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Credit cycles and macro fundamentals ☆

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ABSTRACT

We use an intensity-based framework to study the relation between macroeconomic fundamentals and cycles in defaults and rating activity. Using Standard and Poor's U.S. corporate rating transition and default data over the period 1980–2005, we directly estimate the default and rating cycle from micro data. We relate this cycle to the business cycle, bank lending conditions, and financial market variables. In line with earlier studies, the macro variables appear to explain part of the default cycle. However, we strongly reject the correct dynamic specification of these models. The problem is solved by adding an unobserved dynamic component to the model, which can be interpreted as an omitted systematic credit risk factor. By accounting for this latent factor, many of the observed macro variables loose their significance. There are a few exceptions, but the economic impact of the observed macro variables for credit risk remains low. We also show that systematic credit risk factors differ over transition types, with risk factors for downgrades being noticeably different from those for upgrades. We conclude that portfolio credit risk models based only on observable systematic risk factors omit one of the strongest determinants of credit risk at the portfolio level. This has obvious consequences for current modeling and risk management practices.

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, e.g., Altman (1983). 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., Schönbucher (2001), Lucas et al. (2002), Frey and McNeil (2003). This also holds if bond or loan portfolios are repackaged into products like collateralized debt obligations (CDOs). In order to assess credit risk at the portfolio level it is therefore of vital importance to model the correct dynamics of systematic credit risk components and to uncover their relation to macroeconomic activity.

Systematic credit risk factors reflect two important aspects of credit risk management. On the one hand, companies may directly enter into default. This constitutes one of the major sources of credit losses. On the other hand, the rating of a company may change over time. In a market-to-market setting this also induces a potential credit loss (or gain). Moreover, in a multi-period setting the re-rating activity of rating agencies is an additional important indicator for credit risk, as most defaults are preceded by

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a sequence of smaller downgrades. Modeling the systematic components in rating transitions is therefore just as important as modeling the defaults themselves.

In this paper, we concentrate on modeling systematic risk factors in defaults and rating transitions. We demonstrate that these factors are strongly persistent and display cyclical behavior. Because the factors relate to both components of credit risk (defaults as well as re-ratings), we refer to them jointly as the *credit cycle* in the remainder of the discussion. We are particularly interested in the relation between this credit cycle and macroeconomic activity.

Empirically, the relation between default rates and macro fundamentals has been addressed in a number of studies. Fama (1986) and Wilson (1997a,b) regress default rates on observed macro variables and find cyclicality in probabilities of default (PDs). Particularly in the case of economic downturns PDs increase significantly. Koopman and Lucas (2005) concentrate on the time series dimension of PDs and present evidence of co-cyclicality between Gross Domestic Product (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. (2007) employ the semi-parametric duration model of Cox (1972) conditioning on both firm-specific and macroeconomic variables to analyze a data set on business loans. Duffie et al. (2007) 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. However, this is particularly relevant given the demonstrated stickiness of aggregate rating migrations and defaults.

To test for the correct dynamic specification of intensity models with macroeconomic risk factors, we use the methodology of Koopman et al. (2008a). We estimate the credit cycle directly from rating and default data at the micro level using intensity models with both observed and unobserved 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. The advantage of using continuous-time transition data rather than discrete time counts for credit risk is illustrated in Lando and Skødeberg (2002). We condition the credit cycle on a number of macroeconomic fundamentals, reflecting the state of the business cycle, bank lending conditions, and financial market conditions. In line with earlier 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 autocorrelation, many of the familiar macro variables become insignificant, giving way to a significant unobserved common risk factor.

The fact that the unobserved component in systematic credit risk is more important empirically than many macro fundamentals has obvious relevance for credit risk management. Our results imply that credit risk management models based only on observable risk factors omit one of the most important ingredients of portfolio credit risk. This has important consequences for the regulatory framework as well as for the computation of credit Value-at-Risk levels, Economic Capital, and adequate capital buffers by financial institutions themselves. These results are robust to a variety of specifications of the model and a wide range of macro fundamentals.

The formal testing procedure for dynamic mis-specification introduced in this paper constitutes a powerful tool in the empirical modeling of intensities. We model intensities of rating and default transitions not only in terms of observed macro fundamentals, but also in terms of an unobserved component or frailty factor, see also Duffie et al. (2006), and Koopman et al. (2008b). This unobserved component captures any remaining dynamics in re-rating and default probabilities that is not accounted for by the observed macro fundamentals. 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.

In terms of the current literature on credit risk, our analysis is most closely related to the work by Couderc and Renault (2005) and Duffie et al. (2006). Nevertheless, there are a number of important distinctions. First, our modeling framework is significantly different from that of Couderc and Renault (2005). We use a parameter driven dynamic intensity model that conditions on observable macro fundamentals. By contrast, Couderc and Renault focus on the macro variables 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. By 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. Duffie et al. (2006) use a similar intensity framework as ours. They employ a different estimation methodology than the Simulated Maximum Likelihood (SML) approach presented in this paper. Also, their specification search over explanatory macro variables is different. Third, we do not only consider information from defaults to estimate the credit cycle, but also use 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 debate on the pro-cyclicality of credit ratings as well. Bangia et al. (2002) and Nickell et al. (2000) show that changes in the macroeconomic environment have significant effects on firms' credit rating transitions. Ferri et al. (2001) 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 may not sufficiently encourage commercial banks to lend to perceived high default risk borrowers. 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.

Using rating transition and default data of U.S. corporates from Standard and Poor's over the period 1980–2005 we condition in this paper on three plausible sets of variables: business cycles effects, bank lending conditions, and financial market variables. In line with previous research, our results show that a large set of these macro fundamentals appears at first sight to have explanatory power for re-rating and default behavior. If we account for additional *unobserved* common risk factors, however, most of the observed variables become statistically insignificant. This particularly holds if we allow for multiple unobserved risk factors. The relevant macro variables that remain generally such as GDP growth, the short-term interest rate, default spreads, and stock market volatilities have the intuitively correct signs. For instance, high growth is good for rating upgrades, but decreases downgrade and default intensities. Further, increased stock market volatility following Merton (1974) decreases upgrade probabilities. Throughout all specifications, negative rating assessments are much more correlated with macro fundamentals than upgrades. However, our broad set of common macro fundamentals only helps to a limited extent to explain default rates. It seems that default intensities are driven by other risk factors than the common macro fundamentals and that models based only on such observable risk factors therefore omit the most crucial systematic risk component for credit portfolio management.

The remainder of this 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. 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 index $j=1,\ldots,J$ of each counting process indicates the type of transition that is counted. For example, $j=1$ may correspond to an upgrade from BB to BBB, $j=2$ to a downgrade from BB to CCC, $j=3$ to a default from BB to D, and so on. In the empirical application we use seven rating classes with $J=49$ corresponding transition types. When a rating event of type j occurs for firm k at time t, the counting process $N_{jk}(t)$ jumps by 1. 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. (2008a). In particular, we have

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

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 rated as investment grade, it is not at risk for transitions from sub-investment grade to default. In such a case the corresponding $R_{jk}(t)$ would be equal to zero. 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 credit 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 factor is also known as a frailty factor in related literature, see Duffie et al. (2006). The parameters η_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, whereas re-rating activity is observed daily. 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

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

where the disturbance ε_i is standard normally distributed, the 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 Eq. (1) are able to explain the transition and default dynamics. We impose a unit root (nonstationary) process in Eq. (3) to enforce the estimation algorithm to focus on the long term dynamics. As the durations of the pooled process are on average as low as 2 days, see Section 3, and as we focus on a systematic credit cycle with an empirically reasonable period of several years, the process $\psi(t)$ needs to be highly persistent at the daily frequency. The unit root specification in Eq. (3) is therefore not highly restrictive for the high-frequency data at hand. To account for the fact that the duration between spells may vary over the sample, we introduce heteroskedasticity using the square root of the observed spell lengths as a multiplying factor for the innovation. This

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

would be the correct form of heteroskedasticity if the continuous-time stochastic components $\psi(t)$ were a standard Brownian motion.

The main focus of this paper is on the significance of α_j and β_j in Eq. (1). Previous studies did not explicitly allow for a separate stochastic component $\psi(t)$. One can think of a significance test on the α_j estimates as a simple test for ignorance of first order dynamics in the intensities. The significance of the α_j coefficients can easily be tested by standard likelihood ratio tests.

We define the processes $\tilde{x}(t)=\{x(s)\}_{s=0}^{t}$ and $\tilde{\psi}(t)=\{\psi(s)\}_{s=0}^{t}$ and make two conditional independence assumptions. First, conditional on $\tilde{x}(T)$ and $\tilde{\psi}(T)$, we assume that the firms behave independently so that common factors in rating migrations and defaults are captured by the factors in Eq. (1). This framework is the standard assumption in most of the portfolio credit risk literature. Second, the model is set in a so-called 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 for the pooled process conditional on $\tilde{x}(T)$ and $\tilde{\psi}(T)$ is given by

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

where

$$\rho_j(t)=exp\left(\eta_j+\beta_j'x(t)+\alpha_j\psi(t)\right)$$

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

$$\ell(\theta|\tilde{x}(T))=\int\ell\left(\theta|\tilde{x}(T),\tilde{\psi}(T)\right)dPr\left(\tilde{\psi}(T)\right). \tag{5}$$

Effectively we need to integrate out the unobserved component $\tilde{\psi}(T)$ from the conditional likelihood function(4). Note that the integral in Eq. (5) typically has a high dimension. For example, in the empirical section below, the dimension of the integral is more than 12,000. 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). In effect, Monte Carlo methods are used for the evaluation of integral (5) by considering

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

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 $q(\psi(\mathrm{T}))$ contribute significantly to the likelihood. The alternative route of using Eq. (5) directly for generating samples and evaluating the likelihood is much less efficient and not feasible as the majority of draws from $p(\psi(\mathrm{T}))$ have little resemblance to the observed data and make negligible contributions to the likelihood. The construction of $q(\psi(\mathrm{T}))$ 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

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

where the state vector $\nu_i=\nu(t_i)$, and $\nu(t)$ contains 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 Eq. (3) is a special case of the second equation in Eq. (7). In the case of $\nu(t_i)\equiv\psi(t_i)$, we would have $T_i=1$ and $R_i=\sqrt{t_{i+1}-t_i}$. The fixed coefficients in $\nu(t_i)$ 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 $t=s$. Therefore $\eta_j(t_i)$ and $\beta_j(t_i)$ can also be represented by the second equation in Eq. (7). For example, in case $\nu(t_i)\equiv\beta_j(t_i)$, for some j, we would have $T_i=I_m$ and $R_i=0$. The dimension of the parameter vector θ is reduced considerably as a result since the regression parameters η_j and β_j have become part of the state vector $\nu(t_i)$ 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). 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 (2002). The likelihood function (6) can be reformulated as

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

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

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

where $y_{jk}(t_i)$ is the dummy "transition" variable, $\log \lambda_{jk}(t_i)$ is the log intensity function in Eq. (7) and NID(0, C) refers to the assumption of a normal distribution for mutually and serially independent random variables with mean zero and variance C. The variables c_{ijk} and variances C_{ijk} are known functions of the latent variable $\lambda_{jk}(t_i)$. 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 $\lambda_{jk}(t_i)$, conditional on all data-points $y_{jk}(t_i)$, and to compute new values for c_{ijk} and C_{ijk}. This process converges quickly to a unique solution even in a high-dimensional setting. Given model (9) with the solutions for c_{ijk} and C_{ijk}, simulations for $\log \lambda_{jk}(t_i)$, conditional on all data points $y_{jk}(t_i)$, are obtained by the simulation smoothing algorithm of Durbin and Koopman (2002).[2]

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

$$\hat{\tilde{\nu}}(T) = \int \tilde{\nu}(T) \frac{p\left(\tilde{\nu}(T)\right)}{q\left(\tilde{\nu}(T)\right)} \mathrm{d}q\left(\tilde{\nu}(T)\right).$$

The same importance sampling techniques are therefore applied to the evaluation of $\hat{\tilde{\nu}}(T)$. This estimator includes the estimator of the dynamic latent variable $\psi(t)$ and the regression coefficient estimators for η_j and β_j with $j=1,\ldots, J$. These estimates are reported for the empirical study in Section 4.

3. Data

The data for the empirical study in Section 4 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 seven familiar classes (AAA, AA, A, BBB, BB, B, CCC and below). Later on, we further aggregate these classes into investment grade (BBB and above) and sub-investment grade (BB and below) to check the robustness of our results.

We consider all days on which there is a rating event. Rating events are defined as (i) one of the firms in the database experiences a rating transition (given the rating classes) or default, (ii) a firm becomes non-rated, (iii) a firm enters the sample. All three types of events result in a change in the intensity of the pooled process. We obtain 19,010 events spread over 5351 event days.

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 database during weekends. We transferred all these rating events to the Friday preceding the weekend.[3] Second, if firms enter the database 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 database. Eliminating this type of dependence is important, because it may result in a biased estimate of the systematic credit risk component. To reduce this potential bias, we sequentially 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 history of one of these firms is discarded and substituted by a rating withdrawal.

The macroeconomic variables in our study are taken from the database of the Federal Reserve Bank of St. Louis (FRED) and computed from the CRSP/Compustat database. Our data set 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.

[2] More details on this method of likelihood evaluation by importance sampling for the model of Section 2.1 are given by Koopman et al. (2008a).

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

The business cycle block contains quarterly observations of Gross Domestic Product growth (GDP) and the term spread of interest rates. The term spread is measured as the difference between the 10-year Treasury bond rate and the Federal funds rate. Both GDP growth and the term spread have a record for predicting default rate variation over stages of the business cycle, see for example Bangia et al. (2002), Nickell, Perraudin and Varotto (2000), and Kavvathas (2001). As a signal of current macroeconomic conditions, we therefore expect both variables to be negatively correlated with downgrade and default intensities, and positively with upgrade movements.

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 variables for bank lending conditions: commercial and industrial loans outstanding, money supply, inflation, and the discount rate. 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 tends 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 the 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, should be associated with higher default intensities. Short-term interest rates have a long history as predictors of output changes. We expect the higher the discount rate, the more expensive it is for companies to take lines of fresh credit, the more defaults we observe. The same line of reasoning holds for inflation: we expect that a high rate of inflation leads the Federal Reserve to raise short-term interest rates.

The financial market variables we consider are the returns on the default spread, the annual S&P500 return and its realized volatility, and a market leverage variable. Stock and Watson (1989) show that the default spread is a good predictor of output growth. We measure the default spread as the difference between interest rates on BBB-rated corporate bonds and 10-year Treasury bonds. We expect the default spread to be positively correlated with default intensities. In a traditional Merton (1974)-type model, the two drivers of default probability are leverage and the volatility of firms' assets. We proxy the former by computing the leverage factor for US Industrials. We match the CRSP and Compustat databases and compute the ratio of long term debt (from Compustat) to the sum of debt and equity, while the market equity value is taken from CRSP. To complement the information on the level of leverage, we also account for the annual S&P500 growth rate. We use the realized daily volatility of equity returns over a 1-year period as a proxy for the volatility of the firms' assets. We expect that the S&P500 return is negatively correlated to default and downgrade intensities, whereas volatility and leverage are positively correlated with defaults.

4. Empirical results

4.1. Parameterization

As the model has seven rating classes plus default, there is a large number of 49 possible transitions. Some of these transitions are observed regularly, such as one-notch or two-notch transitions. Other transitions are observed less frequently, such as investment-grade defaults. The large number of transition types gives rise to an unwieldy large number of parameters if model (1) is left unrestricted. We impose parsimony in the following way. The baseline rating intensities η_j are left unrestricted. This gives a total of 49 constants to be estimated. As the baseline levels are not of prime interest in our paper, we do not report them. The coefficients α_j and β_j, however, also depend on the transition type. This would imply another 49 coefficients for the latent component, and another 49 for every macro variable added. As we consider 10 different macro variables, this number of parameters would become difficult to interpret and identify empirically. Therefore, we impose the following structure on the α_j and β_j coefficients. In particular, we assume that the sensitivity of rating transitions to specific (observed or unobserved) risk factors can be pooled across Investment Grade (IG) ratings (BBB− and above) and Sub-investment Grade (SG) ratings (BB+ and below). The sensitivity to GDP growth, for example, of the downgrade transition intensity from any IG rating to any other IG rating is assumed to be the same. Similarly, the sensitivities of upgrade intensities from any IG to any other IG rating, and of the downgrade intensities from any IG to any SG rating or to default are assumed to be identical. This structure of the parameterization is summarized by

$$\alpha = \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_J \end{pmatrix} = \mathrm{vec}\left(\begin{array}{cccc|cccc} \diagdown & \tilde{\alpha}_1 & \cdots & \tilde{\alpha}_1 & \tilde{\alpha}_3 & \cdots & \cdots & \tilde{\alpha}_3 \\ \tilde{\alpha}_2 & \diagdown & \ddots & \vdots & \vdots & & & \vdots \\ \vdots & \ddots & \diagdown & \tilde{\alpha}_1 & \vdots & & & \vdots \\ \tilde{\alpha}_2 & \cdots & \tilde{\alpha}_2 & \diagdown & \tilde{\alpha}_3 & \cdots & \cdots & \tilde{\alpha}_3 \\ \hline \tilde{\alpha}_4 & \cdots & \cdots & \tilde{\alpha}_4 & \diagdown & \tilde{\alpha}_5 & \cdots & \tilde{\alpha}_5 \\ \vdots & & & \vdots & \tilde{\alpha}_6 & \diagdown & \ddots & \vdots \\ \vdots & & & \vdots & \vdots & \ddots & \diagdown & \tilde{\alpha}_5 \\ \tilde{\alpha}_4 & \cdots & \cdots & \tilde{\alpha}_4 & \tilde{\alpha}_6 & \cdots & \tilde{\alpha}_6 & \diagdown \end{array}\right), \tag{10}$$

where vec(·) stacks the columns of a matrix into a vector, and the rows and columns of the coefficient matrix inside the vec operator indicate the initial and end-of-period rating of the company, respectively. A similar structure holds for the coefficients β_j

for the observed macro variables. This limits the number of parameters from 49/risk factor to only 6, while the model still allows for considerable flexibility in terms of different factor sensitivities for different rating transition types. Unreported preliminary results revealed that this flexibility is statistically significant. For example, one uniform sensitivity to a specific risk factor across all transition types ($\alpha_1 = \alpha_2 = \ldots = \alpha_J$) is rejected by the data.

The presentation of the results is set up as follows. We first present the results per block of variables in Subsection 4.2. This highlights the contribution of each block to the explanation of specific rating transition intensities. The models are tested for their dynamic specification by extending each model by a single, unobserved common risk factor. In Subsection 4.3, we pool all blocks of variables and discuss the effect of allowing for different systematic risk factors per rating transition type. Finally, Subsection 4.4 discusses some additional robustness analyses. All computations are implemented using the Ox programming language of Doornik (2002) and the SsfPack 3.0 routines of Koopman et al. (2008c).

4.2. Macro fundamentals and one latent factor

We start our analysis by investigating the empirical relevance of each of our three blocks of macro variables separately, i.e., the observable macro variables are entered per block: business cycle indicators, bank lending conditions, financial markets variables. In the upper panel of Table 1 we show the results for the models that only contain observable factors in the transition intensities.

We learn from these results that a number of variables has a significant impact on re-rating and default activity in line with earlier literature. For the business cycle variables, we expect a positive relation between the business cycle (GDP growth, term structure slope) and upward rating movements, and vice versa for downgrades and defaults. The empirical results are highly significant and in line with our expectations. High growth rates negatively impact downward rating revisions and defaults (columns 1–3). High GDP growth rates have the strongest impact for downward rating transitions from Sub-investment Grade (SG) to Sub-investment grade and Default (SGD). The opposite holds for the upward rating movements (columns 4–6). Here, the strongest effect of high GDP growth rates appears for upgrades from SG to IG. The effect of the term structure variable is statistically less significant and more ambiguous to interpret. The effects are in line with those of GDP growth for the segment of sub-investment-grade companies. We observe a significant negative impact of the term spread on downgrades from SG to SGD, and a significant positive impact for upgrades within the SG category. For the other transition types the signs are not consistent with our expectations. These results are not robust, however, to the addition of a latent component, as we see later on in Section 4.3 and may therefore be partly caused by the dynamic mis-specification of the current model.

It is interesting to see that the impact of the business cycle variables appears strongest for the sub-investment grade downgrades and defaults. The impact of the business cycle on the other rating types is only half the magnitude. The effect is due to two causes. First, the sub-investment-grade class is populated by many firms that are more susceptible to worsening economic conditions. Second, the effect can be partly explained by the rating momentum effect: multi-step downgrades across the investment-grade border as well as defaults are usually implemented by a sequence of smaller downgrades. This makes most of the firms that head towards the default region first pass through the sub-investment-grade ratings.

If we turn to the empirical results of model 2a, we see that many variables reflecting bank lending conditions are statistically significant. The signs, however, are not always straightforward to interpret. The negative correlation between business loans and downgrade intensities is not in line with expectations: as a signal of economic hard times, business loans typically peak in recessions due to the extensive need of companies for additional financing. The negative correlation with upgrade intensities, on the other hand, is supported by the data. In Section 3 we argued that M2 growth should have a negative correlation with downgrade intensities. The results, however, are precisely the opposite. The correlation is positive (negative) with downgrade (upgrade) intensities, respectively. There is no obvious explanation for this, and we show later that the result is not robust to the addition of multiple unobserved risk factors.

The signs for inflation are partly in line with expectations. High inflation rates signal anticipated short rate increases and higher funding costs. This positive (negative) relation with downgrade (upgrade) intensities is in line with the result in Table 1. The main exception is the negative coefficient for large downgrades from the investment-grade class. Again, there is no obvious explanation for this sign and the dynamic specification tests of the model should cast more light on the robustness of this result. The same holds for the short-term interest rate, which has a large positive effect on both upgrade and downgrade intensities.

The estimates of the financial markets variables in model 3a are highly significant and more in line with our expectations. The default spread, measured as the difference between interest rates on BBB-rated corporate bonds and 10-year Treasury bonds, is positively related to downward movements, and negatively to upward movements. A positive change in observed default spreads seems to have the strongest impact on rating upgrades from SG to IG. The effect is four to five times higher than for upgrades from IG and SG, respectively. From the traditional Merton (1974)-type perspective the volatility of the firm assets should be an important driver for default probabilities. High asset volatilities decrease the distance to default, and therefore increase default probabilities. The estimates of 1-year volatility of the S&P500 returns are highly significant and in line with our expectations: volatility is positively related to downward movements, and mostly negatively to upward movements. The effect is the strongest for positive rating changes in the SG category. As expected, the reverse holds for the S&P500 return: it is mostly negatively correlated to default and downgrade intensities, while mostly positively related to rating upgrades. The leverage variable has the peculiar property that it is in five out of six cases positively correlated to rating transition intensities, both upgrade and downgrade. As we see later, this is primarily due to the stock market run-up in the 1990s.

The general conclusion from these first estimations is that several macro variables appear to pick up systematic movements in re-rating and default intensities. As a first check on the robustness of the results, we add our latent common risk component ψ_t to

Table 1
Parameter estimates

Direction	Down	Down	Down	Up	Up	Up	Down	Down	Down	Up	Up	Up	Down	Down	Down	Up	Up	Up
From	IG	IG	SG	IG	SG	SG	IG	IG	SG	IG	SG	SG	IG	IG	SG	IG	SG	SG
To	IG	SGD	SGD	IG	IG	SG	IG	SGD	SGD	IG	IG	SG	IG	SGD	SGD	IG	IG	SG
	Model 1a (business cycle variables)						Model 2a (bank lending conditions)						Model 3a (financial markets variables)					
GDP	−0.16[a]	−0.13[a]	−0.32[a]	0.12[a]	0.15[a]	0.08[a]												
Term	0.04[b]	0.07[b]	−0.11[a]	−0.04	−0.05	0.14[a]												
Bus.Loans							−0.19[a]	−0.30[a]	−0.17[a]	−0.05	−0.12[b]	−0.07						
M2							0.21[a]	0.13[a]	0.25[a]	−0.02	−0.26[a]	−0.28[a]						
Inflation							0.07[b]	−0.16[b]	0.21[a]	−0.29[a]	−0.31[a]	−0.02						
Short rate							0.03	0.40[a]	−0.10	0.57[a]	0.63[a]	−0.06						
Def.Spread													0.17[a]	0.17[a]	0.17[a]	−0.04	−0.19[a]	−0.06
SP500													−0.05[b]	0.08[b]	−0.09[a]	0.20[a]	0.08[b]	−0.01
1Y Vol.													0.09[b]	0.05	0.10[a]	0.01	−0.05	−0.15[a]
Leverage													0.13[a]	0.24[a]	−0.08[a]	0.19[a]	0.18[a]	0.03
LLik	−28,270.45						−28,148.84						−28,147.60					
	Model 1b						Model 2b						Model 3b					
GDP	−0.22[a]	−0.16	−0.33[a]	0.12[a]	0.15[b]	0.10												
Term	−0.10[b]	−0.11	−0.29[a]	−0.04	0.02	0.25[a]												
Bus.Loans							0.09	−0.03	0.34[b]	−0.21[a]	−0.21[a]	−0.29[a]						
M2							0.16[a]	0.06	0.11	0.02	−0.22[a]	−0.22[a]						
Inflation							0.04	−0.22[b]	0.18	−0.27[a]	−0.27[a]	−0.01						
Short rate							0.54[a]	0.99[a]	0.80[a]	0.20[a]	0.39[a]	−0.43[a]						
Def.Spread													0.16[a]	0.16[a]	0.09	−0.05	−0.19[a]	−0.04
SP500													−0.04	0.11[b]	−0.02	0.20[a]	0.08[b]	−0.05
1Y Vol.													0.00	−0.06	−0.02	0.01	−0.05	−0.05
Leverage													0.06[b]	0.16[a]	−0.16[b]	0.18[a]	0.18[a]	0.10[a]
t	−0.058[a]	−0.063[a]	−0.070[a]	0.001	0.024[a]	0.044[a]	−0.057[a]	−0.061[a]	−0.107[a]	0.037[a]	0.022[b]	0.048[a]	−0.043[a]	−0.057[a]	−0.093[a]	−0.003	−0.002	0.047[a]
LLik	−27,973.70						−27,899.88						−27,939.04					

We estimate the intensity models without (model 1a, 2a, 3a) or with a latent component (model 1b, 2b, 3b). We distinguish 7 rating grades (AAA, AA, A, BBB, BB, B, CCC and below) and default. Systematic risk sensitivities are pooled across the transition types from downgrades from Investment Grade (IG) to IG, downgrades from IG to Sub-investment grade and Default (SGD), downgrades from Sub-investment grade (SG) to Sub-investment Grade and Default (SGD), upgrades from IG to IG, etc. The explanatory variables are divided in three blocks. Business cycle indicators: the annual real GDP growth rate, and the term spread (Term) defined as the 10-year minus 1-year yield on Treasury bonds. Bank lending conditions: the growth in the amount of business loan outstanding (Bus.Loans), M2 growth (M2), realized annual inflation (Inflation), Federal Funds rate (Short rate). Financial market variables: the default spread between yields on BBB-rated corporate bonds and 10-year Treasury bonds (Def.Spread), annual realized return on the S&P500 (SP500), annual realized return volatility (using daily data) of the S&P500 (1Y Vol.), and aggregate leverage of the corporate sector (Leverage). Significance at the 1% and 5% level is denoted by [a] and [b], respectively.

the intensity specification in Eq. (1). If the observable macro variables capture the systematic risk adequately, their coefficients should not change much and the latent component would prove redundant. If by contrast the latent component appears to be important, the original model might just be picking up spurious correlations. The results of these estimated models 1b, 2b, and 3b are provided in the lower panel of Table 1.

If we compare the log-likelihood values of the two models, we see that the log-likelihood increases by roughly 200 to 300 points upon adding six α_j parameters. This is highly significant by any conventional standard. In all cases, the latent component has its strongest effect on the downgrades and defaults, especially in the sub-investment-grade cluster, see the ψ_t-row in Table 1. There is also an important (and opposite) effect on small sub-investment-grade upgrades. Larger upgrades as well as investment investment-grade upgrades appear less affected by the latent component, though this partly depends on the observables that are included.

Interestingly, by allowing for dynamic mis-specification of the intensity models 1a–3a using the unobserved component, a number of the earlier results change considerably. For the business cycle variables in model 1b, the coefficients of GDP growth are not affected much, though their significance drops somewhat. The sign of the statistically significant coefficients for the term structure variable, however, is now fully in line with those for GDP growth and our expectations. Downgrades are negatively affected by the business cycle as indicated by the slope of the term structure, and upgrades mostly positively.

The empirical results in model 2b indicate that the variables capturing bank lending conditions appear less significant compared to model 2a, i.e. the original model without the unobserved component. The picture, however, becomes slightly more consistent with expectations. For example, the growth in business loans has a highly significant negative impact on upgrade intensities, as it may be more difficult for companies to access fresh lines of credit. On the other hand, one downgrade intensity is significantly positively affected by business loans growth. Changes in the inflation and M2 growth rates, generally appear to reflect worsened economic circumstances and negatively (positively) impact upgrade (downgrade) intensities. One important exception remains the so-called fallen angels case: the intensity of investment-grade companies falling to sub-investment grade or default is positively correlated with inflation. There is no obvious explanation for this.

Finally, models 3a and 3b are quite comparable. The signs across both specifications appear consistent. Again we observe that some of the variables loose their statistical significance. In particular, the realized volatility variable appears less important for both downgrades and for sub-investment-grade upgrades. The default spread is positively related to downgrade and negatively to upgrade intensities. The leverage variable keeps its peculiar property that it is in five out of six cases positively correlated to both upgrade and downgrade intensities. The short rate retains its positive effect on both upgrades and downgrades. This may be partly due to the fact that we do not separately condition for the stage of the business cycle. We address this issue in the next subsection.

Fig. 1 illustrates in more detail how the original models 1a–3a operate compared to their 1b–3b counterparts including the unobserved component. In this figure, we present three different estimates of the log intensities. The estimates are obtained by

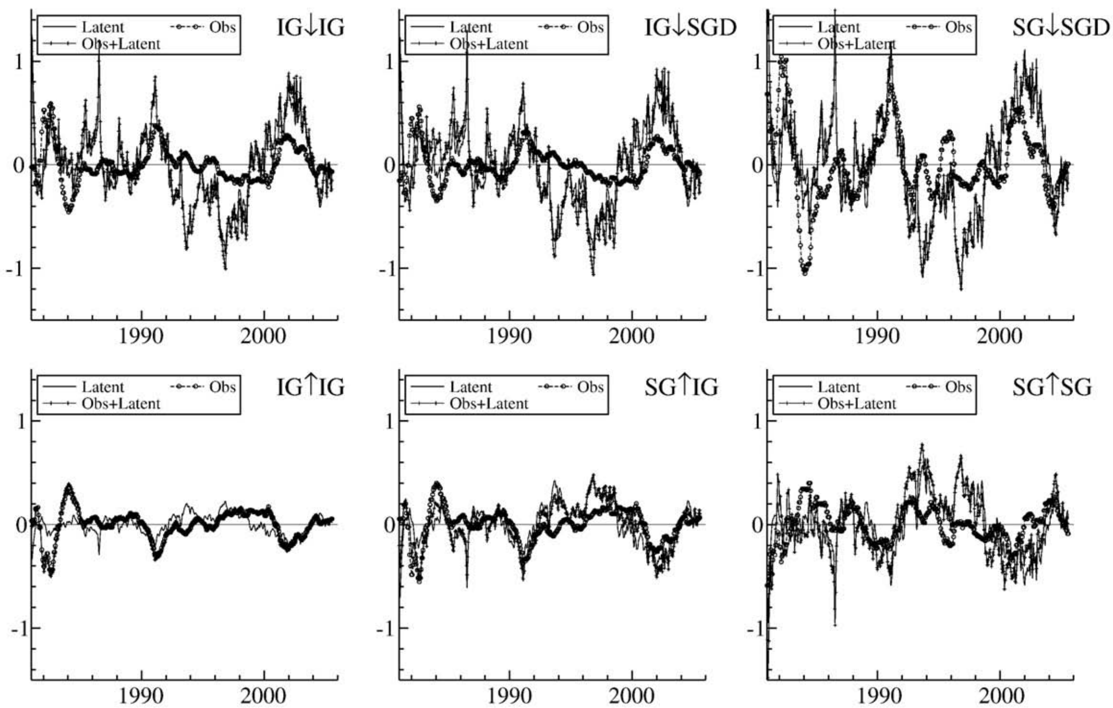

Fig. 1. Estimates of the common risk factors (model 1). The figure contains the smoothed common risk factor for the six transition types, using a model with only a (single) latent component, a model with only observables (model 1a), and a model with observables and a latent factor (model 1b). The observed factors are GDP growth and the term spread.

smoothing the latent states using the algorithm in Koopman et al. (2008a). We obtain estimates for all 49 different transition types. Many of these, however, only differ by the level parameters η_j. Therefore, we only present the different log intensities for the more broadly defined transition types used in Table 1. We do so by subtracting the sample mean from $\hat{\beta}_j' x(t) + \alpha_j \hat{\psi}(t)$ in Eq. (1) and presenting the result in Fig. 1.

The first estimate of the log intensities only uses the latent component. All β_j parameters are set to zero. In this way, we distill the common component directly from the rating transitions data using a pure time series perspective. This serves as a benchmark. If the macro variables contain information for predicting rating dynamics, one would hope that a model with only observable factors mimics this pure time series estimate. If we look at the second estimate of the log intensities, however, this is only true to a limited extent. The second estimate only uses observables and puts all α_js to zero. The large peaks around the early 1990s and 2000s are reasonably captured by the observables, though the magnitude of the peak around 2001 is clearly underestimated. Also the peak in downgrades and defaults around the mid-1980s appears to be missed by the observables. During the stock market run-up of the 1990s, the drop in downgrades and the increase in sub-investment-grade upgrades are missed as well. The third estimate of log intensities uses both observables and a latent component. The difference between the latent component and the latent component plus observables is small compared to the estimate based on observables only. This is in line with the strong significance of the latent component in model 1b in Table 1.

To conclude, both Table 1 and Fig. 1 point in the same direction. It appears that though the broad set of macro variables considered in this paper may be statistically significant, their economic significance compared to the latent component is limited. This suggests that different factors than the ones captured by standard macroeconomic variables drive systematic credit risk dynamics. Models that only allow for observed macro factors are thus prone to missing the strongest determinants of credit risk at the portfolio level. This is a discomforting result given the reliance of many practical models on such observed variables. Our results point out that such models should be augmented to allow for the inclusion of unobserved systematic risk factors to give an adequate reflection of portfolio credit risk.

4.3. Multiple factor models

In this section, we generalize the previous set up in two directions. First, up till now we have only considered the observable variables per block. To allow for any possible spill-over effects, we pool all macro fundamentals in one large intensity model. Note that the number of coefficients to be estimated has now increased considerably. Given the huge increase in the log-likelihood upon adding an unobserved component, we no longer consider the specification without the latent ψ_t. Instead, we opt for a second generalization. As we have seen in Table 1, the addition of a latent component causes some of the observable factors to loose their significance. It is not clear, however, whether a single factor is sufficient to describe all different types of re-rating activities. Therefore, we consider a specification where six independent latent components are present at once in the model. Each of these captures any non-observed common dynamics in credit risk and re-rating behavior. The six factors reflect separate systematic risk factors for each of the six broad transition types from Section 4.1. The empirical results are presented in Table 2.

If we consider the significant coefficients for model 4b, most of the earlier puzzles disappear. In line with our expectations, our two business cycle variables GDP growth and the term spread positively (negatively) impact upgrades (downgrades), although the

Table 2
Robustness to the number of latent components

Direction	Down	Down	Down	Up	Up	Up	Down	Down	Down	Up	Up	Up
From	IG	IG	SG	IG	SG	SG	IG	IG	SG	IG	SG	SG
To	IG	SGD	SGD	IG	IG	SG	IG	SGD	SGD	IG	IG	SG
	Model 4b (one common latent factor)						Model 4c (six independent latent factors)					
GDP	−0.25[a]	−0.36[a]	−0.56[a]	0.01	0.05	0.14[b]	−0.01	−0.11	−0.21	0.18[b]	0.18[a]	0.02
Term	−0.02	0.08	−0.13	0.14[a]	0.00	0.00	−0.08	−0.03	−0.10	0.14	−0.10	−0.16
Bus.Loans	0.08	0.13	0.03	0.01	−0.13[b]	−0.19[b]	0.32[b]	0.02	−0.14	0.06	−0.01	−0.13
M2	0.17[b]	0.19	0.26[b]	−0.01	−0.22[a]	−0.26[a]	0.16	0.04	0.09	0.05	0.03	0.00
Inflation	−0.05	−0.12	0.11	−0.21[a]	−0.30[a]	0.07	0.00	0.00	0.17	0.08	0.04	0.06
Short rate	0.52[a]	0.85[a]	0.69[b]	0.47[a]	0.59[a]	−0.36[b]	−0.36	−0.09	0.88[a]	0.03	−0.04	−0.44
Def.Spread	0.15	0.12	0.03	−0.03	−0.04	−0.05	0.13	0.07	0.21[a]	0.12	0.07	−0.13
SP500	−0.06	0.09	0.05	0.07	0.01	0.07	−0.03	−0.09	0.01	0.05	−0.14	−0.06
1Y Vol.	−0.03	0.00	0.01	−0.02	−0.11[b]	−0.01	0.01	−0.14	0.24	0.01	−0.15[a]	−0.02
Leverage	0.06	0.13	−0.12	−0.01	0.02	0.06	−0.09	0.00	−0.18[b]	−0.16	−0.01	0.00
ψ_t	−0.074[a]	−0.107[a]	−0.121[a]	0.004	−0.002	0.043[b]	−0.076[a]	−0.024[a]	−0.103[a]	0.038	0.015[a]	0.057[a]
LLik	−27,827.05						−27,808.93					

We estimate the intensity models using all explanatory variables and either one latent component (model 4b) or six components (model 4c). We distinguish 7 rating grades (AAA, AA, A, BBB, BB, B, CCC and below) and default. Systematic risk sensitivities are pooled across the transition types from upgrades from Investment Grade (IG) to IG, downgrades from IG to IG, downgrades from IG to Sub-investment Grade and Default (SGD), etc. The explanatory variables are divided in three blocks. Business cycle indicators: the annual real GDP growth rate, and the term spread (Term) defined as the 10-year minus 1-year yield on Treasury bonds. Bank lending conditions: the growth in the amount of business loan outstanding (Bus.Loans), M2 growth (M2), realized annual inflation (Inflation), Federal Funds rate (Short rate). Financial market variables: the default spread between yields on BBB-rated corporate bonds and 10-year Treasury bonds (Def.Spread), annual realized return on the S&P500 (SP500), annual realized return volatility (using daily data) of the S&P500 (1Y Vol.), and aggregate leverage of the corporate sector (Leverage). Significance at the 1% and 5% level is denoted by [a] and [b], respectively.

term spread appears in five out of six cases no longer significant. As for the bank lending condition variables, growth in business loans increases the downgrade intensities and decreases the upgrade intensities but becomes less statistically significant in both model specification 4b and 4c. Inflation and M2 growth have the same sign (when significant) and decrease (increase) upgrade (downgrade) intensities. The financial market variables are generally insignificant, except for volatility, which has a negative impact on large upgrades. This is the correct sign following the Merton model logic. The one remaining puzzle is provided by the loadings on the short-term interest rate. These are uniformly positive and significant for all transition types, except for small sub-investment-grade upgrades. As we now explicitly also control for the business cycle, the interpretation of this result is not straightforward. However, the result is not robust to the inclusion of more than one unobserved risk factor.

The coefficients of the latent component are highly significant and show a similar pattern as in Table 1. The loading for sub-investment-grade downgrades and defaults is largest, followed by that of large and small investment-grade downgrades, respectively. As expected, the single common component has an opposite effect on downgrades versus upgrades.

Upgrades to or within the investment-grade class appear unrelated to the latent common risk factor. This might have two reasons. First, there might be a genuine asymmetry between upward and downward movements. Whereas upward movements are largely driven by idiosyncratic causes, downward movements may be triggered by economy-wide movements. This explanation is less likely though, given the significance of some other, observable common risk factors. An alternative reason might be statistical. The current specification allows for a single latent component. If upward and downward movements are driven by different common components, a single common component mainly reflects the movements of one of these two. In our case, this appears to be the downward common component. To control for this possibility, we extend the specification by having a separate latent component for each of our six rating transition types. The components are specified as independent random walks using the specification in Eq. (3), so that

$$\lambda_{jk}(t) = R_{jk}(t) \cdot exp\Big(\eta_j + \beta_j' x(t) + \alpha_j \psi(t)\Big), \tag{11}$$

where $\psi_j(t)$ is the common component of rating transition type j. The results are presented as model 4c in Table 2.

First we note in model 4c that by introducing multiple latent components many observable factors loose their economic significance. In the end, only seven coefficients appear significant at the 5% or 1% level. By contrast, the magnitude of the common factor capturing the upward movements has increased. The few observable variables that are significant, mostly have the correct sign. Growth has a positive impact on upgrades, high default spreads and high short-term interest rates have a significant positive effect on sub-investment-grade downgrades. Large amounts of outstanding debt increase smaller investment-grade downgrades probabilities, whereas equity volatility has a negative impact on large sub-investment-grade upgrades. The only counterintuitive result is the sign of the leverage variable. Note that the leverage variable is implemented in *levels* to capture the *levels* of default and re-rating intensities. The level of leverage, however, mainly picks up the surge of the stock markets over the 1990s, and its prolonged fall after 2000. This is inversely correlated with the increase in good rating assignments over the 1990s, and the surge in downgrades and defaults at the start of the 21st century. With this in mind, the signs on the leverage variable are easily explained.

Comparing the likelihood values, the model with multiple factors fits the data slightly better than the single factor model. The log-likelihood increases by roughly 18 points. Note, however, that the two models are not nested, so a formal interpretation of this difference as a likelihood ratio test is not possible. Furthermore, the number of latent factors might possibly be reduced. If we consider model 4b, large investment-grade downgrades, and sub-investment-grade downgrades and defaults appear to load both strongly on the same factor. In model 4c, however, the large downgrade factor from the investment-grade class has a much smaller coefficient of −0.024. This is probably due to the fact that this type of transitions is observed much less frequently. As a consequence, the filtering techniques have more trouble in uncovering the systematic risk dynamics of this group reliably from the data. Pooling the risk factors for these transition types might further enhance the model's interpretability.

To study the economic significance of the observable risk factors vis-à-vis the unobservable ones, we present Fig. 2. The figure presents the log intensity for the one-factor model (4b) and the six-factor model (4c) for the six different transition types.

Fig. 2 reveals several interesting patterns. First of all, the one-factor and six-factor model most closely align on the systematic downgrade dynamics of the investment-grade class. The systematic dynamics within the sub-investment-grade class are still reasonably in line between the two models, though less than for the investment-grade downgrades. In particular, the systematic sub-investment-grade downgrades dynamics appear much more volatile than in the one-factor model, especially in the first and last part of the sample. Moreover, the one-factor model misses a large drop in smaller sub-investment-grade upgrades in the mid-1990s, as well as the increasing sub-investment investment-grade upgrade intensity already after 1999.

The most striking differences are observed for the systematic dynamics in the upgrade intensities towards and within the investment-grade class. Clearly, these types of rating transitions appear to be driven by a different factor than the downgrades. The one-factor model appears much too optimistic on the upgrade intensity in the early 2000s, whereas the six-factor model shows that within the investment-grade category, rating upgrades were unlikely at the time.

Summarizing, the extended model shows that more than one latent component may be needed to capture systematic rating transition dynamics. In particular, there appear separate factors for downgrades from the investment-grade class, upgrades in the investment-grade class, and finally, within sub-investment-grade upgrades and downgrades. The fact that different factors may

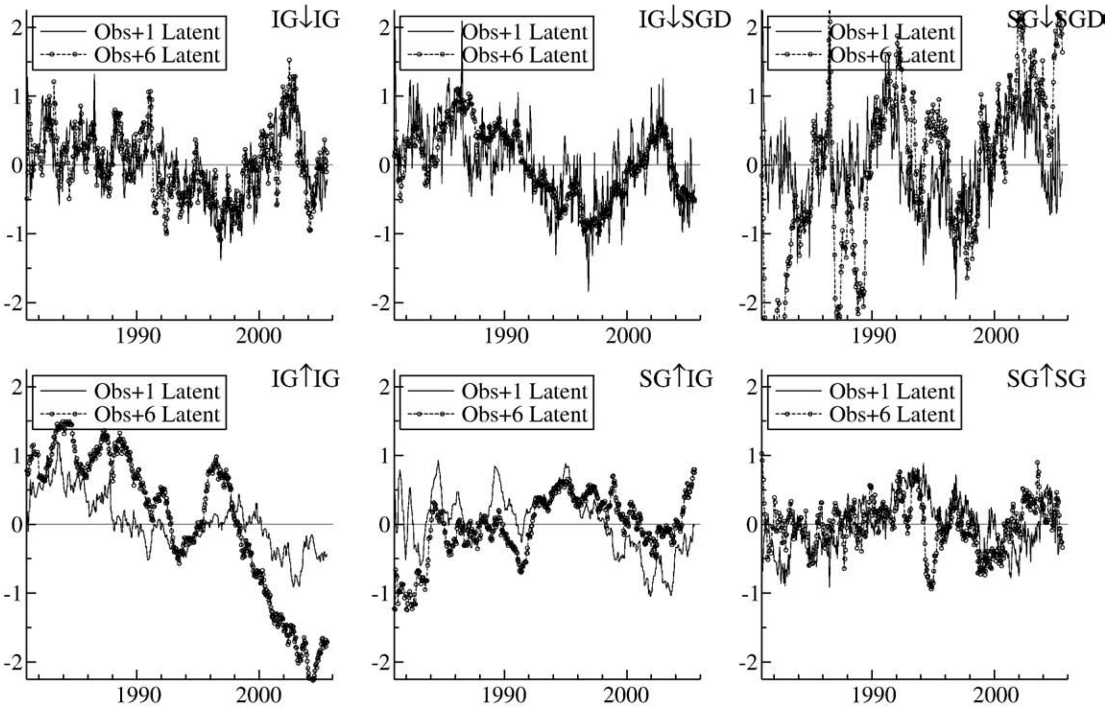

Fig. 2. Estimates of the common risk factors (model 4). The figure contains the smoothed common risk factor for the six transition types, using a model with all observables and a single latent component (model 4b), as well as a model with all observables and six independent latent factors (model 4c). The observed factors are given in Table 2.

drive these dynamics has consequences for risk management of credit portfolios. In particular, the one-factor approach propagated by the formal Basel II guidelines, may be overly simplistic given the current empirical results.

4.4. Robustness analyses

To test for the robustness of our results, we performed a number of sensitivity checks. First, we also performed the analysis on a coarser rating grid of two classes, considering only investment grade, sub-investment grade, and default, as well as all the transitions between them. This contrasts with the model from the previous section, where we keep all seven rating classes distinct, and pool the systematic risk sensitivities only according to Eq. (11). By considering a two-grade rating system, the number of parameters is reduced considerably, as only 4 rather than 49 baseline intensities need to be estimated. The results are robust. Omitting additional latent factors from the model specification proves many of the observable risk factors to be spuriously significant.

As a second robustness check, we included all explanatory variables in lags rather than contemporaneously. At lags of up to 8 quarters, the results remain unaltered in the sense that models with only observed macro fundamentals appear dynamically misspecified. Including a latent component $\psi(t)$ in all cases significantly increases the likelihood. If $\psi(t)$ is included, some of the macro variables loose their significance for specific transition types, similar to the results in Tables 1 and 2. The effect of lagging explanatory variables 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.

Finally, we investigated the effect of incorporating a non-constant baseline hazard rate. In our two-grade analysis, we replaced the constant η_j in (1) by $\eta_{0j}+\eta_{1j}\delta_k(t)$, 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 baseline hazard rate allows us to capture non-Markovian behavior of rating transitions, see Fledelius, et al., (2004). 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 $\psi(t)$.

5. Conclusions

In this paper we conducted a systematic search for the determinants of corporate credit rating and default dynamics. Using rating transition and default data of U.S. corporates from Standard and Poor's over the period 1980–2005 we directly estimated the credit cycle from the micro rating data. We used a novel econometric methodology introduced by Koopman et al. (2008a). The framework is set in a continuous-time duration model. We conditioned on three sets of variables: 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 candidates are GDP growth, the short-term interest rate, default spreads, and stock market volatilities. The results appear robust over a variety of model specifications. The results lead to the conclusion that models with only observable risk factors may seriously underestimate adequate capital buffers for credit risky portfolios.

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 to an overly optimistic re-rating policy in the late 1990s, 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 fundamentals only helps to a limited extent in explaining default 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 such variables are correlated with any missing systematic effect in the credit risk dynamics. Finally, we could enlarge the class of dynamic models for the latent common risk component from the current random walk specification to a more richly specified autoregressive structure.

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