Credit Cycles and Macro Fundamentals

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Abstract

We study the relation between the credit cycle and macro economic fundamentals in an intensity based framework. Using rating transition and default data of U.S. corporates from Standard and Poor's over the period 1980–2005 we directly estimate the credit cycle from the micro rating data. We relate this cycle to the business cycle, bank lending conditions, and financial market variables. In line with earlier studies, these variables appear to explain part of the credit cycle. As our main contribution, we test for the correct dynamic specification of these models. In all cases, the hypothesis of correct dynamic specification is strongly rejected. Moreover, if we account for the dynamic mis-specification, many of the variables thought to explain the credit cycle, turn out to be insignificant. The main exceptions are GDP growth, and to some extent stock returns and stock return volatilities. Their economic significance appears low, however. This raises the puzzle of what macro-economic fundamentals explain default and rating dynamics.

Keywords: credit cycles, business cycles, bank lending conditions, unobserved component models, intensity models, Monte Carlo likelihood.

JEL classification codes: G11, G21.

1   Introduction

Systematic credit risk factors play a dominant role in current credit risk management. Traditionally, credit scoring methodologies focus on assessing the credit risk of individual counterparties (see i.a. Altman (1983), Altman (2000)). Though important, at the portfolio level most of the idiosyncratic risks can be diversified and only the systematic credit risk components remain, see, e.g., Lucas et al. (2002), Schönbucher (2001), Frey and McNeil (2003). This also

holds if bond or loan portfolios are repackaged into new products like CDOs. In order to assess the credit risk at the portfolio level, it is important to model the correct dynamics of systematic credit risk components.

In this paper, we use the methodology of Koopman et al. (2005) to estimate the credit cycle directly from rating and default data at the micro level using intensity models with latent common risk factors. The data used are rating and default transitions for U.S. corporates rated by Standard and Poor's and observed over December 1980 to June 2005. We condition the credit cycle on a number of macro economic fundamentals, reflecting the state of the business cycle, bank lending conditions, and financial market conditions. In line with results by for example Couderc and Renault (2005), these variables appear to capture part of the credit cycle dynamics. The models, however, turn out to be dynamically mis-specified as there is strong remaining autocorrelation in the intensities. If we account for this, the significance of many of the macro variables disappears. The results are robust to a variety of specifications of the model. This leaves us with the puzzle of what macro fundamentals drive default and (re-)rating behavior.

The formal testing procedure for dynamic mis-specification introduced in this paper constitutes a powerful tool in the empirical modeling of intensities. For example, in the current paper we model intensities of rating and default transitions on both observed macro fundamentals and on an unobserved credit cycle component. If the fundamentals explain the credit cycle completely, the unobserved component should drop from the analysis. This can be tested using standard likelihood ratio tests. The computation of the likelihood ratio test, however, is not trivial because the latent component must be integrated out of the likelihood. We describe the importance sampling methodology that makes these types of tests possible.

Empirically, the relation between default rates and growth has been addressed in a number of studies. Fama (1986) and Wilson (1997), regress default rates on observed macro variables and find cyclicality in probabilities of default (PDs), particularly in the case of economic downturns when PDs increase significantly. Koopman and Lucas (2005) concentrate on the time series dimension of PDs and present evidence of co-cyclicality between GDP and default rates. Kavvathas (2001) shows the influence of the term structure of interest rates over the rating migration (including default) intensities using parametric and semi-parametric duration models. Carling et al. (2002) employ the semi-parametric duration model of Cox (1972) conditioning on both firm specific and macroeconomic variables to analyze a dataset on business loans. Duffie, Saita and Wang (2006) also incorporate firm specific information in their duration models. Their results indicate that both the level of real economic activity and the term structure of interest rates are important determinants of default risk. A commonality between the papers based on the intensity framework for credit risk is that hardly any attention is paid to the correct specification of the model. This is particularly relevant given the demonstrated stickiness of aggregate rating migrations and defaults.

Our results in this paper show that out of a number of possible macro fundamentals, many appear to describe rating and default behavior. If we account for a single unobserved common risk factor, however, most of the variables become statistically insignificant. At first sight, it appears that downgrades, up-grades, and defaults are all driven by different sets of macros. If we further refine the model to allow for three unobserved risk factors, however, the only relevant macros turn out to be GDP growth, and to some extent stock market returns and return volatilities. GDP has the significant and expected impact on both upgrade intensities (positive), and downgrade and default intensities (negative). The stock market variables only appear relevant for the upgrade intensities. In line with the basic structural model of Merton (1974), returns have a positive impact on upgrade intensities, whereas volatilities have a negative effect. More importantly, however, is that in all cases there is a significant unobserved component

present in the model. This component is not captured by the macro variables included.

In terms of the related literature, our analysis is most closely related to the work by Couderc and Renault (2005). There are a number of important differences. First, our modeling framework is significantly different. We use a parameter driven dynamic intensity model that conditions on observable macro variables. Couderc and Renault focus more on the macros only or on an observation driven autoregressive conditional duration (ACD) model for defaults. Second, Couderc and Renault condition intensities on the value of fundamentals at the start of the company's rating. In contrast, we allow the intensities to change over time due to both changes in observables and unobservables. This is an explicit advantage of the intensity framework over an approach starting directly from durations. Third, we do not only consider information from defaults to estimate the credit cycle, but also information from downgrades and upgrades. In this way we can test to what extent rating changes co-vary with the business cycle. This allows us to address some of the concerns in the pro-cyclicality debate as well. Bangia, Diebold and Schuermann (2000) and Nickel, Perraudin and Varotto (2000) show that changes in the macro-economic environment have significant effects on firms' credit rating transitions. Ferri, Liu and Majnoni (2000) and Kräussl (2003) provide empirical evidence that credit rating agencies behave cyclically, especially when assessing credit risk of sovereign borrowers. The proliferation of credit risk models may accentuate the pro-cyclical tendencies of banking with potential sharp macroeconomic consequences. For instance, if credit risk models are overly pessimistic during economic downturns, then even the most expansionary monetary policy many not sufficiently encourage commercial banks to lend to borrowers that are perceived to be of high default risk. If, as this paper shows, the relation between systematic credit risk and business cycles is only limited, pro-cyclicality concerns might be put into a more moderated perspective.

The paper is set up as follows. In Section 2, we explain the modeling and estimation framework. In Section 3, we present the data. The empirical results can be found in Section 4. Finally, Section 5 concludes.

2 The model and likelihood function

2.1 The model

Our modeling framework builds on standard (marked) point process methodology, see Andersen et al. (1993) for a textbook exposition on this topic. Consider a set of counting processes $N_{jk}(t)$ for firm $k = 1, \ldots, K$. The type $j = 1, \ldots, J$ of each counting process indicates the type of transition that is counted. For example, $j = 1$ may correspond to a transition from investment grade to sub-investment grade, $j = 2$ from investment grade into default, $j = 3$ from sub-investment grade to investment grade, and $j = 4$ from sub-investment grade into default. When a rating event of type j occurs for firm k at time t, the counting process $N_{jk}(t)$ jumps by U. It is assumed that we can model the count processes through their intensities. Let $\lambda_{jk}(t)$ be the intensity at time t of the counting process $N_{jk}(t)$. The intensities are modeled through the latent factor intensity model of Koopman et al. (2005). In particular, we have

$$\lambda_{jk}(t) = R_{jk}(t) \cdot \exp\left(\eta_j + \beta_j' x(t) + \alpha_j \psi(t)\right). \tag{1}$$

where $R_{jk}(t)$ is a dummy variable indicating whether firm k is at risk for transition type j at time t. The model explicitly accounts for the fact that if, for example, the firm is currently investment grade, it is not at risk for transitions from sub-investment grade to default. The vector $x(t) \in \mathbb{R}^m$ contains observable macro fundamentals. It is straightforward to see that the model can easily be generalized to account for firm-specific information as well. This, however,

is not the focus of our current analysis. Here we concentrate on the systematic factors that drive migration and default risk and summarize all the firm-specific information in the ratings. The scalar process $\psi(t)$ is an unobserved (latent) dynamic factor, capturing dynamics in default and migration intensities that are not picked up by the observed variables $x(t)$. The parameters $\eta_j, \alpha_j \in \mathbb{R}$, and $\beta_j \in \mathbb{R}^m$ are unknown and need to be estimated.[1] We define the pooled process as

$$N(t) = \sum_{j,k} N_{jk}(t). \tag{2}$$

The pooled process jumps each time when one of the underlying K firms experiences a particular type of transition $j = 1, \ldots, J$. Process (2) is observed for $t \in [0, T]$. Note that both processes $x(t)$ and $\psi(t)$ are set in continuous time. In practice, however, we observe the data at a daily, monthly, or quarterly frequency. For the macro variables used in the current paper, we have monthly and quarterly observations. To incorporate the mix of daily observations for $N(t)$ and monthly (quarterly) observations for $x(t)$ within our framework, process $x(t)$ is taken as a step-function that jumps to a new level each time a new observation of the macro variable becomes available. Similarly, we assume that the latent process $\psi(t)$ is piecewise constant over the spells of the pooled process. In particular, we assume that

$$\psi(t_i) = \psi(t_{i-1}) + \varepsilon_i, \tag{3}$$

where disturbance ε_i is standard normally distributed, initial value $\psi(0) = 0$ is fixed and the N event times of the pooled process are $0 = t_0 < t_1 < \ldots < t_N = T$. This modeling framework provides a straightforward way of testing whether the observed macro variables $x(t)$ in (1) are able to explain the transition and default dynamics. We impose an unit root (nonstationary) process in (3) to enforce the estimation algorithm to focus on the long term dynamics. Long term is here in terms of days as the durations of the pooled process are on average as low as 2 days, see Section 3. Since we focus on a systematic credit cycle with an empirically reasonable period of say several years, the process $\psi(t)$ needs to be highly persistent at the daily frequency. The unit root specification in (3) is therefore not very restrictive given the high-frequency data at hand. Our prime focus in this paper is on the significance of the α and β parameters. Previous studies did not explicitly allow for a separate stochastic components $\psi(t)$. One can think of a significance test on the α coefficients as a simple tests for missed first order dynamics in the intensities. The significance of the αs can easily be tested by standard likelihood ratio tests. In order to define the likelihood for the pooled process, we make two conditional independence assumptions. Define the processes $\tilde{x}(t) = \{x(s)\}_{s=0}^t$ and $\tilde{\psi}(t) = \{\psi(s)\}_{s=0}^t$. First, conditional on $\tilde{x}(T)$ and $\tilde{\psi}(T)$, we assume that the firms behave independently. This means that common factors in rating migrations and defaults are captured by the factors in (1). This is the standard assumption in most of the portfolio credit risk literature. Second, the model is set in a competing risks framework. For each firm, the time to its next rating event is the minimum of J latent duration processes. To ensure identification of the model, we assume that these latent processes are independent conditional on $\tilde{x}(T)$ and $\tilde{\psi}(T)$. Collecting parameters η_j, α_j, and β_j for $j = 1, \ldots, J$ into the vector θ, the likelihood function conditional on $\tilde{x}(T)$ and $\tilde{\psi}(T)$ is given by

$$\ell(\theta | \tilde{x}(T), \tilde{\psi}(T)) = \prod_{i=1}^{N} \prod_{j,k} \exp\left(y_{jk} \ln(\rho_{jk}(t_i)) - \int_{t_{i-1}}^{t_i} \lambda_{jk}(t) \mathrm{d}t \right), \tag{4}$$

where

$$\rho_{jk}(t) = \exp\left(\eta_j + \beta_j' x(t) + \alpha_j \psi(t) \right)$$

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[1]To identify all α_js and $\psi(t)$s simultaneously, we need to impose a sign restriction, e.g. $\alpha_J < 0$.

is the conditional hazard rate, $y_{jk}(t)$ is a dummy variable equal to one if firm k at time t experienced a transition of type j and zero otherwise. The parameter vector θ will be estimated by optimizing the likelihood function

$$\ell(\theta|\tilde{x}(T)) = \int \ell(\theta|\tilde{x}(T), \tilde{\psi}(T))\mathrm{d}\Pr(\tilde{\psi}(T)). \tag{5}$$

Effectively we need to integrate out the unobserved component $\tilde{\psi}(T)$ from the conditional likelihood function (4). Note that the integral in (5) typically has a very high dimension. For example, in the empirical section, the dimension of the integral is more than 12000. This integral must be evaluated for every trial value of the parameter vector θ during the numerical optimization of the likelihood function. Computational efficiency is therefore an important issue and is tackled using our estimation approach as described in the next subsection.

2.2 Parameter estimation

Estimation is based on the importance sampling techniques as set out in Durbin and Koopman (2001, Part II). In effect, Monte Carlo methods are used for the evaluation of integral (5) by considering

$$\ell(\theta|\tilde{x}(T)) = \int \ell(\theta|\tilde{x}(T), \tilde{\psi}(T))\frac{p(\tilde{\psi}(T))}{q(\tilde{\psi}(T))}\mathrm{d}q(\tilde{\psi}(T)), \tag{6}$$

where $p(\tilde{\psi}(T))$ is the marginal density of the latent process and $q(\tilde{\psi}(T))$ is the density of $\tilde{\psi}(T)$ given the observed data. The so-called importance density $q(\tilde{\psi}(T))$ is ideally as close as possible to the conditional density corresponding to $\ell(\theta|\tilde{x}(T))$, but at the same time should be more convenient for the generation of samples of $\tilde{\psi}(T)$ conditional on the observed data. Samples from $q(\tilde{\psi}(T))$ are used to evaluate the integral (6), also known as Monte Carlo integration. The main advantage is that the simulations through $q(\psi(T))$ contribute significantly to the likelihood. The alternative route of using (5) directly for generating samples and evaluating the likelihood is much less efficient and not feasible as the majority of draws from $p(\psi(T))$ have little resemblance to the observed data and make negligible contributions to the likelihood. The construction of $q(\psi(T))$ is based on linear approximations to non-Gaussian state space models. The current model falls in this general class of time series models, see Durbin and Koopman (2001). The stochastic log intensity function $\log \lambda_{jk}(t)$ can be generally presented as a linear function of fixed coefficients and linear dynamic stochastic processes. In particular, we have

$$\log \lambda_{jk}(t_i) = Z_{ijk}\nu_i, \qquad \nu_{iU} = T_i\nu_i + R_i\xi_i, \qquad i = 1, \ldots, N, \tag{7}$$

where the state vector $\nu_i = \nu(t_i)$ and $\nu(t)$ consists of the unobserved process $\psi(t)$ and the unknown coefficients η_j and β_j for $j = 1, \ldots, J$. The row vector Z_{ijk} is a selection loaded with zeros and ones or exogenous regressors. The unobserved process for $\psi(t_i)$ in (3) is a special case of the second equation in (7). The fixed coefficients are transformed to functions of time but are made subject to the identities $\eta_j \equiv \eta_j(t) = \eta_j(s)$ and $\beta_j \equiv \beta_j(t) = \beta_j(s)$ for any $t \neq s$. Therefore $\eta_j(t_i)$ and $\beta_j(t_i)$ can also be represented by the second equation in (7). As a result the dimension of the parameter vector θ is reduced considerably since the regression parameters η_j and β_j have become part of the state vector that will be integrated out using importance sampling. Although the Monte Carlo integration applies to a larger state vector $\nu(t_i)$ rather than to $\psi(t_i)$ only, we save on the estimation of a large vector θ by the numerical maximization of the likelihood function (5). Also note that by including $\eta_j \equiv \eta_{ij}$ and $\beta_j \equiv \beta_{ij}$ in the state vector ν_i, the parameter vector θ is reduced to the coefficients α_j only, for $j = 1 \ldots, J$.

Numerical efficiency and computational speed is primarily obtained through the reduction of the dimension of θ and the efficient importance sampling algorithm of Durbin and Koopman (2001). The likelihood function (6) can be reformulated as

$$\ell(\theta|\tilde{x}(T)) = \ell(\alpha|\tilde{x}(T)) = \int \ell(\alpha|\tilde{x}(T), \tilde{\nu}(T)) \frac{p(\tilde{\nu}(T))}{q(\tilde{\nu}(T))} dq(\tilde{\nu}(T)), \qquad (8)$$

where $\alpha = (\alpha_1, \ldots, \alpha_J)'$ and $\tilde{\nu}(t) = \{\nu(s)\}_{s=0}^t$. Samples from the Gaussian importance density function $q(\tilde{\nu}(T))$ are based on the linear Gaussian model

$$y_{jk}(t_i) = c_{ijk} + \log \lambda_{jk}(t_i) + u_{ijk}, \qquad u_{ijk} \sim NID(0, C_{ijk}), \qquad (9)$$

where NID refers to the assumption of a normal distribution for mutually and serially independent random variables. The variables c_{ijk} and C_{ijk} are known functions of the unobservable $\lambda_{jk}(t_i)$. The functions are implied by the density (4). Appropriate values for c_{ijk} and C_{ijk} are found by repeatedly applying the Kalman filter and smoothing equations to obtain new estimates of $\lambda_{jk}(t_i)$ (based on all data-points $y_{jk}(t_i)$) and to compute new values for c_{ijk} and C_{ijk}. This process converges quickly to an unique solution. Given model (9) with the solutions for c_{ijk} and C_{ijk}, simulations for $\log \lambda_{jk}(t_i)$ (based on all data-points $y_{jk}(t_i)$) are obtained by the simulation smoothing algorithm of Durbin and Koopman (2002). More details on this method of likelihood evaluation by importance sampling for the model of Section 2 are given by Koopman, Lucas and Monteiro (2005).

The likelihood function evaluated by importance sampling methods is subject to the value of α. Numerical optimization methods can be used to obtain the maximum likelihood estimate of α. Given an estimate of α, the state vector can be estimated as part of the numerical integration process of the likelihood function since

$$\widehat{\tilde{\nu}}(T) = \int \tilde{\nu}(T) \frac{p(\tilde{\nu}(T))}{q(\tilde{\nu}(T))} dq(\tilde{\nu}(T)),$$

where $\tilde{\nu}(T) = \{\nu(t_i)\}_{i=1}^N$. The same importance sampling techniques are therefore applied to the evaluation of $\widehat{\tilde{\nu}}(T)$. This estimator includes the estimator of the unobservable variable $\psi(t)$ and the regression coefficient estimators for η_j and β_j with $j = 1, \ldots, J$. The estimates are reported for the empirical study in the sections below.

3 Data

The data come from several sources. For rating transition and default data, we use the CreditPro 7.0 data set of Standard and Poor's over the period December 1980 to June 2005. The data set contains the rating histories of all firms rated by Standard and Poor's. We select all U.S. firms and use a broad rating category classification of investment grade (BBB- and above) and subinvestment grade (BB+ and below). We consider all days on which there was an event. Events are defined as (i) one of the firms in the database experiencing a rating transition (given the two rating classes) or default, (ii) a firm becoming non-rated, (iii) a firm entering the sample. All three types of events result in a change in the intensity of the pooled process. We obtain 4437 event days over the period.

We make three further modifications to the data. First, we remove weekends from the data and measure durations in terms of working days. Some of the rating events are recorded in the data base during the weekends. We transferred all these rating events to the Friday preceding

the weekend.[2] Second, if firms enter the data base or if their rating is withdrawn, this is treated as a non-informative event. For example, if the rating is withdrawn, we only use the fact that the company has survived up to the point of the rating withdrawal. The main exception is when the company defaults at some later stage after the rating withdrawal. These defaults are recorded in the database. If there is a default following a rating withdrawal, we discard the withdrawal event and treat the default as a default from its last recorded rating category. Third, we try to eliminate rating clustering as much as possible. If companies merge or are taken over, ratings of the merged companies move in lock-step for the remainder of their history in the data base. Eliminating this type of dependence is important, because it may result in an over-estimation of the systematic component in the credit and default risk. To reduce this potential bias, we subsequently look for firms that have (the maximum of) 11 down to 3 rating events precisely on the same day. If two such firms are found, the most recent rating events of one of these are discarded and substituted by a rating withdrawal.

The 9 macroeconomic variables in our study are taken from the data base of the Federal Reserve Bank of St. Louis (FRED). Our dataset of explanatory variables includes both current information and forward looking indicators such as interest rate-based measures and stock market variables.

We distinguish three blocks of variables: business cycle, bank lending conditions, and financial market variables. The business cycle block contains the Gross Domestic Product (GDP). We convert the data to annual growth rates, observed quarterly.

Bangia, Diebold and Schuermann (2000) and Nickell, Perraudin and Varotto (2000) find evidence of macroeconomic effects on corporate rating transitions. They show that corporate defaults are more likely during downturns in economic activity. As a signal of current macro-economic conditions, we expect that the variable real GDP growth and its four ingredients are negatively correlated with short-term default probabilities. We are not considering industrial production, manufacturer's orders, and capacity utilization, as explanatory variables since they are already captured in GDP developments. We are also not considering employment series and personal income growth since they are lagging the business cycle.

Besides general economic variables we expect that indicators of current bank lending conditions prove valuable in explaining default intensities. We consider in our empirical analysis four different bank lending conditions variables: commercial and industrial loans outstanding, money supply / M2 growth rate, discount rate, and the quality spread.

The series commercial and industrial loans outstanding measures the volume of business loans held by banks, and commercial paper issued by non-financial companies. The series tend to peak during recessions, when many firms need additional outside funding to replace declining or even negative cash flow. We expect this series to positively correlate with default intensities as higher borrowing is an indicator of economic difficulties.

The series M2 growth rate measures the aggregate money supply in the economy. It is either directly or indirectly affected by both Federal Reserve policy (usually showing an inverse relationship with interest rates) and private demand for credit and liquidity. We expect that a lower M2 growth rate and, thus, less credit supply by commercial banks, lower market liquidity should be associated with higher default intensities.

Short-term interest rates have a long history of use as predictors of output changes. We expect the higher the discount rate, the more expensive it is for companies to take a fresh credit, the more defaults we observe.

Stock and Watson (1989) show that the quality spread is a potent predictor of output

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[2]The fact that rating decisions taken on a Friday are recorded during weekends is a technical administration issue in the S&P data base.

growth. We measure the quality spread as the difference between interest rates on BBB and AAA corporate bonds. We expect that the higher this quality spread, the harder the bank lending conditions, the higher the default intensities.

The financial market variables we consider are the returns on the S&P500, the volatility of the S&P500 returns, and the interest rate spread.

A simple model of stock price valuation is that stock prices equal the discounted expected value of future earnings. This implies that short- and mid-term economic performance should be positively correlated with the returns on the S&P500. In addition, an increase in equity prices tends to decrease firm leverage. We expect that the lower the stock market index S&P500, the higher the default intensities.

In a traditional Merton (1974)-type model, the two drivers of default probability are leverage and the volatility of firms' assets. (We use the volatility of equity returns as a proxy for the volatility of firms' assets.) We expect that the (daily) realized annual volatility of the S&P500 returns computed over the last 260 trading days to be positively correlated with the default intensities.

Various studies have shown that the interest rate spread has significant predictive power for output growth, in particular at horizons of one or two years. This term spread series measures the difference between the 10-year Treasury bond rate and the Federal funds rate. It is felt to be a reliable indicator of the stance of monetary policy and general financial conditions, because it rises (falls) when short rates are relatively low (high). When the term spread becomes negative, i.e. short rates are higher than long rates, and the yield curve inverts, its record as an indicator of recessions is particularly strong. We expect a positive impact on default intensities since higher interest rate levels imply higher cost of borrowing.

4 Empirical results

4.1 No macro fundamentals

We first implement our model without any macro fundamentals to obtain a preliminary estimate of the credit cycle present in our data set. The results are presented in Table 1 and Figure 1. We estimate five different models. In model 0a, no systematic credit risk component is present. All defaults and rating migrations are idiosyncratically driven. We then proceed to introduce the common factor $\psi(t)$. First, in model 0b we restrict the loading to be the same for all transition types. The increase in likelihood from model 0a to model 0b clearly signals that there is common risk in default and rating migrations. We proceed by relaxing the assumption of a common loading across transition types. Model 0c allows for a different sensitivity to the common risk factor between investment grade and sub-investment grade companies. The likelihood increases by 3.8 points upon adding one parameter. This is statistically significant at the 1% level. If we allow a different sensitivity to $\psi(t)$ for every transition type, the results for model 0e show that the increase in likelihood is again significant: 17.3 points for 2 additional parameters. The values of the parameter estimates are also interesting. In particular, default intensities appear much more sensitive to systematic risk factors than upgrades and downgrades, whereas downgrades are slightly more sensitive than upgrades. This is in line with earlier empirical results, see for example Kavvathas (2001) and Das et al. (2002) and Lucas and Klaassen (2006). The estimated component $\psi(t)$ visualized in Figure 1 shows the clear troughs in the mid 1980s, early 1990s, and early 2000s. As the number of investment grade defaults is very small, the precision of α_j for this transition type is low. To limit the number of parameters, we test whether we can pool the investment grade and sub-investment grade defaults. Model 0d restricts the

Table 1: Benchmark model estimates

The table presents the estimated parameters for the benchmark model in (1) with $\beta_j \equiv 0$, i.e., without explanatory macro fundamentals for the migration intensities. Transition types j are from investment grade to sub-investment grade ($I \rightarrow S$), from investment grade to default ($I \rightarrow D$), from sub-investment grade to investment grade ($S \rightarrow I$), and from sub-investment grade to default ($S \rightarrow D$). The models 0a-0e have a univariate common risk factor $\psi(t)$. Model 0f has three separate common risk factors $\psi_j(t)$ for $j = I \rightarrow S, S \rightarrow I, (I, S) \rightarrow D$.

	Transition type j				Transition type j			
	$I \rightarrow S$	$I \rightarrow D$	$S \rightarrow I$	$S \rightarrow D$	$I \rightarrow S$	$I \rightarrow D$	$S \rightarrow I$	$S \rightarrow D$
	Model 0a				Model 0b			
η_j	-3.43	-6.54	-3.13	-2.56	-3.91	-7.05	-2.80	-3.10
α_j	——	——	——	——	-0.030	-0.030	0.030	-0.030
	Log-lik = -10384.6				Log-lik = -10168.6			
	Model 0c				Model 0d			
η_j	-3.82	-6.96	-2.69	-3.26	-3.84	-7.44	-2.85	-3.50
α_j	-0.022	-0.022	0.034	-0.034	-0.023	-0.043	0.019	-0.043
	Log-lik = -10162.8				Log-lik = -10145.7			
	Model 0e				Model 0f			
η_j	-3.85	-7.71	-2.84	-3.49	-3.51	-7.55	-2.82	-3.63
α_j	-0.023	-0.053	0.019	-0.043	-0.029	-0.042	0.014	-0.042
	Log-lik = -10145.5				Log-lik = -10096.3			

loadings for investment grade and sub-investment grade transitions to default to be the same, $\alpha_{I \rightarrow D} = \alpha_{SI \rightarrow D}$. The reduction in likelihood compared to model 0e is insignificant. Therefore, from now on we pool the sensitivity parameters to systemic risk factors (i.e., α_j and β_j) for investment grade and sub-investment grade defaults.[3]

As a preliminary analysis, we took the estimated credit cycle from Figure 1 and ran a simple regression on the explanatory macro factors presented in Section 3. The regression explains up to 60%-70% of the credit cycle using our macro fundamentals. This percentage is in line with results obtained by Couderc and Renault (2005). The regression is, however, dynamically misspecified as the Durbin Watson is very close to zero. Including an autoregressive error term in the regression reduces this problem substantially, but at the same time renders many of the regressors statistically insignificant. It is not straightforward, however, that such a procedure is econometrically sound. The credit cycle from Figure 1 is a smoothed estimate. The smoothing procedure by itself may introduce correlations between observations and thus influence the regression results. We therefore proceed by directly incorporating the macro fundamentals in the specification of the intensities. This allows us to test formally for their significance before and after the inclusion of a latent component $\psi(t)$. The model estimates are presented in Tables 2 and 3.

4.2 Macro fundamentals: GDP

Without the latent component $\psi(t)$ (upper panel), model 1 in Table 2 shows that real GDP growth is a significant determinant of all transition type intensities. The signs are intuitively clear. Downgrade and default intensities depend negatively on growth. High growth results

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[3] Also note that it is empirically very difficult, if not impossible to calibrate the sensitivity to (up to) 10 systematic risk factors separately for investment grade to default transitions, as these transitions are very rare.

Figure 1: Smoothed estimates of the common risk factor $\psi(t)$
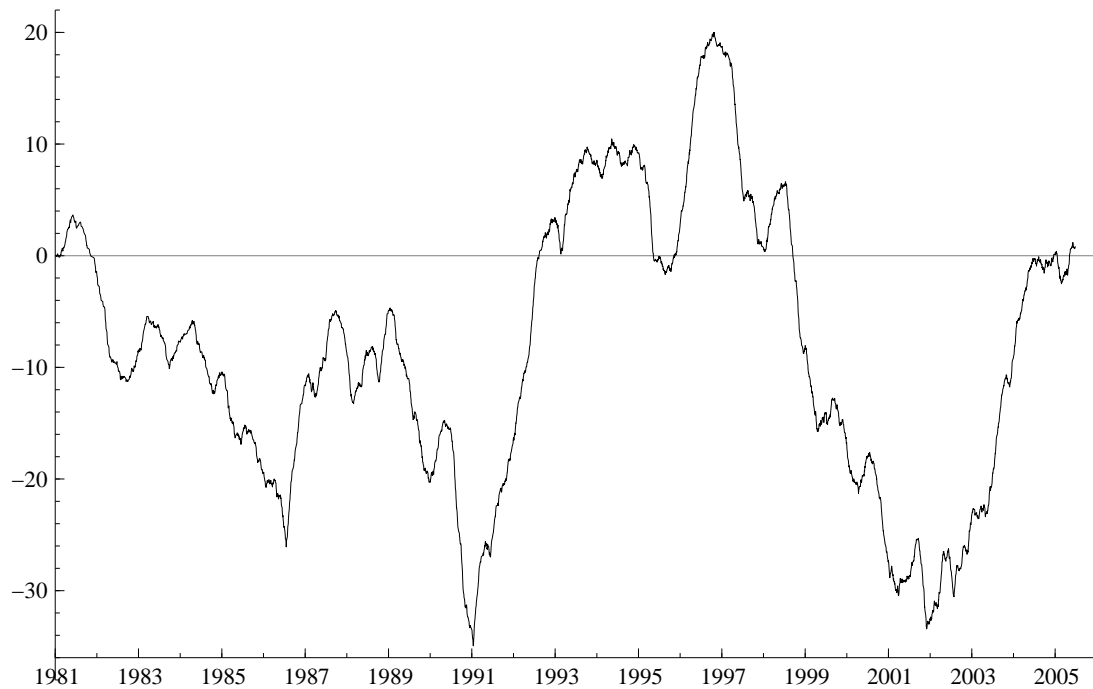
in fewer defaults and downgrades. Conversely, upgrades are more frequent if growth is high. This co-variation with the business cycle has been demonstrated in a number of earlier papers, Bangia et al. (2002), Nickell et al. (2000). The result suggest that not only defaults, but also re-ratings depend on the business cycle. This result questions whether the rating agencies' rating policies are indeed through-the-cycle.

If we look at the likelihood value of model 1 in Table 2 compared to model 0a in Table 1, we see a significant increase in likelihood upon adding real GDP growth as a systematic risk factor. Comparing the likelihoods for models 1a and 0d, however, shows that the increase due to the observed GDP growth is much smaller than that due to the unobserved component $\psi(t)$.

The lower-left panel of Table 2 presents the results for a model with both real GDP growth and an unobserved component $\psi(t)$. Interestingly, the results are markedly different from those in the top panel. Default intensities still co-vary negatively with real GDP growth. The re-rating policies, however, appear independent of the business cycle variable as both coefficients are insignificant. The unobserved systematic risk factor $\psi(t)$ is strongly significant for all transition types. Also note that the magnitude of both the GDP and $\psi(t)$ coefficients (model 1b) has decreased compared to a model with only one source of systematic risk (models 0d and 1a). The real GDP thus explains some, but not all variation in default intensities.

To illustrate how the model operates in more detail, we present Figures 2 and 3. In Figure 2, we first plot the estimate of the credit cycle from model 0d, which is the model without exogenous variables and with a univariate $\psi(t)$ factor. In the same graph, we present the result of model 1b, which is the model with the exogenous factor (in this case GDP growth) only. The factors are multiplied by their loadings presented in Tables 1 and 2, respectively. It is clear that GDP has some of the peaks and troughs roughly in common with the latent component $\psi(t)$, but there are also a number of significant differences. For example, during the early eighties, the GDP swings do not at all resemble the movements in the unobserved credit cycle. Also in later

Table 2: Intensity model with latent component and macro fundamentals
We use the latent component intensity model (1) to determine the impact of macro fundamentals and an unobserved component ($\psi(t)$) on transition intensities. The explanatory variables are divided in three blocks. Business cycle: real GDP growth. Bank lending conditions: growth in the amount of business loan outstanding (BLOAN), M2 growth (M2), realized annual inflation (INFL), Federal Funds rate (FFund), default spread between yields on BBB rated corporate bonds and 10-year treasury bonds (DSPR). Financial market variables: term spread defined as 10 year minus 1 year yield on treasury bonds (TSPR), annual realized return on the S&P500 (SP500), annual realized return volatility (using daily data) of the S&P500 (SPVOL). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively. Transition types are from investment grade (I) to sub-investment grade (S) or vice versa, or from either of these states into default (D).

	Transition type			Transition type			Transition type		
	$I \to S$	$S \to I$	$S \to D$ $I \to D$	$I \to S$	$S \to I$	$S \to D$ $I \to D$	$I \to S$	$S \to I$	$S \to D$ $I \to D$
	model 1a			model 2a			model 3a		
GDP	-0.12***	0.13***	-0.38***						
BLOAN				-0.17***	-0.13**	-0.24***			
M2				0.07	-0.26***	0.08			
INFL				-0.05	-0.26***	0.09			
FFund				0.18**	0.54***	0.04			
DSPR				0.21***	-0.10*	0.21***			
TSPR							0.05	-0.07	-0.05*
SP							-0.11**	0.01	-0.24***
SPVOL							0.14***	-0.28***	0.20***
	Log-lik = -10278.5			Log-lik = -10212.2			Log-lik = -10244.4		
	model 1b			model 2b			model 3b		
GDP	-0.07	0.07	-0.27***						
BLOAN				-0.09	-0.20***	-0.01			
M2				0.09	-0.29***	0.09			
INFL				-0.03	-0.27***	0.03			
FFund				0.13	0.60***	-0.15			
DSPR				0.18***	-0.05	0.07			
TSPR							0.04	-0.06	-0.04
SP							-0.07	-0.01	-0.09
SPVOL							0.05	-0.23***	0.07
$\psi(t)$	-0.022***	0.017***	-0.031***	-0.013***	0.011**	-0.042***	-0.020***	0.009*	-0.044***
	Log-lik = -10137.1			Log-lik = -10105.0			Log-lik = -10134.6		

years, there are periods that the dynamics of GDP do not match those of $\psi(t)$. In the late 1990s, GDP growth shows hardly any variation, whereas the $\psi(t)$ clearly experiences a trough and a sharp increase.[4] Figure 3 continues this pattern. The first curve is the univariate credit cycle $\psi(t)$ estimated from model 0d. The second curve is the cycle $\psi(t)$ from model 1b, so where we condition on GDP growth as an explanatory variable. The third curve combines the latter estimate of $\psi(t)$ for model 1b with its loading on GDP growth. Clearly and as expected, the first and third curve are very similar. Using the differences between the first and second curve, we can get an idea of what part of the credit cycle is captured by GDP growth. First, we note that the proportion of credit cycle variance explained by GDP growth is quite modest. The latent component in models 0d and 1b are very similar. Second, GDP growth appears to explain some of the peak default intensities near 1991 and 2000-2001. Generally speaking, however, given the unconditional variation of $\psi(t)$, the additional contribution of GDP is limited. So

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[4]At first sight, there may appear a closer resemblance between GDP growth and the credit cycle in the Greenspan period, so after September 1987. We re-estimated the model on this sub-sample, but the results remained robust.

Figure 2: Estimates of the common risk factor $\psi(t)$ (models 0d and 1a)
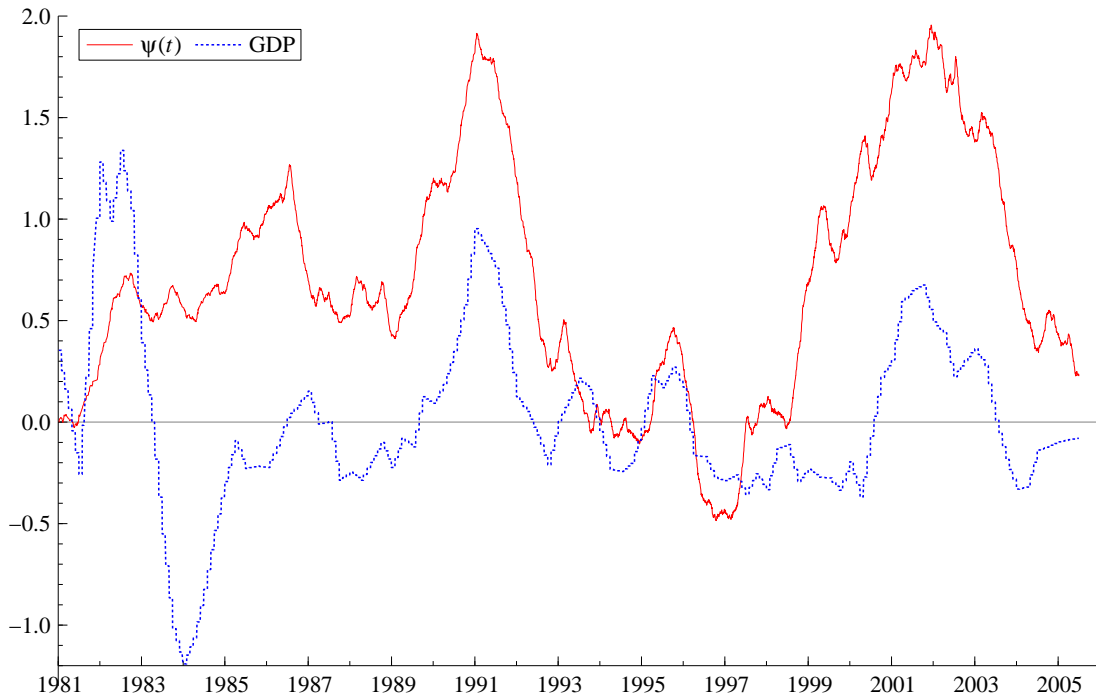
The figure contains the smoothed common factor risk $\psi(t)$ estimated on both the default data and the rating transition data. The solid curve presents the estimated latent risk factor multiplied by its default transition loading from model 0d in Table 1 (-0.043). The dotted curve gives the GDP growth multiplied by its default transition loading from model 1a (-0.38).

even though the statistical significance is clear, the economic significance of GDP growth for default dynamics is questionable.

4.3 Macro fundamentals: multivariate analysis

In the middle panels (model 2a,2b) we can see the impact of the variables measuring bank lending conditions. Again, the increase in likelihood compared to the model without systematic risk (model 0a) is significant. The increase, however, is much less than that of including a single unobserved component (model 0d). The bank lending conditions are particularly important for the upgrade intensity. If we include both the bank lending variables and $\psi(t)$ (model 2b), the likelihood increases significantly. The α_j coefficients have the correct signs. For downgrade intensities, the default spread is a significant indicator. Higher spreads signal a higher perceived default risk and result in a larger number of downgrades. Note that if $\psi(t)$ is excluded and the model is dynamically mis-specified, also the business loan and Federal funds rate appear significant. For the default intensities, none of the bank lending variables appears significant once we allow for an unobserved credit risk factor. Upgrade intensities on the other hand are significantly influenced by the growth in bank loans, M2 growth, inflation, and the Federal funds rate.

The financial markets' variables (model 3a,3b) again highlight the importance of allowing for unobserved systematic risk factors. Model 3a shows that high stock returns negatively correlate with downgrades and defaults. Stock market volatility on the other hand positively correlates

Figure 3: Estimates of the common risk factor $\psi(t)$ (models 1a and 1b)
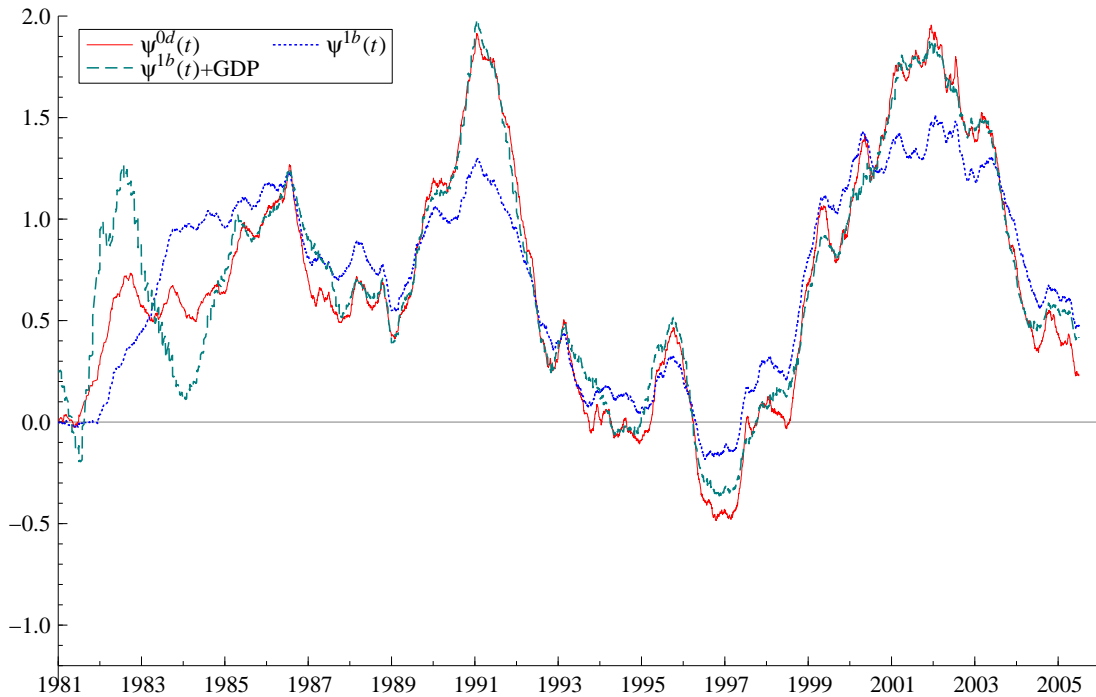
The figure contains the smoothed common factor risk $\psi(t)$ estimated on both the default data and the rating transition data. The solid curve presents the estimated latent risk factor from model 0d multiplied by its default transition loading from Table 1 (-0.043). The dotted curve presents the estimated latent risk factor from model 1b multiplied by its default transition loading from Table 2 (-0.031). The dashed curve presents the composite of the dotted curve and the GDP growth from model 1b, multiplied by its loading from Table 2 (-0.27).

with downgrades and defaults, but negatively correlates with upgrades. These findings are in line with the basic structural model for corporate debt of Merton (1973). For a given default barrier, higher stock market returns (corrected for volatility) increase the distance of the firm's asset value to the default barrier. Higher volatilities, on the other hand, decrease this distance measured in terms of standard deviations. After adding $\psi(t)$ (model 3b), however, most of the effects disappear. Only the reduced upgrade intensity in high volatility regimes remains.

So far, we concentrated on each of the three different blocks of variables when considered in isolation. We now proceed by a full multivariate analysis. The results are in Table 3.

The results for models 4a and 5a clearly support those in Table 2. By including other systematic risk factors, the importance of GDP growth for re-rating intensities vanishes. Only the negative correlation between default intensities and GDP growth appears robust. Similarly the importance of the stock index returns vanishes if we also include GDP growth as an explanatory variable (model 5a). Adding an unobserved systematic risk factor significantly increases the likelihood for both model 4 and 5. In addition, we see similar changes in the significance of coefficients as in Table 2. In particular, the signs, magnitudes, and significance of coefficients for models 4b and 5b can be retraced directly to the relevant variables in models 1b-3b.

Finally, model 6 contains the full set of results. When including all variables of the 3 blocks as explanatory regressors for the intensities, the results are unaffected. Macro fundamentals significantly explain transition and default intensities. A number of these relations, however, is spurious and caused by dynamic mis-specification of the model. Including an unobserved

Table 3: Intensity model with latent component and macro fundamentals

We use the latent component intensity model (1) to determine the impact of macro fundamentals and an unobserved component ($\psi(t)$) on transition intensities. The explanatory variables are divided in three blocks. Business cycle: real GDP growth. Bank lending conditions: growth in the amount of business loan outstanding (BLOAN), M2 growth (M2), realized annual inflation (INFL), Federal Funds rate (FFund), default spread between yields on BBB rated corporate bonds and 10-year treasury bonds (DSPR). Financial market variables: term spread defined as 10 year minus 1 year yield on treasury bonds (TSPR), annual realized return on the S&P500 (SP500), annual realized return volatility (using daily data) of the S&P500 (SPVOL). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively. Transition types are from investment grade (I) to sub-investment grade (S) or vice versa, or from either of these states into default (D).

	Transition type			Transition type			Transition type		
	$I \to S$	$S \to I$	$S \to D$ $I \to D$	$I \to S$	$S \to I$	$S \to D$ $I \to D$	$I \to S$	$S \to I$	$S \to D$ $I \to D$
	model 4a			model 5a			model 6a		
GDP	0.01	0.06	-0.34***	-0.07	0.11**	-0.34***	0.03	0.08	-0.36***
BLOAN	-0.17***	-0.12*	-0.21***				-0.17***	-0.13**	-0.31***
M2	0.06	-0.28***	0.10**				0.09	-0.19**	0.02
INFL	-0.05	-0.21***	-0.09				-0.10	-0.20**	-0.15**
FFund	0.19**	0.51***	0.07				0.23***	0.48***	0.15*
DSPR	0.23***	-0.06	0.02				0.18***	-0.01	-0.08*
TSPR				0.07*	-0.07*	-0.02	-0.01	-0.01	-0.19***
SP				-0.07	-0.04	-0.02	-0.11***	-0.02	-0.06
SPVOL				0.15***	-0.28***	0.26***	-0.03	-0.17**	0.17***
	Log-lik = -10171.3			Log-lik = -10195.2			Log-lik = -10135.4		
	model 4b			model 5b			model 6b		
GDP	0.03	0.06	-0.27***	-0.04	0.09*	-0.25***	0.01	0.07	-0.30***
BLOAN	-0.09	-0.17**	-0.04				-0.05	-0.18***	-0.12
M2	0.04	-0.27***	0.04				0.09	-0.19***	0.04
INFL	0.01	-0.25***	-0.05				0.04	-0.25***	-0.05
FFund	0.14	0.57***	-0.09				-0.05	0.58***	-0.25
DSPR	0.21***	-0.01	-0.04				0.17**	0.01	-0.12
TSPR				0.03	-0.06	-0.04	-0.03	0.00	-0.16
SP				-0.07	-0.04	-0.03	-0.09*	-0.02	-0.09
SPVOL				0.02	-0.25***	0.09	-0.07	-0.16**	0.06
$\psi(t)$	-0.018***	0.011**	-0.038***	-0.026***	0.006	-0.034***	-0.023***	0.007	-0.038***
	Log-lik = -10098.3			Log-lik = -10127.3			Log-lik = -10090.8		

dynamic factor $\psi(t)$ significantly increases the likelihood. This is mainly due to the fact that default and downgrade intensities are not fully captured by the observed macro variables. Upgrade intensities appear to be captured sufficiently by bank lending conditions and the volatility regime, in line with our earlier discussion. Interestingly, real GDP only explains default intensities and not re-rating intensities. This is in line with the claimed through-the-cycle rating methodology adopted by rating agencies. For downward rating movements, however, agencies also appear to draw information from financial markets in the form of default spreads and (marginally) stock returns.

4.4 Robustness analyses

To test for the robustness of these results, we performed a number of sensitivity checks. First included all explanatory variables in lagged rather than contemporaneous form. Both at lags of one and two years, the results remain unaltered in the sense that models with only observed

macro variables appear dynamically mis-specified. Including a latent component $\psi(t)$ in all cases significantly increases the likelihood. If $\psi(t)$ is included, some of the macros loose their significance for specific transition types, similar to Tables 2 and 3. The effect of lagging on the likelihood values does not reveal a clear-cut pattern and is overall limited. Moreover, including lagged business cycle variables in several cases produces non-intuitive signs for the coefficients, e.g., a positive relation between past growth and current defaults or downgrades. We also considered including leads of the observed macro variables. Again, however, the results are highly similar. Macro variables capture some of the default and re-rating activity, but certainly not all.

As a further check we also incorporated a non-constant baseline hazard rate. We replace the constant η_j in (1) by $\eta_j + \gamma_j \delta_k(t)$, with $\delta_k(t)$ an indicator variable that equals 1 if firm k is less than one year in its current rating category. This non-constant base-line hazard rate allows us to capture non-Markovian behavior of rating transitions, see Lando and Fledelius (2004).[5] The results show that our findings remain robust. Though adding the non-constant baseline hazard increases the likelihood, it does not affect the sign, size, or significance of the macro variables and the unobserved $\psi(t)$.

The most puzzling fact in Table 3, model 6b, is the apparent block structure of the macro variables across the transition types. This result may be caused by a similar phenomenon as the significance of the macro variables in model 6a versus 6b. Because of the broad rating buckets, it is likely that the $\psi(t)$ factor is mainly capturing the default cycle of subinvestment grade companies. The macro variables can then be used to account for systematic effects in the upgrade and downgrade intensities. To allow for upgrade and downgrade intensities to have their own systematic component, we enlarge model (1) to

$$\lambda_{jk}(t) = R_{jk}(t) \cdot \exp\left(\eta_j + \beta_j' x(t) + \alpha_j \psi_j(t)\right), \qquad (10)$$

where we know have three different $\psi_j(t)$ factors. The estimation results are in Table 4.

Model (10) is not nested in (1), so the likelihoods between the models in Tables 2 and 3 cannot be compared directly to those in Table 4. Generally speaking, however, the likelihood values increase by having more $\psi_j(t)$ factors. Interestingly, the phenomenon witnessed earlier when going from the 1a-6a models to the 1b-6b models, repeats itself when considering the 1c-6c models. In particular, the importance of the economic variables is further reduced. Effectively, there only appear three important variables. GDP growth explains a part of all four types of transitions. The signs are as expected. The intensities of downgrades and defaults react negatively to growth, whereas upgrades react positively. Furthermore, there is a marginally significant effect of stock market returns and stock market return volatilities on upgrade intensities. The signs are in line with the standard structural model of Merton. High stock returns increase the distance to default and therefore increase upgrade intensities. High volatilities, on the other hand, decrease the distance to default and therefore decrease upgrade intensities.

Two other things worth noting in Table 4 concern the sizes of the α_j coefficients. Again, the upgrade intensities appear much less driven by unobserved systematic risk than the downgrade and default intensities. In contrast to some of the results in Tables 2 and 3, however, the effect always remains significantly different from zero. The other important difference with the earlier results is the magnitude of the α_j corresponding to investment grade downgrades. Though this coefficient is still lower than its default intensity counterpart, they are now much closer. We conclude that both downgrade and default intensities are driven to a similar extent by common components. The commonality in all results, however, remains that the macro variables only explain part of the credit cycle. The unobserved credit risk components appear to be at least

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[5]The estimates of the macro variables for this variant of the model are available upon request.

as important to describe the dynamics of rating intensities.

We again illustrate the model by looking at the estimated latent risk components $\psi_j(t)$. We concentrate on model 1c. The results are presented in Figure 4. In the top line of graphs in Figure 4, we compare the estimation results for models with a univariate latent risk factor (model 1b) with those for three risk factors. It is easily seen that the univariate common risk factor mainly captures the dynamics of the default intensity. The estimated $\psi_j(t)$ component is for this type of transition very similar between models 0d and 1c. Again, there are many discrepancies with the dynamics of GDP growth. It is very interesting to see the large differences between the univariate estimate of $\psi(t)$ and the multivariate $\psi_j(t)$ for downgrades and upgrades. Although some of the peaks are shared between downgrade and default activity, the overall difference in dynamics between the two series is significant. For example, the decline in downgrade intensities during the stock market boom is much more pronounced than the decline in default intensities. The difference is even more striking for the upgrade intensity. We do not only obtain the result that upgrade activity is much less driven by systematic factors, as witnessed by the smaller loading coefficients α_j. In addition, the estimated risk factor $\psi_{S \to I}(t)$ shows a markedly different behavior. In the early 2000s, whereas macroeconomic activity was already picking up and default intensities decreased, the systematic effect in upgrade intensities remained at a very low level. This might be linked with a possible prudential re-rating policy of the major rating agencies after the bad credit years around the turn of the century.

In Figure 4 we can assess the economic significance of the results. The figure shows the individual latent components $\psi_j(t)$ with and without conditioning on the GDP growth. Though there are some differences between the two estimates, the main feature of the graphs is that the estimates are quite similar. Again, this underlines the fact that even though some macro fundamentals may be statistically significant, their economic significance for default and rating transition dynamics is much less clear-cut.

5 Conclusions

In this paper we conducted a systematic search on the determinants of corporate credit rating migrations and defaults. We used a novel econometric methodology introduced Koopman et al. (2005). The framework is set in a continuous time duration model where we focus on the dynamics of migration intensities. We conditioned on three sets of variables: GDP growth (for business cycle effects), bank lending conditions, and financial markets variables. In line with previous studies we found that the level of economic activity, bank lending conditions, and financial markets variables are all important determinants of default and rating migration intensities. The models, however, appear significantly dynamically mis-specified. Once we account for this mis-specification, many of the macro fundamentals fall out of the model. The prime remaining candidate is GDP growth, and to some extent financial markets' variables like stock returns and stock return volatilities. The results appear robust over a variety of model specifications. For example, we checked the robustness over the Greenspan era (post 1987) and using various choices of leads and lags of the macro variables included.

Throughout all specifications, defaults (and downgrades) were much more subject to common risk factors than upgrades. In addition, we also found significant departures between the systematic risk components in defaults, downgrades, and upgrades themselves. The results point out to an overly optimistic re-rating policy in the late nineties, followed by a possibly overly pessimistic lack of upward rating revisions in the early 2000s.

The current research opens up a number of interesting alternative research questions. If the current broad set of macro variables only helps to a limited extent in explaining default

Figure 4: Estimates of the common risk factor $\psi(t)$ (model 1c)
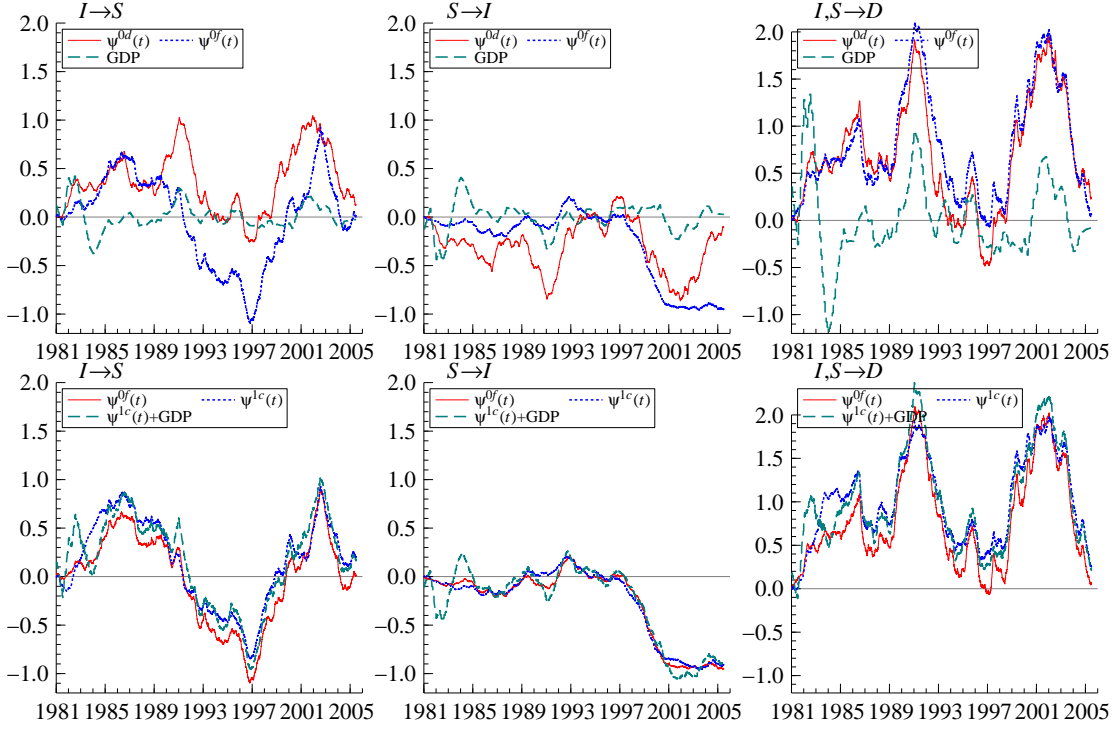
The figure contains the smoothed common factor risk $\psi_j(t)$ for each of the transition types $j = I \rightarrow S$ (left column), $j = S \rightarrow I$ (middle column), and $j = (I, S) \rightarrow D$ (right column). The top row of graphs presents the (solid curve) estimated latent risk factor from model 0d multiplied by its loading from Table 1, the (dotted curve) estimated latent risk factor from model 0f multiplied by its default transition loading from Table 1, and the GDP growth from model 1a multiplied by its loading from Table 2. The bottom row of graphs presents the (solid curve) estimated latent risk factor from model 0f multiplied by its loading from Table 1, the (dotted curve) estimated latent risk factor from model 1c multiplied by its default transition loading from Table 4, and composite of the latent risk factor from model 1c and the GDP growth component, both multiplied by their loading from Table 4.

and re-rating intensities, we should look for other variables that capture intensity dynamics. Some obvious ways forward appear to be variables capturing industry and contagion effects. Alternatively, we could enlarge the model by the inclusion of firm-specific variables. The latter, however, would only help if they are correlated with any missing systematic effect in the credit risk dynamics. Finally, we can enlarge the class of dynamic models for the latent common risk component from the current random walk to a more richly specified autoregressive structure.

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Table 4: Intensity model with macro fundamentals and three latent components

We use the latent component intensity model (10) to determine the impact of macro fundamentals and three unobserved components ($\psi_j(t)$) on transition intensities. The three latent processes are independent random walks that load on the Investment grade to Sub-investment grade downgrade intensities, the (reverse) upward intensities, and the default intensities (pooled over both rating types), respectively. The explanatory variables are divided in three blocks. Business cycle: real GDP growth. Bank lending conditions: growth in the amount of business loan outstanding (BLOAN), M2 growth (M2), realized annual inflation (INFL), Federal Funds rate (FFund), default spread between yields on BBB rated corporate bonds and 10-year treasury bonds (DSPR). Financial market variables: term spread defined as 10 year minus 1 year yield on treasury bonds (TSPR), annual realized return on the S&P500 (SP500), annual realized return volatility (using daily data) of the S&P500 (SPVOL). Significance at the 1%, 5%, and 10% level is denoted by ***, **, and *, respectively. Transition types are from investment grade (I) to sub-investment grade (S) or vice versa, or from either of these states into default (D).

	Transition type			Transition type			Transition type		
	$I \to S$	$S \to I$	$S \to D$ $I \to D$	$I \to S$	$S \to I$	$S \to D$ $I \to D$	$I \to S$	$S \to I$	$S \to D$ $I \to D$
	model 1c			model 2c			model 3c		
GDP	-0.15***	0.11**	-0.18***						
BLOAN				0.06	-0.02	-0.04			
M2				0.05	-0.14	0.11			
INFL				0.10	-0.07	0.02			
R				-0.10	0.13	-0.07			
DSPR				0.14*	-0.06	0.14**			
TSPR							-0.04	-0.06	0.00
SP							-0.09	-0.07	-0.07
SPVOL							-0.04	-0.17*	0.14
$\psi_j(t)$	-0.027***	0.013***	-0.037***	-0.021***	0.014***	-0.035***	-0.028***	0.013**	-0.039***
	Log-lik = -10087.3			Log-lik = -10089.3			Log-lik = -10089.2		

	model 4c			model 5c			model 6c		
GDP	-0.12*	0.11**	-0.17**	-0.13**	0.14***	-0.17**	-0.14*	0.15*	-0.17*
BLOAN	-0.04	-0.02	-0.01				-0.10	-0.04	-0.14
M2	-0.02	-0.08	0.16				0.01	-0.01	0.03
INFL	0.09	-0.01	-0.05				0.09	0.02	-0.11
R	-0.05	0.08	-0.07				-0.27	-0.15	-0.11
DSPR	0.09	0.01	0.04				0.01	0.02	-0.03
TSPR				-0.05	-0.09*	0.02	-0.15	-0.16	-0.12
SP				-0.08	-0.11*	-0.04	-0.11	-0.11*	-0.10
SPVOL				-0.02	-0.16*	0.14	-0.11	-0.18**	0.09
$\psi_j(t)$	-0.029***	0.014***	-0.040***	-0.031***	0.014***	-0.037***	-0.030***	0.012***	-0.037***
	Log-lik =-10084.8			Log-lik =-10081.5			Log-lik =-10078.8		