic activity and higher corporate earnings. A higher interest rate increases the interest expenditure on corporate loans, which tends to raise EDF. The link between inflation and EDF is mainly twofold, through factor prices and the prices companies charge for their goods and services. Higher factor prices lead to increased production costs and tend to impair credit quality. Higher product prices can boost earnings and thereby improve creditworthiness. The relative strength of these two effects of inflation is determined by the structure of the markets for factors of production and the company's output.

2. Data

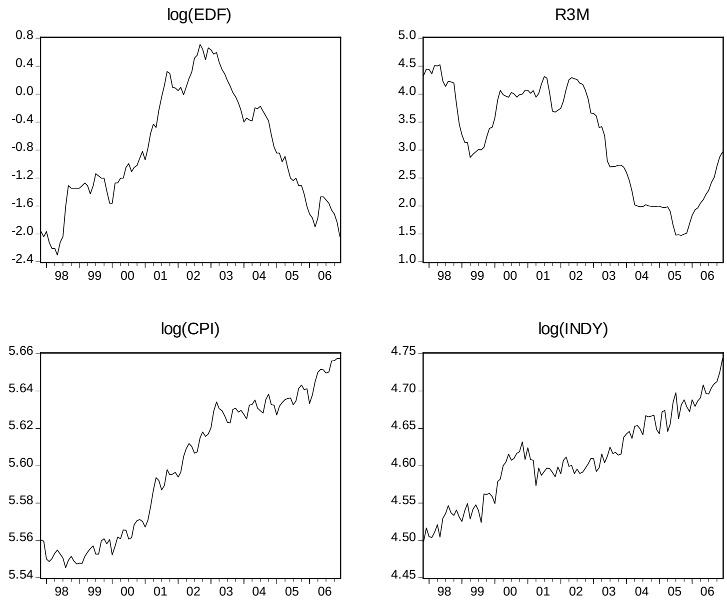
The estimations are based on monthly data of expected default frequency (EDF) covering the period from November 1997 up to and including March 2006. Data on the empirical expected default frequency for non-financial listed companies *(EDF)* are from the Credit Monitor (Moody's-KMV). The index for industrial production ($INDY$) has been taken from EcoWin[4]. The consumer price index (CPI) and interest rates on three-month treasury bills ($R3M$)

[4] EcoWin is a provider of economic and financial market data. For more information about EcoWin, the reader is referred to http://www.ecowin.com/.

come from Statistics Sweden. Data for *INDY* are available for the period from January 1990 until and including December 2006. Data for *CPI* and *R3M* are available for the period from January 1970 until and including December 2006.

Descriptive statistics for the variables included can be found in Figure 1 and they show a positive trend for *INDY* and *CPI*. The short-term interest rate, *R3M*, displays a negative trend until the end of 2005 and a positive trend thereafter. The trend for *EDF* is initially positive before it turns negative at the end of the period.

Figure 1: Monthly Development of *log(EDF), log(INDY), log(CPI) and R3M*.



Tests to find out whether series are stationary can be carried out using Unit Root tests. These tests indicate that all variables used in the estimates of the VEC models in this paper appear to be non-stationary, i.e. they have unit roots and are I(1) variables (Table 1). However, even if we realize that the *EDF* may not be a genuine I(1) variable, it seems to behave as an I(1) variable during the sample period studied in this paper. The indication in the unit root test that *R3M* has a unit root is due to a shift in levels around 1993. It is more than possible that *R3M* is not genuinely I(1). Nor is it necessary for the analysis in this paper for *R3M* to be a I(1) variable, even though this is what the test indicates. The test also indicates that *INDY* may not be stationary (non-stationary along a trend). Even if a specific series is not stationary, combinations of such series may have a cointegrating connection. Thus, the test for the occurrence of cointegration in the next section does not presume that all series are I(1) variables.

Table 1: Unit Root tests.

Variables	***Level***	***Level with Constant***	***Level with trend + constant***	***First difference***
$\log(EDF)$	-0.76 (0.39)	-1.09 (0.72)	-0.52 (0.98)	-7.09 (0.00)***
$\log(INDY)$	2.88 (0.99)	-0.16 (0.94)	-3.76 (0.03)**	-10.07 (0.00)***
$\log(CPI)$	2.70 (0.99)	-0.33 (0.92)	-2.21 (0.48)	-2.52 (0.01)**
$R3M$	-1.06 (0.26)	-1.77 (0.39)	-1.69 (0.75)	-5.65 (0.00)***

Note: Unit root tests use Dickey-Fullers estimation method. * (**) *** indicates significant results at the 10 (5) 1 per cent level.

3. VEC model for the aggregate expected default frequency (EDF)

In the analysis of the time-series, it is possible to show that even though all series prove to be non-stationary, a linear combination of them may nevertheless be stationary, i.e. integrated at the order of zero. If this is the case for the data series on which our model is based, we can conclude that EDF, $INDY$, CPI and $R3M$ are cointegrated. This means that the linear combination cancels out the stochastic trends in these series.

Using Johansen's (1998) method is one way of testing whether a data series is cointegrated. Table 2 presents the test statistics for this method (λ_{trace}). The test indicates that we can reject the hypothesis that there exists no cointegrated relationship at the 5 per cent significance level, i.e. there is at least one cointegrating vector.[5] The test also indicates that there is only one cointegrating relationship out of the possible four. Annex 2 contains a graphic representation of the cointegrating relationship. The relationship has been normalised on basis of EDF, as our primary interest is in the effects of the macro economic variables on EDF. The test provides support for a long-term relationship between EDF, $INDY$, CPI and $R3M$.[6]

Table 2: Johansen's test for cointegrating relationships

Null hypothesis	λ_{trace}	***5% critical value***	***P value***
$r = 0$	51.2076	47.8561	0.0234
$r \leq 1$	18.3348	29.7970	0.5414

Note: Since the cointegrating vector is not identified, we impose different identifying restrictions on the cointegrating vector. The likelihood ratio test indicates that the variables are cointegrated notwithstanding which variable we use for the normalization. This indicates that a subset of the variables cannot be cointegrated.

After having tested for cointegrating relationships, we also need to decide on the appropriate lag structure for the model. The choice of lag structure is basically an empirical question and the lag structure chosen in the specified empirical model is based on three different criteria. First, a residual test is made using a serial correlation LM test. This test is an alternative to the Q-statistics for testing serial correlation. The LM-test is used to test for higher order ARMA errors. Second, when the possibility that the errors exhibit autocorrelation has been excluded for a given lag structure, we also investigate whether the estimated coefficients in the cointegrating relationship are stable. This is done by investigating whether the estimated coefficients in the cointegrating relationship change when new observations are added to the database. Finally, we investigate the out of sample forecasting accuracy for different models

[5] However, it should be noted that we cannot reject the null hypothesis that the number of cointegrating vectors is less than or equal to one ($r \leq 1$).
[6] A maximum characteristic root test also indicates that there is only one cointegrating relationship.

with different lag structures. We choose the model that gives the lowest forecast error in terms of RMSE.[7] After having determined the lag structure, we specify the VECM model:

$$(3) \qquad \Delta x_t = \delta_0 + \Gamma_1 \Delta x_{t-1} + \Gamma_2 \Delta x_{t-2} + \Gamma_3 \Delta x_{t-5} + \Gamma_4 \Delta x_{t-6} + \alpha\beta' x_{t-1} + \varepsilon_t$$

where $x_t = [\log(EDF_t), R3M_t, \log(CPI_t), \log(INDY_t)]$, $\delta_0 = \Gamma_0 - \alpha\beta_0$, and $\varepsilon_t \sim N(0,\Omega)$.[8] Two important parameters estimated in this model are β and α. The cointegrating vector, summarized by matrix β, describes the long-run relationships between the endogenous variables. The loading (or adjustment) coefficients forming matrix α describe the dynamic adjustment of the endogenous variables to deviations from long-run equilibrium by $\beta' x$.[9]

Table 3 below summarises the maximum likelihood estimate (ML-estimate) for the beta parameters in the long-run relationships in the estimated model. All the coefficients are significant and have the expected signs. This means that in the long-term, industrial production, $INDY$, has a negative effect on EDF while CPI and $R3M$ have a positive effect on EDF.

The test that $\beta = 0$ and $\alpha = 0$ entails restrictions on cointegrating vectors or the adjustments parameters. The likelihood ratio tests indicates that we can reject each and every one of the following hypotheses: $\beta_2 = 0$, $\beta_3 = 0$, $\beta_4 = 0$, $\alpha_1 = 0$, and $\alpha_4 = 0$. However, we cannot reject that $\alpha_2 = 0$, $\alpha_3 = 0$, which is also indicated by the t-values. We were also able to reject the

[7] The outcomes of these tests and evaluations can be provided by the authors upon request.
[8] A specification of the model where the implied volatility of the stock market was included has been estimated to capture some measure of market risk. This caused some problems with multi colinearity in the model and therefore, we chose the specification where the volatility measure is excluded.
[9] When the *EDF* deviates from its estimated long-term level, $\alpha = 0.1$ indicates that ten per cent of the deviation will be corrected in the subsequent period. How long it will take before the system returns to long-term equilibrium can be calculated using α.

hypothesis that $\beta = (0,1,x,x)$, where "x" denotes a free parameter. The hypothesis excludes *EDF* from the cointegrating vector, imposes an identifying restriction on *R3M* and estimates *INDY* and *CPI*. This indicates that the macroeconomic variables cannot be integrated with each other.

Table 3: Estimated beta-parameters for long-term relationship

	β	α
$\log(EDF)$	1	-0.064 (-4.55)
$R3M$	1.07 (-3.86)	0.012 (0.81)
$\log(CPI)$	27.25 (-2.98)	0.000 (0.45)
$\log(INDY)$	-16.58 (2.27)	-0.004 (-2.48)

Note: T-values are presented in parenthesis.

Adjustments of the variables to the long-run level after shocks have occurred take place via adjustment coefficients or the "error correction terms", α. Table 3 offers a summary of the estimated adjustment coefficients. The most interesting result is that the error correction terms for EDF, and $INDY$, i.e. α_1, and α_4 are significant, while the error correction terms for CPI (α_3) and $R3M$ (α_2) are not significant. The error correction terms α_1 and α_4 are negative, indicating convergence towards the long-run equilibrium. The fact that α_2 and α_3 are positive numbers does not constitute a problem as Johansen's test reveals that the model converges towards long-run equilibrium. To save space, the rest of the results of the estimation are presented in annex 3.[10]

[10] Due to lack of space, we have opted not to present t-values for the short-term coefficients. Naturally, these can be supplied by the authors upon request.

Table 5 presents the results for various specification tests of the estimated model. The autocorrelation LM-test reports the multivariate LM test statistics for residual correlation. This test indicates that there is no autocorrelation in the residuals. White's heteroskedasticity test is used to test for no heteroskedasticity. This test indicates that there are no heteroskedasticity problems in the residuals. The normality test reports the multivariate extensions of the Jarque-Bera residual normality test, which compares the third and fourth moments of the residuals to those from the normal distribution. For the multivariate test, a factorization of the residuals that are orthogonal to each other must be chosen. We have used the factorization method suggested by Urzua (1997).[11] Testing for whether the residuals are normally distributed reveals this to be the case.

Table 5: LM-test for autocorrelation, White's test for heteroskedasticity and Jarque-Berras test for normal distribution in the residuals

Test for H_0		**P value**
No autocorrelation	Lag 1	0.6658
	Lag 2	0.6243
	Lag 3	0.6852
	Lag 4	0.1910
	Lag 5	0.5823
No heteroskedasticity		0.4607
Normality		0.2265

4. Evaluation of the VEC model

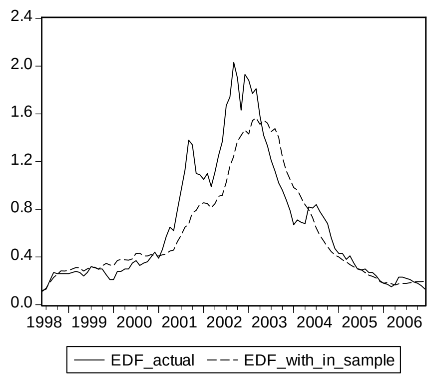
In this section, we evaluate the VEC model by analysing within-sample properties as well as its out of-sample properties.

[11] This test has a specific alternative, which is the quadratic exponential distribution. According to Urzua, this is the "most likely" alternative to the multivariate normal with finite fourth moments, since it can approximate the multivariate Pearson family "as close as needed". As recommended by Urzua, a small sample correction is also made to the transformed residuals before computing the statistics.

4.1 Within-sample forecasts

A comparison between within-sample forecasts for the VEC model with the actual outcomes for the sample period shows that the model replicates the actual distribution of EDF relatively well, see Figure 2. However, the important question is how good "out-of-sample" forecasts of EDF will be.

Figure 2: Within-sample forecasts for EDF over time



4.2 Out-of-sample forecasts

The VEC model is evaluated in three ways. *One* is by comparing RMSE for the VEC model with Root Mean Square Error (RMSE) for the forecasts made using a naive model (such as a random walk model or an AR(1) model). A *second* is through the comparison of RMSE for the forecasted EDF for 1 month, 3 months, 6 months, 1 year and 2 years ahead with the standard deviation for EDF. A *third* is a by conducting a sign test.

RMSE for the VEC model vs. RMSE for naïve models: The procedures used are as follows:

The VEC model for EDF is estimated on data from June 1998 up to and including December 2002. The estimated VEC model is used to make three different forecasts for the period from

January 2003 up to and including December 2006. *First*, we make endogenous forecasts which means that the models generate trajectories for all variables included in the model. *Second*, the estimated VEC model is used to make a conditioned forecast for the period from January 2003 up to and including December 2006; in this case conditioned on the Riksbank's official forecasts for the macroeconomic variables in its inflation reports 2003:1 – 2006:3. *Third*, an exogenous forecast is made for the period from January 2003 up to and including December 2006. This is made possible by conditioning the EDF forecasts on the outcomes for the macroeconomic variables for the period from January 2003 up to and including December 2006.

EDF is also estimated using a simpler AR(1) model: $EDF_t = \alpha EDF_{t-1} + \varepsilon_t$. The estimated AR(1) model for EDF is used to make alternative EDF forecasts. In addition, a random-walk model is used to make EDF forecasts. The premise for this naive forecast is that the best forecast for future EDF is provided by the most recent information about the outcomes for the same variable.

Then, we proceed step by step by increasing the sample one month at a time and making new estimates of the model and forecasts using the various models as described above. Finally, the RMSE is calculated for the three forecasts that have been produced using the VEC model, the AR(1) model and the random-walk model. The RMSE for the different models is calculated as follows

$$(4) \qquad RMSE = \sqrt{\frac{1}{T}\sum_{t=s}^{2006:3}\left(EDF_t^{forecast} - EDF_t^{actual}\right)^2}\ ,$$

where $EDF_t^{forecast} - EDF_t^{actual}$ is the forecast error. The forecast errors are squared so that both overestimates and underestimates will have the same weight. Then, the average of the squared forecast errors is calculated. The square root of this figure then provides the $RMSE$.

For endogenous and exogenous forecasts, the number of periods selected is $T = 39$ and the starting period for the forecast is $s = 2003:1$ for those with 1 month forecast horizons ($T = 37$ and $s = 2003:3$ for forecasts with 3 month forecast horizons; $T = 34$ and $s = 2003:6$ for forecasts with 6 month forecast horizons; $T = 28$ and $s = 2003:12$ for forecasts with 1 year forecast horizons; $T = 16$ and $s = 2004:12$ for forecasts with 2 year forecast horizons).

Table 8 presents a summary of the RMSE results for the five EDF forecasts produced using the VEC model (endogenous forecasts, forecasts conditioned on the Riksbank's forecasts of the macroeconomic variables in the monetary policy reports, forecasts conditioned on the outcomes of the macroeconomic variables), the AR(1)-model and the random-walk model.

The endogenous forecasts made using the model have consistently higher RMSE figures than the two forecasts based on the AR(1) model and a random-walk model. The same is true for the VEC forecasts conditioned on the Riksbank's macro forecasts in the monetary policy reports (this does not apply to forecasts with 1 month and 2 month horizons, however). The model in this paper is estimated using monthly data. To make conditioned forecasts with this model, we need monthly forecasts for the macroeconomic variables. However, the Riksbank's macro forecasts are usually presented quarterly (this is especially the case for GDP-forecasts). This means that we are obliged to transform these quarterly forecasts into monthly forecasts using a rather simple method. In this way, we introduce a measurement error when making the forecasts that may magnify RMSE.

What is interesting in this context seems to be that VEC forecasts conditioned on the outcomes of macroeconomic variables are better than VEC forecasts conditioned on the Riksbank's forecasts for the macroeconomic variables. The RMSE declines for the entire period when uncertainty about macroeconomic developments is eliminated by conditioning the forecasts on the outcomes for macroeconomic variables. This indicates that the estimated equation for the EDF has good forecasting properties. Moreover, the RMSE falls below the RMSE for forecasts made using the AR(1) model and the random-walk model.

Table 8: RMSE for EDF

Period	**VEC - endo-genous forecasts**	**VEC - forecasts conditioned on Riksbank's macro forecasts**	**VEC forecasts conditioned on outcomes**	**AR(1)**	**Random walk**
1 month	0.09	0.04	0.09	0.07	0.08
3 months	0.23	0.19	0.19	0.20	0.19
6 months	0.46	0.47	0.32	0.39	0.34
1 year	0.97	0.83	0.37	0.66	0.54
2 years	2.20	1.42	0.53	1.25	0.93

RMSE vs. the standard deviation of EDF: Another way of evaluating the RMSE for the different forecasts (and the different periods of time) is to relate the RMSE to the standard deviation of the EDF, which in this case is 0.51. This comparison indicates that the endogenous forecasts are reliable for up to 6 months. The same is true for the forecasts conditioned on the Riksbank's macro forecasts, the AR(1) model and the random-walk model. The RMSE for forecasts conditioned on the outcomes for the macroeconomic variables is lower than 0.51 for up to 1 year.

Sign test: Yet another way of evaluating the VEC model is to conduct a sign test to study the extent to which the model's forecasts develop in the same direction as EDF outcomes; see table 9. The results of a test of this kind can lie between 0 and 100 per cent. A zero result means that the forecast model can never indicate whether EDF will rise or fall during the forecast period, and 100 per cent indicates the opposite. A sign test indicates that the model specifications that exclude macrovariables (AR(1) and random-walk models) do not have any pure prediction capacity as compared to VEC models that include macro variables. The predictive capacity of the VEC model is particularly good if the EDF forecasts are conditioned on macroeconomic forecasts with a high degree of precision.

Table 9: Sign test

Period	**VEC - endogenous forecasts**	**VEC-forecasts conditioned on the Riksbank's macro forecasts**	**VEC forecasts conditioned on outcomes**	**AR(1)**	**Random Walk**
1 month	40	73	38	52	4
3 months	35	27	37	37	0
6 months	33	27	42	28	2
1 year	16	33	68	3	0
2 years	4	8	72	0	0

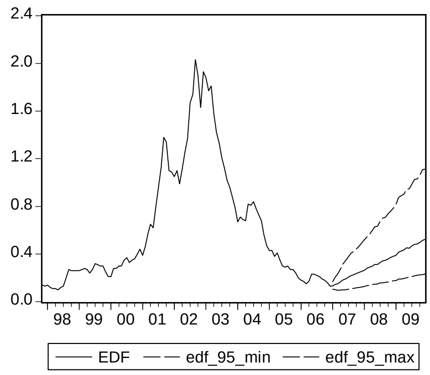
5. Conditional forecasts

The VEC model's conditional EDF forecasts are obtained by allowing the macroeconomic forecasts made in the Riksbank's monetary policy report 2007:1 to determine the development of the macroeconomic variables in the model. In this report, it was judged that GDP in Sweden would increase by 3.5 per cent in 2007, by 2.9 per cent in 2008 and by 2.6 per cent in 2009. Inflation measured in terms of CPI was expected to rise by 2.3 per cent in

2007, 2.1 per cent in 2008 and 2.1 per cent in 2009. These forecasts were made assuming a short-term interest rate of 3.7 per cent in 2007, 3.8 per cent in 2008 and 3.9 per cent in 2009.

The EDF forecasts for the same period are summarised in Figure 3. The conditioned forecast indicates that aggregate EDF will rise from 0.13 per cent in December 2006 to about 0.52 per cent in December 2009. This indicates that there will be a turn in the credit cycle during the forecast period and that this already begins in January 2007.

Figure 3: Conditioned forecasts of aggregate EDF



The variability of forecasts is measured by the forecast standard errors. We use these standard errors to form forecast intervals. In Figure 3, we also plot the forecasts with plus and minus two standard error bands. These two standard error bands provide an approximate 95% forecast interval.[12]

[12] This means that if we (hypothetically) make many forecasts, the actual value of the dependent variable will fall inside these bounds 95 per cent of the time.

6. Stress-testing using the EDF model

The estimated model can be used to make conditioned EDF forecasts based on less advantageous macroeconomic development than in the basic scenario presented in the Riksbank's monetary policy reports. To construct this scenario, we have made use of impulse responses in RAMSES[13]. A shock in consumer prices in RAMSES in the form of a mark-up of wages by 1 percentage unit implies a rise in short-term interest rates of 0.25 percentage units and a reduction in the GDP gap of 0.41 per cent. In the following year, the shock declines so that consumer prices are only 0.29 percentage units higher. Interest rates are 0.089 percentage units higher and the GDP gap 0.8 percentage units lower as compared to the initial situation. In the final year, the shock subsides completely so that inflation is 0.04 percentage units lower as compared to the situation before the shock occurred. Short-term interest rates are 0.05 percentage units lower and the GDP gap 0.76 percentage units lower as compared to the situation preceding the shock. The rules of thumb we have applied largely follow the impulse responses from RAMSES. However, we have made a correction for a reaction to the initial shock with a raise in interest rates of 25 points to 0.5 percentage units. We have also reduced the inflation shock for the following year by half.

The envisaged scenario is the following. It is assumed that a supply shock has taken place in the economy that drives inflation up to 3.5 per cent in 2007. The market expects the interest rate to initially react to this shock by 0.6 percentage units. The market then expects the short-term interest rates to become 4.0 per cent in 2008 and 3.8 per cent in 2009. During the same period, inflation would be 3.5 per cent in 2007, 2.5 per cent in 2008 and 2.2 per cent in 2009. As a result of the rise in interest rates, GDP growth declines as compared to the Riksbank's basic scenario. During this period, the rate of GDP growth is 2.5 per cent in 2007, 0.9 per cent in 2008 and 0.6 per cent in 2009.

[13] This is the name of the dynamic stochastic general equilibrium model used for policy simulations in Sveriges Riksbank.

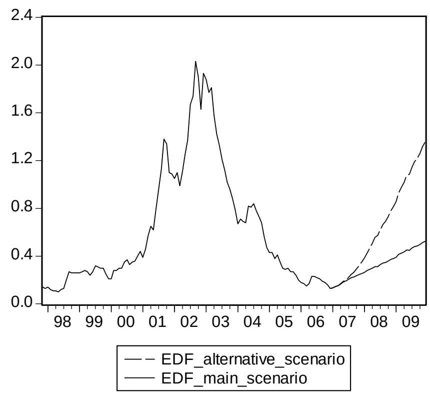
Table 10 and Figure 4 show that the VEC model predicts that aggregate EDF will rise from 0.13 per cent in March 2006 to 0.36 per cent in December 2007, 0.82 per cent in 2008 and 1.35 per cent in 2009.

Table 10: Macroeconomic scenarios and results of stress test*

Year	**2006**	**2007**	**2008**	**2009**
CPI	1.64 (1.64)**	3.53 (2.33)	2.47 (2.13)	2.20 (2.09)
R3M	2.96 (2.96)	4.28 (3.68)	4.00 (3.78)	3.75 (3.88)
INDY	4.32 (4.32)	2.49 (3.47)	0.88 (2.87)	0.57 (2.55)
EDF	0.13 (0.13)	0.35 (0.26)	0.82 (0.38)	1.35 (0.52)

* The consumer price index and the industrial production index are given as annual percentage changes while interest rates and EDF are shown as percentage units.
** Figures in parentheses indicate developments in the main scenario.

Figure 4: Development of aggregate EDF in the main scenario and the alternative scenario



7. Conclusions

In this paper, we estimate a time series model for predicting future credit quality in the corporate sector. The model is based on aggregated data and a few variables only. This means that it is relatively straightforward and can be used in the ongoing analysis. The variable which represents credit quality is expected default frequency (EDF), a market-based indicator of the probability of a company not being able to meet its commitments within a specified period. The model uses the median EDF for the corporate sector, which is an aggregated measure of credit quality with all company-specific risks eliminated, so that it is solely affected by risk factors that all companies have in common. The model estimates the relationships between the EDF and three macroeconomic variables: inflation, manufacturing output and the short-term interest rate. The estimates are then used together with forecasts for the three macroeconomic variables to predict credit quality.

A vector error correction model (VECM) is used to catch long-run relationships between the variables studied as well as short-run fluctuations around these relationships. The effects of different factors on credit quality are ultimately an empirical matter. Estimations using monthly data for the period November 1997 to December 2006 show that increased manufacturing output is accompanied by a lower expected default frequency. Rising inflation leads to the opposite scenario: a higher expected default frequency and thereby poorer corporate credit quality. However, the short-term interest rate has the strongest impact on corporate credit quality among the three macro economic variables. Higher interest rate leads to a higher expected default frequency. The predictions of credit quality are based on the main scenario for economic development in the Riksbank's *Monetary Policy Report*. In order to demonstrate the uncertainty around the estimated parameters, the confidence interval on either side of the predictions is also calculated.

The model's performance is evaluated with three tests. One compares the root mean square error (RMSE) for predicted credit quality with the standard deviation of recorded credit quality. Another test compares RMSE for predicted credit quality in the VEC model with credit quality predicted with a naïve model (i.e. based on an AR(1) model or a random-walk model). The third is a sign test to determine to what extent the model's predictions develop in the same direction as actual credit quality. Tests indicate that the model's ability to predict corporate credit quality is satisfactory. This means that the model's predictions of future credit quality can be expected to co-vary with actual credit quality to a high degree. Less uncertainty in the macro forecast naturally leads to greater precision in the model's predictions.

The VEC model's EDF forecasts conditioned on the Riksbank's official view of macroeconomic developments show that there will be a gradual increase in aggregate default expectancy during the forecast period. This development, in turn, indicates a turn in the credit cycle. At the same time, the stress test shows that a supply shock in a situation where the credit cycle is expected to turn during the forecast period and which is countered by the Riksbank with a rise in interest rates leads to a twofold increase in aggregate expected default frequency at the end of the forecast period.

The model can be used as one of a number of instruments for forward assessments of banks' credit risks. The EDF predictions can be used as inputs to calculate the economic capital individual banks should hold to cover unexpected credit losses which give a clear indicator of the credit risk in each bank's loan portfolio. The model can also be used for the analysis of scenarios to test alternative assumptions about macroeconomic developments.

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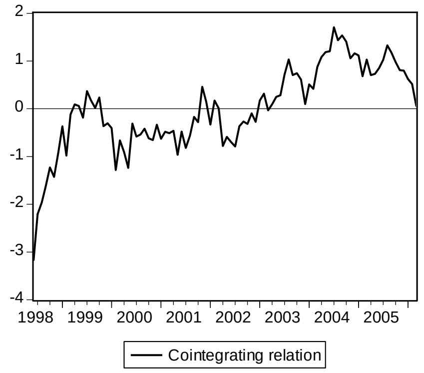
Annex 1: Cointegrated relationship



Annex 2: Results of estimations

Cointegrating Eq:	CointEq1			
LOG(EDF(-1))	1.0000			
R3M(-1)	-1.0689			
LOG(CPI(-1))	-27.2494			
LOG(INDY(-1))	16.5750			
C	80.2408			
Error Correction:	D(LOG(EDF))	D(R3M)	D(LOG(CPI))	D(LOG(INDY))
CointEq1	-0.064269	0.012003	0.000199	-0.003926
D(LOG(EDF(-1)))	0.208770	0.079022	0.003019	-0.021263
D(LOG(EDF(-2)))	-0.039823	-0.181765	0.000146	-0.013913
D(LOG(EDF(-5)))	-0.074417	-0.075826	0.001576	-0.009339
D(LOG(EDF(-6)))	-0.111559	0.036274	-0.001328	-0.010712
D(R3M(-1))	0.094664	0.636505	0.002856	-0.004574
D(R3M(-2))	-0.204731	-0.128462	0.000414	0.006750
D(R3M(-5))	0.128760	0.167719	-0.001555	0.000340
D(R3M(-6))	-0.046708	-0.116621	-0.000556	0.003268
D(LOG(CPIM(-1)))	0.016435	-0.982000	0.066037	0.100161
D(LOG(CPIM(-2)))	1.190429	5.003439	-0.155322	-0.238521
D(LOG(CPIM(-5)))	4.646218	2.607870	0.053381	0.371263
D(LOG(CPIM(-6)))	-0.788875	-0.858449	0.424610	0.025233
D(LOG(INDY(-1)))	0.717772	0.215876	-0.027221	-0.348807
D(LOG(INDY(-2)))	0.406629	-0.943493	-0.054906	-0.221486
D(LOG(INDY(-5)))	0.607683	-0.342035	-0.009982	-0.143951
D(LOG(INDY(-6)))	-1.477441	0.696585	0.011859	-0.082075
C	-0.002469	-0.010370	0.000818	0.004015
R^2	0.379174	0.408824	0.341724	0.280213
Adj. R^2	0.255009	0.290588	0.210069	0.136255

Appendix. Expected default frequency (EDF) and macroeconomics

Moody's KMV Credit Monitor calculates EDF as a function of distance to default (DD): $EDF = f(DD)$.[14] The premise for Moody's KMV model is that a company becomes bankrupt when $MV_A < D$ or $MV_E = MV_A - D < 0$.[15] The distance to default (*DD*) is defined as follows

(A.1) $$DD = \frac{MV_A - D}{\sigma_A} = \frac{MV_E}{\sigma_A}.$$

As neither MV_A nor σ_A can be directly observed, an additional assumption must be made to be able to calculate *DD*. Merton (1974) drew attention to the fact that the cost of guaranteeing the value of a company's loans corresponds to the value of a call-option on the market value of the company's assets (MV_A) with a redemption price (D) at time T. In parity with this argument, the yield on a company's equity, MV_E, corresponds to the yield of a call-option on the company's assets: $MV_E = \max[0, MV_A - D]$. The lenders either receive the market value of the company's assets (if the market value of these assets is less than the company's debts) or full repayment of the loan when it becomes due for settlement: $MV_D = \min[MV_A, D]$ $= \min[MV_A - D, 0] + D$. This yield is equivalent to holding a bond with the nominal value of D and issuing a call option on the company's assets with D as the redemption price. The market value of a company's assets and their volatility can be calculated with the help of Black and Scholes (1972).

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[14] For a short description of the method used by Moody's-KMV Credit Monitor to derive EDF, the interested reader is referred to Florian and Markus (2001).

[15] The default barrier is assumed to be deterministic and consists of the nominal value of the debt, i.e. short-term debt + 0.5*long-term debt.

The approach used in this paper is to estimate the empirical relationship between EDF and the macroeconomic conditions. We know that EDF is a function of DD, i.e. $EDF = f(DD)$. The elasticity between EDF and DD is defined as $\varepsilon = \frac{dEDF}{dDD}\frac{DD}{EDF}$. Thereby, we assume EDF to be a non-linear function of DD: $EDF = DD^{\varepsilon}e^{u}$,[16] where u denotes the residual. Taking the logarithms on both sides of this equation, we obtain

(A.2) $\log(EDF) = \varepsilon \log(DD) + u$.

Further, taking the logarithms on both sides of equation (A.1), we obtain

(A.3) $\log(DD) = \log(MV_E) - \log(\sigma_A)$.

The market value of the company's equity is a function of the current value of all future cash flows the company can be expected to generate. General economic developments play an important role for the development of company cash flows. Therefore, it can be assumed that $MV_E = f_1(X)$ where $X = [INDY, CPI, R3M]$. This means, in turn, that the volatility of the market value of the assets should be a function of macroeconomic development: $\sigma_A = f_2(X)$. It is difficult to know a priori what effect the macroeconomic variables can be considered to have on MV_E and σ_A. The elasticity between MV_E and X is defined as $\mathrm{E}^1 = \frac{dMV_E}{dX}\frac{X}{MV_E}$. Further, the elasticity between σ_A and X is defined as $\mathrm{E}^2 = \frac{d\sigma_A}{dX}\frac{X}{\sigma_A}$. Thereby, we assume

[16] This function is known as the exponential regression model.

that MV_E and σ_A have the following functional forms: $MV_E = \mathrm{E}_0^1 e^{\mathrm{E}_1^1 R3M} INDY^{\mathrm{E}_2^1} CPI^{\mathrm{E}_3^1}$ and $\sigma_A = \mathrm{E}_0^2 e^{\mathrm{E}_1^2 R3M} INDY^{\mathrm{E}_2^2} CPI^{\mathrm{E}_3^2}$. Taking the logarithms on both sides of these equations, we obtain[17]

(A.4) $\log(MV_E) = \log(\mathrm{E}_0^1) + \mathrm{E}_1^1 R3M + \mathrm{E}_2^1 \log(INDY) + \mathrm{E}_3^1 \log(CPI)$

(A.5) $\log(\sigma_A) = \log(\mathrm{E}_0^2) + \mathrm{E}_1^2 R3M + \mathrm{E}_2^2 \log(INDY) + \mathrm{E}_3^2 \log(CPI)$.

Inserting (A.6) and (A.7) into (A.3), we can rewrite (A.2) as follows

(A.6) $\log(EDF) = \beta_0 + \beta_1 R3M + \beta_2 \log(INDY) + \beta_3 \log(CPI) + u$,

where $\beta_0 = \varepsilon\left[\log(\mathrm{E}_0^1) - \log(\mathrm{E}_0^2)\right]$, $\beta_1 = \varepsilon(\mathrm{E}_1^1 - \mathrm{E}_1^2)$, $\beta_2 = \varepsilon(\mathrm{E}_2^1 - \mathrm{E}_2^2)$, and $\beta_3 = \varepsilon(\mathrm{E}_3^1 - \mathrm{E}_3^2)$ are the coefficients we want to estimate. As is evident, it is difficult to know a priori what effect the macroeconomic variables can be considered to have on EDF.

[17] Using differential calculus, it can be shown that $\mathrm{E}_1^1 = d(\log MV_E)/dR3M = \left[d(MV_E)/dR3M\right]/MV_E$, which is the relative change in regressand divided by the absolute change in the regressor. If we multiply the relative change in MV_E by 100, E_1^1 will then give the percentage change, or the growth rate, in MV_E for an absolute change in $R3M$. In the literature, this is known as the semielasticity of MV_E with respect to $R3M$.

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