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COVID-19, Credit Risk and Macro Fundamentals

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Abstract

We investigate the relationship between macro fundamentals and credit risk, rating migrations and defaults during the start of the COVID-19 pandemic. We find that credit risk models that use macro fundamentals as covariates overestimate credit risk incidence due to the unprecedented drops in economic activity in the first lockdowns. We argue that this break in the macro-credit linkage is less affected if we take an unobserved components modeling framework, both at shorter and longer credit risk horizons. An additional advantage of these models is that they automatically provide an integrated forecasting approach for both the credit and macro variables in the model. An effort to repair the macro-credit link via the addition of government subsidy expenses, though better in-sample, provides a worse fit to credits if implemented pre-covid.

Keywords: COVID-19, credit risk, macro fundamentals, frailty factors, dynamic latent factors.
JEL codes: G21, C22.

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1 Introduction

The COVID-19 pandemic has had a large impact on economic activity worldwide (see e.g. Zhang et al., 2020; Pellegrino et al., 2021 and Ludvigson et al., 2020). This has led to substantial research on the effects of the pandemic on asset markets, asset prices, volatility dynamics, sentiment trading and the housing market; see for instance Corbet et al. (2020); John and Li (2021) and Apergis (2021). Moreover, in a paper by Augustin et al. (2021), the consequences of COVID-19 on government debt markets using credit default swap time series has been studied. However, to the best of our knowledge, there is hardly any research in the academic literature on the pandemic's effect for corporate debt markets, and in particular on the credit risk incidence and risks. The current paper tries to fill part of this gap.

Our contribution lies in that we compare two different strands of credit risk modeling, one based on observed covariates, and one based on unobserved factors and credit frailty dynamics, and investigate their implications for the macro-credit relationship over the unfolding of the pandemic. The use of credit frailty components has been shown to be empirically important before; see for instance Duffie et al. (2007, 2009), Koopman et al. (2008, 2009, 2011) and Azizpour et al. (2018). They find that such factors are able to capture variables that are otherwise difficult to measure, such as the borrowing climate or the strictness of lending conditions. In the setting of COVID-19, we can also think of the unforeseen effects of the pandemic or, conversely, of the effect of compensating government measures. We use the rating transition modeling set-up of Creal et al. (2014) based on the methodology of Creal et al. (2013). This model directly allows for both re-ratings and defaults as well as a joint modeling of macro and credit rating dynamics. We provide a new intuitive explanation of the equation that governs the rating transition dynamics of this model. In the context of mortgage default modeling, Babii et al. (2019) used the same model, but without any re-rating part.

We address three main questions. First, are models that use macro variables as covariates more prone to a break in the macro-credit linkage than pure frailty based models when applied to the extreme COVID-19 pandemic conditions? Second, when used to compute credit risk quantiles, are models that take an unobserved components approach to credit risk and to the macro-credit linkage safe to use from before to within the covid period? And third, can the macro-credit linkage be re-established post-covid by adapting the covariates to accounting for government rescue programs?

We find that models that lean on covariates typically suffer from a break in the macro-credit linkage with the start of COVID-19. Using the typical correlations between economic activity and credit incidence as estimated in pre-covid times, the large drops in production during the lockdown periods of the pandemic results in overshooting: credit incidence is predicted much larger than actually observed. By contrast, the endogenous dynamics of frailty factors are such that this type of overshooting does not occur and credit dynamics are followed more closely.

Regarding credit risk forecasting, we first acknowledge that credit risk forecasting 12 months ahead during pandemic times is very challenging. We observe that macro risk quantiles in our setting miss the severity of the lockdown drops in economic activity. Nevertheless, an unobserved components model for macro-credit dynamics still results in compound 12 month default rate quantiles that are just covered by extreme quantiles. Credit VaR violations for specific individual months, however, as still observed. As these models provide an integrated risk forecasting approach, they remain interesting starting points also under severe stress scenarios.

Finally, we extend our model with a growth in government subsidies covariate to see whether such a variable can repair the macro-credit linkage. We find that this is not the case. In particular, if we estimate such an extended model on pre-covid data and evaluate its fit in the covid period, we find that downgrades and defaults are under-predicted. As the government rescue plans were of unprecedented size and scope, the relationship between subsidies and credit risk does not survive the pre-post covid transition. If the model is estimated on the full pre- and post-covid data, the model fares better, but such a model would be infeasible ex-ante.

The remainder of the paper is set up as follows. Section 2 describes the data. Section 3 introduces the dynamic unobserved factor methodology of Creal et al. (2014) used to capture the dynamics between credits and the macro economy and provides some new intuition for the transition equation of the model. Section 4 discusses the three empirical questions in separate subsections. Section 5 concludes.

2 Data

We combine two data sources: one on rating transitions and defaults, and one on macroeconomic variables. We briefly introduce each of these in turn.

2.1 S&P credit ratings

Standard and Poor's credit rating data were obtained from the Capital IQ database via the Wharton Research Data Services (WRDS) interface and span a period of 25 years from August 1995 to August 2020. Following Creal et al. (2014), we focus on the local currency long term rating scale. We regroup the original ratings into three different rating classes: investment grade (IG) holding the original ratings AAA–BBB^{-}, non-prime (NP) holding the original ratings BB^{+}–C, and default (D). Using these two broader rating categories, we can concentrate on the secular movements of rating transitions and defaults, without over-complicating the empirical model. We condition in our analysis on firms being rated both at the start and end of each month, and firm-month observations that result in a rating withdrawal.

A summary of the rating transition data is shown in Figure 1. The figure shows the frequencies of each of the six possible transitions, where frequencies are with respect to the number of firms at risk of transitioning at the start of the month. For instance, if 2000 firms are rated investment grade (IG) at the start of the month, and 20 downgrade to non-prime (NP) by the end of the month, the IG to NP transition rate for that month is 1%. The red dashed line indicates December 2019, the month in which the World Health Organization (WHO) was informed for the first time about an increasing number of cases of viral pneumonia in China. In March 2020, the WHO officially announced the outbreak of the COVID-19 virus as a pandemic. In that month, a considerable peak can be observed in the transition rate from non-prime (NP) to default (D). Interestingly, also other transition rates such as IG to NP show increases over 2020 that are smaller and shorter lived

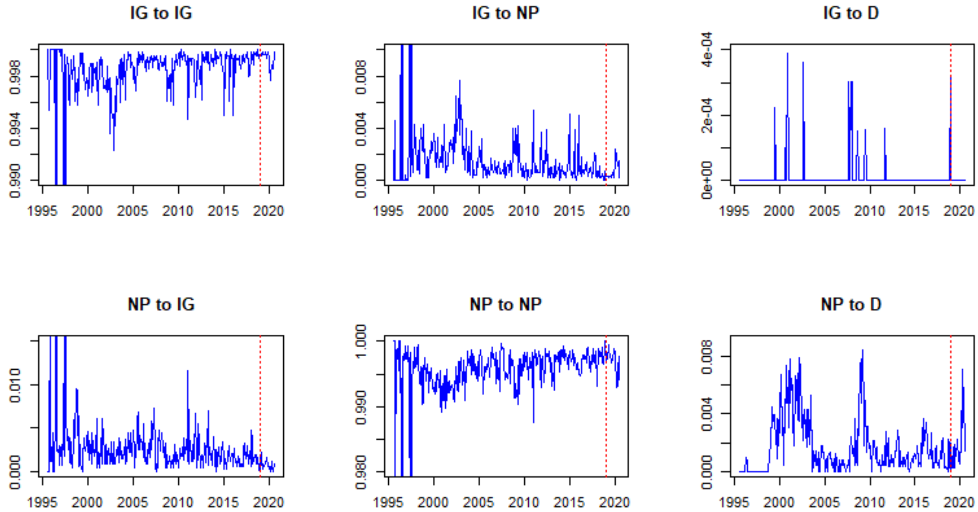


Figure 1: S&P credit rating transitions over 1995–2020

Note: empirical rating transitions from investment grade (IG) to IG, non-prime (NP) and default (D) in top row, and from NP to IG, NP, and D in bottom row over the period Aug 1995–Aug 2020 based on S&P ratings. Vertical dashed line (in red) indicates December 2019.

than those following the 2008 financial crisis. One of the reasons could be that government support measures "artificially" prevented a deterioration in ratings and an increase in defaults. We come back to this later.

Figure 1 also shows that jumps from investment grade (IG) to default (D) are scarce and noisy. This is an institutional feature of the rating process. Unless there are sudden large shocks (such as the Lehman default in 2008) or fraud revelations, IG rated firms typically only move into default more gradually via intermediate downgrades to the NP category, a feature known as rating momentum.

2.2 Macroeconomic variables

The macroeconomic variables are obtained from the Federal Reserve Economic Data (FRED) database. To measure fundamental economic activity, we use monthly observations of annual growth rates in the US Industrial Production (IP) index. Figure 2 shows the corresponding time series. From

Figure 2: Economic activity measured by year-to-year monthly growth rate in US industrial production (IP). Vertical dashed line (in red) indicates December 2019.

March 2020 onwards, we observe large negative IP growth rates, in particular the severe -16.3% and -15.7% drops in April and May 2020. These initial extreme decreases are related to the COVID-19 lockdown and the corresponding freeze of the economy. The partial recovery of the economy in the period after is due to the government stimulus measures. This readjustment is more apparent in case we consider the more noisy month-to-month IP growth rates (not shown here). In that series, a drastic trough of -12.7% in April 2020 is followed by a stabilization ($+0.7\%$) in May and continues to recover with a $+6.2\%$ growth rate in June 2020.

The macroeconomic activity index also reveals another interesting result. The decline in activity in 2020 is of comparable magnitude (though shorter lived) as in the 2008 financial crisis, and larger than during the 2000 burst of the dotcom bubble. The NP to default frequencies in Figure 1 appear to show a comparable pattern, except that the increase in defaults in the early 2000s is much more pronounced. By contrast, the IG to NP downgrade frequencies appear more benign during the COVID-19 pandemic than in the aftermath of the financial crisis, and certainly smaller than in the early 2000s. The patterns reveal that it is quite challenging to relate default and downgrade activity to macroeconomic activity across this range of crisis. The frailty model introduced in the next section therefore also allows credit markets to be partly driven by their own dynamics alongside economic activity.

3 Empirical modeling framework

To measure credit risk and its co-movement with macroeconomic fundamentals, we use a condensed version of the dynamic ordered logit model of Creal et al. (2014). Ordered logit and probit models are the standard framework underlying many of the credit risk models currently used in banking, such as CreditMetrics. Our dynamic extension of the model allows us to include macroeconomic observable variables as well as unobserved latent components to link credit risk to macro developments. The *ordered* logit specification explicitly accounts for the ordinal nature of credit rating data and, as such, has the distinct advantage over multinomial logit or probit modeling appoaches as found in for instance Koopman et al. (2008, 2009). We briefly explain the basic model and its estimation in Section 3.1 and its dynamic extension of Creal et al. (2014) in Section 3.2.

3.1 A frailty model for credit risk and macro fundamentals

As discussed in Section 2, we consider time series observations of a set of macroeconomic variables y_t^M, as well as of rating migration counts $y_{i,j,t}^R$, where $t = 1, \ldots, T$, $i = 1, 2$, and $j = 1, 2, 3$, with $i = j = 1 = IG$, $i = j = 2 = NP$, and $j = 3 = D$. Here $y_{i,j,t}^R$ denotes the number of firms that migrated from rating i to rating j between $t-1$ and t. We also define the number of firms $n_{i,j,t}$ that are rated in category i at time $t-1$, and rated in category j or higher at time t as $n_{i,j,t} = \sum_j y_{i,j,t}$, where we used the fact that we condition on firms being rated both at $t-1$ and t. The total number of firms considered in the sample in period t is $n_{i,t} = n_{i,1,t} = \sum_{j=1}^{3} y_{i,j,t}$. Note that $n_{i,t}$ is already known at time $t-1$, as we know the number of firms in the sample at the start of each period. We stack all rating and exposure series $y^R_{i,j,t}$ and $n_{i,t}$ into vectors y^R_t and n_t, respectively.

Our general model uses latent factors to link the dynamics of the macro variables y^M_t with those of the credit risk observations y^R_t. More specifically, we assume that

$$y^M_t = \mu^M + f^M_t + \varepsilon_t, \qquad \varepsilon_t \overset{\text{i.i.d.}}{\sim} \mathrm{N}(0, \sigma^2_\varepsilon), \tag{1}$$

$$y^R_t \sim \text{Ordered-logit}\left(\pi(f^M_t, f^R_t), n_t\right). \tag{2}$$

where, μ^M is an intercept, and $\pi(f^M_t, f^R_t)$ is a ratings transition matrix from rating i (row) into rating j (column), which satisfies a particular structure that is explained later. The latent factors f^M_t and f^R_t are not observed. Though we can easily allow for higher dimensional f^M_t and f^R_t, we take both common factors as univariate in our current set-up.

The macro factor f^M_t influences the model in two different places. First, the macro unobserved or frailty factor directly influences the macro observations in equation (1). Second, the macro factor also influences the credit risk observations via equation (2). We expect positive economic conditions to increase upgrade probabilities and simultaneously decrease downgrade and default probabilities. The rating transitions y^R_t are also influenced by a second, unobserved factor f^R_t. This second factor picks up any systematic variation in rating probabilities above and beyond what is already captured by the macroeconomic factor f^M_t. Prime candidates can be changes in the lending climate or in lending standards, but also changes in financial market conditions. In our current context, f^R_t may also pick up unmodeled government support packages that affect credit risk incidence outside general fundamental macro conditions.

In order to model the rating transition probability matrix $\pi(f^M_t, f^R_t)$ of the ordered logit, we first define the cumulative probabilities $\tilde{\pi}_{i,j,t}(f^M_t, f^R_t) = \mathbb{P}[R_{k,t} \geq j \mid R_{k,t-1} = i, f^M_t, f^R_t]$, i.e., the probability that the rating of firm k at time t, denoted by $R_{k,t}$, equals or exceeds j given that its rating at time $t-1$ is given by i. These cumulative probabilities are well-defined due to the ordinal nature of credit ratings. The cumulative probabilities $\tilde{\pi}_{i,j,t}(f^M_t, f^R_t)$

have a standard logistic specification:

$$\tilde{\pi}_{i,j,t}(f_t^M, f_t^R) = \frac{\exp\left(\mu_{i,j}^R + \gamma_i f_t^M + \delta_i f_t^R\right)}{1 + \exp\left(\mu_{i,j}^R + \gamma_i f_t^M + \delta_i f_t^R\right)}, \tag{3}$$

for $i = 1, 2$ and $j = 2, 3$, and where we set $\tilde{\pi}_{i,1,t} \equiv 1$ and $\tilde{\pi}_{i,4,t} \equiv 0$ for $i = 1, 2$. The intercepts $\mu_{i,j}^R$, and the factor loadings γ_i and δ_i are all parameters to be estimated from the data. For identification, we have to impose a restriction on one of the δ_i parameters. Without loss of generality, we set $\delta_2 = \delta_{NP} = 1$. Empirically, this is the most sensible solution as most of the signal on the default frailty factor is then taken from the non-prime to default transition frequencies. We do not need a similar restriction on the γ_i, as the macro frailty factor is already defined from the macro data via equation (1). Note that the dependence of γ_i and δ_i on the initial rating i and not on the output rating j, induces the ordered logit structure for the probabilities: per initial rating, the thresholds $\mu_{i,j}^R + \gamma_i f_t^M + \delta_i f_t^R$ for all output ratings j move in parallel, both in-sample and out-of-sample, following the dynamics of f_t^M and f_t^R.

Using (3), the transition probabilities follow directly as

$$\pi_{i,j,t} = \tilde{\pi}_{i,j,t} - \tilde{\pi}_{i,j+1,t}, \qquad i = 1, 2, \quad j = 1, 2, 3. \tag{4}$$

Estimation is then straightforward using maximum likelihood and the log-likelihood function is given by

$$\ell(\theta) = \ell^M(\theta) + \ell^R(\theta) = \sum_{t=1}^{T} \ell_t^M(\theta) + \ell_t^R(\theta) = \sum_{t=1}^{T} \ell_t(\theta), \tag{5}$$

$$\ell_t^M(\theta) = -\tfrac{1}{2}\log(2\pi\sigma_\varepsilon^2) - \tfrac{1}{2}\frac{(y_t^M - f_t^M)^2}{\sigma_\varepsilon^2}, \tag{6}$$

$$\ell_t^R(\theta) = \sum_{i=1}^{2}\sum_{j=1}^{3} y_{i,j,t}^R \log \pi_{i,j,t}, \tag{7}$$

where θ gathers all the static parameters in the model, such as μ^M, σ_ε^2, $\mu_{i,j}^R$, γ_i, and δ_i. The likelihood in (5) can be maximized numerically, and its inverse Hessian at the maximum can be used to compute standard errors.

3.2 Modeling the dynamics of the frailty factors

The dynamic latent factors f_t^M and f_t^R for the macro and credit variables, respectively, are likely to exhibit substantial autocorrelation. Both macro variables and the credit climate move in line with the regular pace of macro conditions. Creal et al. (2014) impose an autoregressive type structure on the factor evolution based on the score dynamics of Creal et al. (2013) and Harvey and Luati (2014). This is numerically considerably easier than a parameter driven set-up as in Koopman et al. (2011). The score-driven dynamics for the factors are given by

$$\begin{pmatrix} f_{t+1}^M \\ f_{t+1}^R \end{pmatrix} = \begin{pmatrix} \beta_M & 0 \\ 0 & \beta_R \end{pmatrix} \begin{pmatrix} f_t^M \\ f_t^R \end{pmatrix} + \begin{pmatrix} \alpha_M & 0 \\ 0 & \alpha_R \end{pmatrix} \begin{pmatrix} s_t^M \\ s_t^R \end{pmatrix}, \tag{8}$$

$$\begin{pmatrix} s_t^M \\ s_t^R \end{pmatrix} = S_t \cdot \begin{pmatrix} \partial \ell_t(\theta)/\partial f_t^M \\ \partial \ell_t(\theta)/\partial f_t^R \end{pmatrix}, \tag{9}$$

where S_t is a scaling matrix that depends on the parameters and on the factors and observations up to time t. The updates s_t^M and s_t^R in (8) modify the factors each step in order to locally improve the fit of the model given the most recent information in the data. They do so using a steepest ascent type step of the local likelihood based on the gradient (9) in order to minimize the Kullback-Leibler divergence between the model and the data; see Blasques et al. (2015). In our current setting and following Creal et al. (2014), we have

$$\frac{\partial \ell_t(\theta)}{\partial f_t^M} = \frac{y_t^M - f_t^M}{\sigma_\varepsilon^2} + \sum_{i=1}^{2} \gamma_i \cdot s_{i,t}^R, \tag{10}$$

$$\frac{\partial \ell_t(\theta)}{\partial f_t^R} = \sum_{i=1}^{2} \delta_i \cdot s_{i,t}^R, \tag{11}$$

with

$$
\begin{aligned}
s^R_{i,t} &= \sum_{j=1}^{3} y^R_{i,j,t} \cdot \frac{\tilde{\pi}_{i,j,t}(1-\tilde{\pi}_{i,j,t}) - \tilde{\pi}_{i,j+1,t}(1-\tilde{\pi}_{i,j+1,t})}{\pi_{i,j,t}} \\
&= \sum_{j=1}^{3} y^R_{i,j,t} \cdot (1 - \tilde{\pi}_{i,j,t} - \tilde{\pi}_{i,j+1,t}) \\
&= n_{i,t} \cdot \left(\frac{n_{i,2,t}}{n_{i,t}} - \tilde{\pi}_{i,2,t} \right) + \tilde{\pi}_{i,2,t} n_{i,2,t} \cdot \left(\frac{n_{i,3,t}}{n_{i,2,t}} - \frac{\tilde{\pi}_{i,3,t}}{\tilde{\pi}_{i,2,t}} \right),
\end{aligned}
\tag{12}
$$

where we have somewhat rewritten equations (10)–(12) compared to Creal et al. (2014) to better reveal the core intuition of the updates. The first term in the update for the macro factor in (10) is clearly intuitive: if the observed realization y^M_t is higher than its conditional expectation $\mu^M + f^M_t$, we update the macro factor upwards. This form of the first term in the update follows from the normality assumption in equation (1). More robust versions of the updating equations to account for possible outliers in y^M_t are easily constructed using a fat-tailed distribution instead, such as the Student's t distribution (see Harvey and Luati, 2014). In that case, the update steps are automatically downweighted if y^M_t is a tail observation.

The second term in (10) can best be understood by looking at the updates of the credit frailty factor via equations (11)–(12). These updates seem more involved, but are again highly intuitive upon closer inspection. The updates consist of two terms. The first term in (12) measures the discrepancy between the empirical frequency $(n_{i,2,t}/n_{i,t})$ of moving from rating i at $t-1$ into rating 2 or higher at time t, and its theoretically counterpart, the probability $\tilde{\pi}_{2,i,t}$. If the empirical frequency is higher than the model probability, we want to adjust the model probability upwards, which we do by moving the credit frailty factor upwards for $\delta_i > 0$, or downwards for $\delta_i < 0$. This first term is weighted by the total number of firms $n_{i,t}$. Due to the ordered logit structure, there is however a further signal. This is impounded into the second term in (12). This term measures takes the empirical conditional frequency $(n_{i,3,t}/n_{i,2,t})$ of moving from rating i at time $t-1$ into rating 3 or higher at time t *given that* the firm moved at least to rating 2 or higher. It then confronts this empirical conditional frequency with its model-implied counterpart $(\tilde{\pi}_{3,i,t}/\tilde{\pi}_{i,2,t})$. Again, if the empirical frequency is higher than its model-based counterpart, the credit frailty factor is moved upward for $\delta_i > 0$, or downward for $\delta_i < 0$.

Finally, the signals on f_t^R from the rating transitions are aggregated over all possible initial ratings i via the summation over i in (11), using the slope coefficients δ_i appropriate for each initial rating. As the macro factor f_t^M also affects all rating probabilities, there is also a second set of terms in (10). Here, of course, the contributions $s_{i,t}^R$ are weighted by the slope coefficients γ_i of the macro factor in the credit risk part of the model. If the γ_i parameters are zero, the macro factor has no effect on the credit part of the model, and, conversely, the credit observations reveal no information on how to adjust the macro factors to better fit the data.

To complete the dynamic model specification, we use the same scaling as in Creal et al. (2014) and set

$$S_t = \left[\begin{pmatrix} 1/\sigma_\varepsilon^2 & 0 \\ 0 & 0 \end{pmatrix} + \sum_{i=1}^{2} n_{i,t} \cdot c_{i,t} \cdot \begin{pmatrix} \gamma_i^2 & \gamma_i\delta_i \\ \gamma_i\delta_i & \delta_i^2 \end{pmatrix} \right]^{-1}, \tag{13}$$

$$c_{i,t} = \sum_{j=1}^{3} \frac{\left(\tilde{\pi}_{i,j,t}(1-\tilde{\pi}_{i,j,t}) - \tilde{\pi}_{i,j+1,t}(1-\tilde{\pi}_{i,j+1,t})\right)^2}{\pi_{i,j,t}}.$$

This scaling choice automatically assigns more weight to either (10) or (11), depending on whether the macro or credit part of the model contains most information on the current position of the unobserved factors f_t^M and f_t^R.

Though the model may look quite daunting at first sight, it is again easily estimated by maximum likelihood. First, we augment the vector of parameters with the parameters β_M, β_R, α_M, and α_R. Next, for a given parameter vector θ, we recursively process equation (8) to obtain f_t^M and f_t^R for all $t = 1, \ldots, T$, starting at the unconditional means $f_1^M = f_1^R = 0$. Finally, using these values for the factors, we can immediately compute the log-likelihood function (5), which can subsequently be maximized. R-code for the model is made available alongside as supplementary material.

3.3 Special cases: factors versus covariates

It is straightforward to include further explanatory variables in either the macro or credit risk part of the model as

$$y_t^M = \mu^M + f_t^M + \omega_M' z_t + \varepsilon_t, \tag{14}$$

$$\tilde{\pi}_{i,j,t}(f_t^M, f_t^R) = \frac{\exp\left(\mu_{i,j}^R + \gamma_i f_t^M + \delta_i f_t^R + \omega_{i,R}' z_t\right)}{1 + \exp\left(\mu_{i,j}^R + \gamma_i f_t^M + \delta_i f_t^R + \omega_{i,R}' z_t\right)}, \tag{15}$$

where z_t is a vector of observed covariates, and ω_M and $\omega_{i,R}$ for $i = 1, 2$ are vectors with slope coefficients for z_t that can be inserted into θ for estimation and inference.

The inclusion of covariates also allows us to reduce the model to a familiar generalized linear model as often used in the literature. For instance, by setting $\gamma_i = \delta_i = 0$ for all i, we obtain a standard static ordered logit model for credit risk, either with ($\omega_{i,R} \neq 0$) or without ($\omega_{i,R} = 0$) additional regressors.

The current set-up of the model has two distinct advantages over a specification with y_t^M as a covariate in an ordered-logit specification for y_t^R. First, if we model the macro and credit evolution jointly with unobserved components as we do, there is no need to construct a separate forecasting model for y_t^M when treated as a covariate. The forecasting model automatically follows from the dynamic specification of the macro part of the model in equation (1). Such forecasts are required if we want to use the model to compute credit risk quantiles for portfolios of loans. Second, by dealing with the macro variable as the sum of an unobserved component plus measurement noise, we allow the macro variable to have incidental large fluctuations via the measurement noise ε_t in (1) that have no direct impact on f_t^M, and therefore, have no immediate direct impact on the credit part of the model. By contrast, if y_t^M is dealt with as a covariate in the credit part of the model, any large fluctuation in y_t^M immediately impacts the predicted credit experience. Given the large fluctuations in industrial production as visualized earlier in Figure 2 this difference can play a major role when modeling the evolution of credit markets during the covid period. We will, however, still explicitly compare in the next section our current set-up with both macro and credit factors to a set-up with macro covariates in the credit part of the model.

Finally, note that we can also obtain a pure frailty driven model by eliminating the macro factor from the credit risk part of the model, i.e., by setting $\gamma_i = 0$. This can be compared to the pure frailty type models or the frailty models with or without covariates of for instance Duffie et al. (2007, 2009), Koopman et al. (2008, 2009, 2011), Azizpour et al. (2018), and Babii et al. (2019).

4 Empirical results

To investigate how the COVID-19 pandemic has influenced the relationship between credit risk and macro fundamentals, we estimate the models from the previous section on both the pre-covid (August 1995 until December 2019) and the full sample.[1] We include the complete year 2019 in our pre-covid period, as the WHO was officially informed about cases of viral pneumonia in China on the 31st of December, 2019.

4.1 Pre-covid results

The estimation results for six relevant model specifications on the pre-covid sample are in Table 1. The first model is fully static and neither has a macro nor a credit frailty variable. Given the persistent dynamics of both y_t^M and y_t^R, the model obviously fits very poorly, which we see by comparing its likelihood to that of the subsequent models. To allow the macroeconomic variable y_t^M to exhibit serial correlation and to link these dynamics to those of the credit risk variable y_t^R, the next two models introduce an unobserved macro factor y_t^M. In model 2, y_t^M only enters the macro part of the model, while y_t^R still only has static parameters. In model 3, however, f_t^M is also allowed to affect the credit rating transitions. By only adding 6 (versus 7) parameters, the total likelihood increases by 444 (versus 633) points using model 2 (respectively, model 3), resulting in a clear preference of these dynamic models compared to their static counterpart.

[1] Whereas macroeconomic variables can be found up to more recent dates, the credit rating data via WRDS/Capital IQ is only available up until August 2020.

Table 1: Estimation results (pre-covid sample)

Note: each column represents an estimated model. The top panel includes parameter estimates with corresponding heteroskedasticity-robust standard errors. The panel below displays the log-likelihood values (macro part, credit ratings part and joint) and information criteria for the different models.

	Constant (model 1)	Macro frailty (model 2)	Macro frailty in credits (model 3)	Macro frailty in credits & credit frailty (model 4)	Macro frailty with credit covariate (model 5)	Macro frailty, credit frailty & credit covariate (model 6)
μ^M	1.757	4.472	4.123	4.181	4.472	4.472
	(0.240)	(0.502)	(0.872)	(0.786)	(0.502)	(0.502)
σ_ε^2	16.854	0.806	0.700	0.686	0.806	0.806
	(2.570)	(0.107)	(0.107)	(0.104)	(0.107)	(0.107)
α_M		1.147	0.983	1.005	1.147	1.147
		(0.065)	(0.057)	(0.101)	(0.065)	(0.065)
α_R				0.209		0.180
				(0.050)		(0.109)
β_M		0.979	0.977	0.977	0.979	0.979
		(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
β_R				0.939		0.947
				(0.034)		(0.032)
μ_{11}^R	-6.550	-6.550	-6.618	-6.652	-6.538	-6.654
	(0.070)	(0.071)	(0.101)	(0.168)	(0.065)	(0.192)
μ_{12}^R	-11.337	-11.337	-11.405	-11.439	-11.325	-11.441
	(0.286)	(0.286)	(0.291)	(0.313)	(0.287)	(0.323)
μ_{21}^R	5.982	5.982	5.814	5.850	6.187	6.174
	(0.086)	(0.086)	(0.134)	(0.183)	(0.067)	(0.112)
μ_{22}^R	-6.437	-6.437	-6.711	-6.729	-6.377	-6.428
	(0.062)	(0.062)	(0.116)	(0.150)	(0.055)	(0.141)
γ_1			-0.023	-0.010		
			(0.015)	(0.025)		
γ_2			-0.083	-0.072		
			(0.012)	(0.022)		
δ_1				1.194		1.609
				(0.327)		(2.038)
δ_2				1		1
				—		—
$\omega_{1,R}^{IP}$					-0.010	-0.004
					(0.018)	(0.035)
$\omega_{2,R}^{IP}$					-0.094	-0.093
					(0.012)	(0.033)
$\ell^M(\theta)$	-826.7	-382.8	-426.3	-417.6	-382.8	-382.8
$\ell^R(\theta)$	-38,873.2	-38,873.2	-38,640.7	-38,430.1	-38,654.2	-38,423.2
$\ell(\theta)$	-39,699.9	-39,256.0	-39,066.9	-38,847.7	-39,036.9	-38,806.0
AIC	79,411.8	78,528.0	78,153.9	77,721.3	78,093.9	77,638.0
BIC	79,433.9	78,557.4	78,190.6	77,769.1	78,130.7	77,685.8

For both models, the macro frailty factor is highly persistent with $\widehat{\beta}_M \approx 0.98$. The introduction of a dynamic specification leads to an obvious major reduction in the estimated value of σ_ε^2. Most importantly, however, are the γ_i coefficients in model 3. There is no convincing evidence on the impact of the macro variable on investment grade (IG) rating dynamics as γ_1 is statistically insignificant. The coefficient γ_1 is, however, still negative as expected, with higher growth coinciding with fewer downgrades and defaults. Note that the months in 2020 are excluded from the current sample, such that the covid period does not affect the estimation results in Table 1. Turning to γ_2, there is clear statistical evidence for the impact of macroeconomic activity on the non-prime (NP) rating dynamics. Again the sign is negative as expected, such that higher growth correlates with fewer defaults and more upgrades.

We also see that the macro factor has to balance the information in the two parts of the data: macro and credit data. The increase in likelihood from model 1 to model 2 can be entirely attributed to the macro part of the model. When moving from model 2 to 3, however, we see a large increase in likelihood for the credit part of the model, but a decrease in likelihood for the macro part of the model. This is the first sign that the macro and credit dynamics may not align, even in the pre-covid period, and that a single unobserved component cannot capture both dynamics at the same time.

Figure 3 compares the empirical (blue solid line) and model-induced (red dashed line) transition probabilities. We observe that the model captures the default dynamics reasonably well, in particular the NP–D transition (bottom right). It underestimates, however, the large peak in non-prime defaults following the 2008 financial crisis. In addition, the factor fails to set the expected default rate close to zero during extensive periods where the experienced defaults are very low, such as around 2005, 2011, or 2014.

To improve the model's fit during times of distress as well as during uneventful times, we introduce a separate credit risk frailty factor into the model, which leads us to model 4 in Table 1. The value of the log-likelihood increases by more than 200 points in the credit part of the model for just 3 extra parameters. The likelihood also increases for the macro part of the model, but not to the extent as in model 2, where the macro factor can be fully exploited to pick up the macro dynamics. This suggests that the

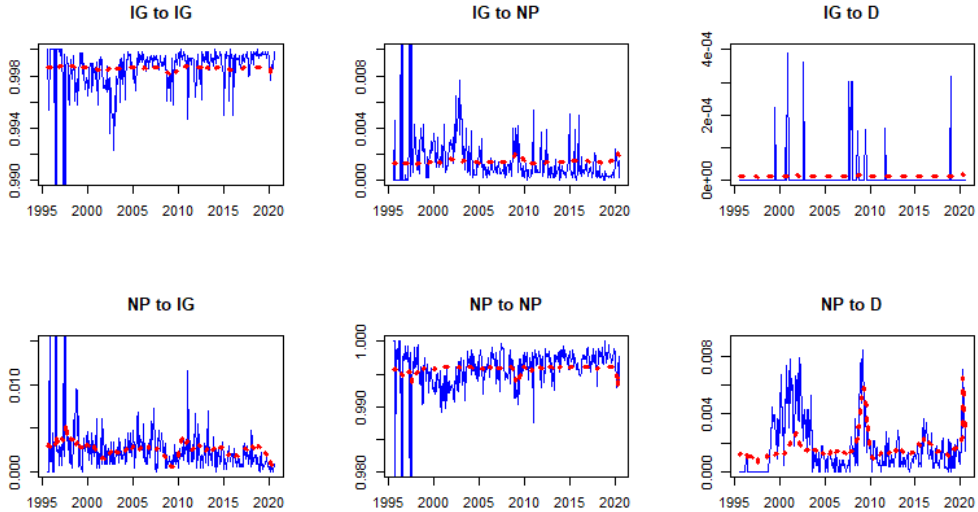


Figure 3: Empirical rating transitions (blue) and model induced probabilities (red) for the model with macro frailty in credits (no credit frailty)

macro fundamentals are still important for the credit experience, something underlined by the significance of the γ_2 coefficient in model 4. The parameter δ_1 is estimated close to one, indicating that the credit frailty factor f_t^R is roughly equally relevant for both investment-grade and non-prime rating dynamics. All of the credit data can thus be used to back out the credit frailty dynamics.

Figure 4 shows the fit of the different models. Note that we estimated the models on the pre-covid sample only, but also evaluate their fit over the covid period, each time using the data available up to that moment to obtain the estimates of the unobserved factors f_t^M and f_t^R. For the macro part of the model, we see that there is very little difference between the fit of models 3 and 4. For the credit part, out of the 6 possible rating transition rates, we focus on the non-prime to default series, which provides the clearest picture. We see that the fit to the NP default rate of model 4 compared to 3 improves over the pre-covid sample: the peak in defaults during the financial crisis and the height and dynamics of the default rate during the early 2000s are captured better. Also the low default rates during the relatively calm periods

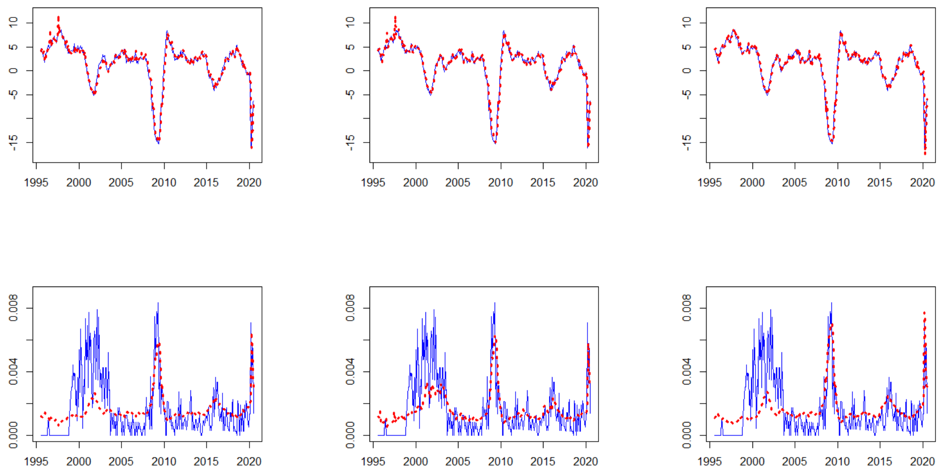


Figure 4: Macro fit (top row) and NP-D fit for model 3, 4 and 5

Note: Top row shows the macro variable annual IP growth in solid blue and estimated $\mu^M + f_t^M$ in dashed red. Bottom row shows realized transition probabilities in solid blue and the model-induced counterparts in dashed red.

preceding and following the 2008 crisis, which were too high in model 3, are closer to zero in model 4. Interestingly, both models also provide a reasonable fit over the covid period using the extreme realizations of the IP series early 2020. The relations thus appear reasonably stable over time for the sample at hand, even if the stressed covid period is not part of the estimation sample.

In model 5, we consider a model close to the generalized linear regression models often used in the literature. In this model, we include industrial production growth directly as a covariate in the credit part of the model. The coefficients for industrial production $\omega_{i,R}^{IP}$ both have the expected negative sign, but only the coefficient for the non-prime rating dynamics $(\omega_{2,R}^{IP})$ is statistically significant. Still, using the macro variable as a covariate in the credit part of the model does not seem like a good idea. Though the total likelihood is higher for model 5 than for model 3, it is still lower than that of model 4. Even the increase with respect to model 3 is only due to the macro part of the model: the likelihood for the credit part $\ell^R(\theta)$ actually deteriorates from model 3 to model 5, suggesting that an approach based on unobserved components like model 3 or 4 is preferable for the credit data.

If we look at model 5's fit to the non-prime default rate in Figure 4, we see that using the macro variable as a covariate changes the overall picture somewhat. In particular, we see that when we evaluate the model over the covid months of 2020, we overestimate the NP default rate substantially. This is of course understandable: the lockdown measures during the pandemic were unprecedented, and the corresponding collapse in economic growth were much larger than in pre-covid times. The credit experience did not move in tandem due to government measures, but possibly also relaxed lending standards and re-negotiations between the financial sector and debtors. In fact, we see a partial delinkage between the credit experience and the macro fundamentals during covid times when directly used as a covariate. Again, we conclude from this that the usual modeling approach based on macro covariates may not be a good idea when moving into distressed times, and that a model based on frailty factors may be much better at picking up the default dynamics.

Note that across all model specifications, both the persistence (β_M) and the size (α_M) of the credit frailty factor remain robust, as well as the rating bucket intercepts (μ_{ij}^R). This also holds for the final model specification, model 6, where we extend model 5 to also include a credit frailty factor. The value of $\ell^R(\theta)$ relating to the credit part of model in this case is comparable between models 4 and 6, with a limited increase of only 7 points. The parameter δ_1 now turns substantially larger than before with a larger standard error, rendering it insignificant, signaling some potential instability of model 6. The fit (not shown) of model 6 is comparable to that of model 4 in the pre-covid sample, but to model 5 during covid: also in model 6 the use of industrial production growth as a covariate leads to overestimation of the default experience given the extreme drop in IP growth during covid for a default-macro relation that is estimated over a pre-covid period. For this reason, and given the very small log-likelihood increase from model 4 to 6, we take model 4 as our benchmark in the subsequent analysis. This is the more relevant for the forecasting context to which we turn next, as model 4 does not need any auxiliary model for forecasting covariates, whereas model 6 would.

4.2 COVID-19 from a credit risk perspective

In the previous subsection, we estimated all models over the pre-covid sample and evaluated their fit both pre-covid and after. In this section, we use the same models for forecasting purposes from a credit risk perspective. In particular, we are interested whether any of the models is able to predict the increased default incidence during the COVID-19 pandemic well in advance based on extreme credit risk quantiles. We consider a 12-month-ahead forecasting horizon. At this horizon, we either forecast the one-month transition frequencies, or the integrated transition frequencies over the past 12 months. For clarity, we focus on the non-prime (NP) to default (D) transition frequencies.

We use estimates based on the pre-covid sample only. For forecasting the one month transition frequencies at the horizon T, we run the model filter up to time $T-12$ to obtain our estimates of f_t^M and f_t^R. These are then used to generate the next factor values f_{t+1}^M and f_{t+1}^R via the transition equations (10)–(12), which result in the next transition matrix $\pi(f_{t+1}^M, f_{t+1}^R)$. This new transition matrix can be used to generate realizations of y_{t+1}^M and y_{t+1}^R, which can then be used to update to f_{t+2}^M and f_{t+2}^R. The process is repeated from $T-11$ to T, and the simulated distribution for time T is used to derive the mean forecast and the quantiles. We use 100,000 simulations.

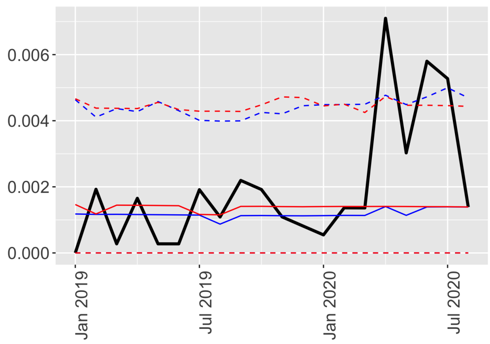
Note that generating the forecasts would also require a forecasting model for the covariates if these are present in the model. By contrast, the frailty based models do not require such an auxiliary model, as the macro variable is modeled simultaneously with the credit risk factor. We therefore restrict our attention to model 4. Note that this model had a very similar fit to the model with the macro variable treated as a covariate (model 6). Model 4 therefore provides an adequate benchmark for a model where macro and credit frailty factors jointly determine future credit risk experience. As a second model, we consider a 'pure frailty' type model 4′, where we break the link from macroeconomic fundamentals to the credit experience by putting $\gamma_i = 0$ for $i = 1, 2$. Credit risk is in this setting purely driven by an unobserved component, that does not need to adapt itself to macro dynamics as well.

Rather than only looking at the default experience in a single month, we also consider a compound 12-month NP-Default rate based on the empirical transition frequencies for $T-11, \ldots, T$, treating default as an absorbing state. Let $\hat{\pi}_{T-k}$ for $k = 0, \ldots, 11$ denote a 3×3 empirical transition matrix with its first two rows equal to the empirical transition frequencies for that month, and the bottom row equal to $(0, 0, 1)$. We estimate the compound 12-month NP-Default rate by the (2,3) element of $\hat{\pi}_{T-11}\hat{\pi}_{T-10} \cdots \hat{\pi}_T$. We also compute the same compound frequencies for all 100,000 simulations, thus obtaining mean forecasts and the corresponding quantiles.

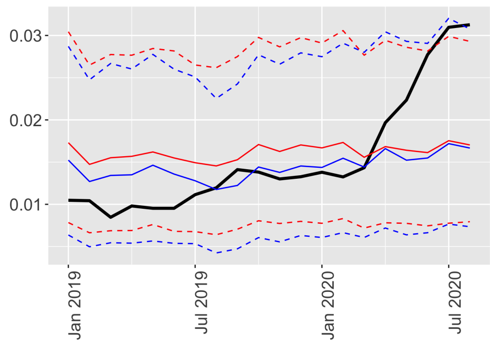
The results are presented in Figure 5. If we look at Figure 5a, models 4 and 4′ result in similar patterns, both for the 1 month and compound 12 month default rate forecasts. Note that both forecasts are constructed using a 12-month-ahead horizon. It is hard to forecast the increased default experience during the pandemic for specific months, which we see by the credit VaR violations in April, June and July 2020. This is due to the low levels in the pre-covid period. Starting from such low levels, there are very few scenarios that result in such high 1-month default rates as actually experienced mid 2020.

Hitting particular credit risk realizations in specific months more than a year in advance is quite a challenging exercise. If Figure 5b we see the performance of the 12 months compound default rate forecasts. Looking at the black line, we see a different empirical pattern than in Figure 5a. The default experience over 12 month periods starts going up with the start of the COVID-19 period, and keeps rising as more months in the pandemic are added as the high default numbers are repeated over these COVID-19 months, while preceding low credit incidence months from the pre-covid period drop out of the 12 month forecasting horizon.

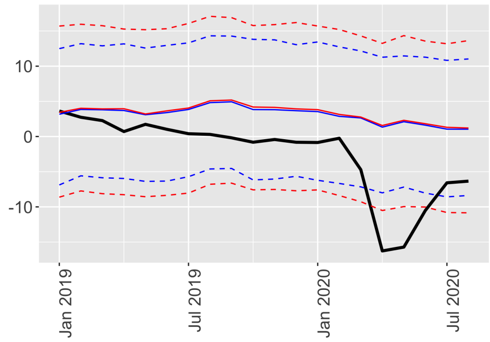
For this more realistic setting, we see interesting differences between models 4 and 4′. Model 4 (in blue) which models a macro factor and links it back to the credit experience impounds the worsening economic conditions over 2019 more clearly in the credit risk forecast and its quantiles. We can see this back in the macro forecasts and risk quantiles in Figure 5c. The median IP annual growth forecast 12 months ahead of the forecasting horizon gradually shifts down for both model 4 and 4′. This move is not linked back to the credit dynamics in model 4′, causing the red curves in Figure 5b to move rather



(a) 1m NP-Default rate



(b) 12m NP-Default rate



(c) 1m IP index growth

Figure 5: 12-month-ahead forecasts

Note: The top-left panel contain the one-month NP-Default rates in black The top-right panel holds the 12 month compount default rate constructed at time $T-12$ by multiplying the monthly empirical rating transition matrices for periods $T-11, \ldots, T$. The bottom graph holds the Industrial Production index growth realization. The blue curves are the median forecast with 0.01% and 99.99% quantiles based on model 4 with macro and credit frailty factors, and the macro factor also entering the credit equation ($\gamma_i \neq 0$). The red curves are based on model $4'$ with macro and credit frailty factors, but the macro factor not entering the credit equation ($\gamma_i = 0$).

horizontally. By contrast, the NP default rate forecasts for model 4 start a bit lower, but increase gradually by the macro-credit linkage as economic conditions worsen over 2019. Looking more closely at the 1 month rates in Figure 5a, we see a similar movement of the median forecast, though smaller in magnitude. In the end, this causes the macro and frailty model's quantiles for the 12month compound default rate to even exceed the credit risk experience up to Aug 2020, though it is clearly a close call. It is also clear that the normality assumption for the macro variable is inadequate to capture the

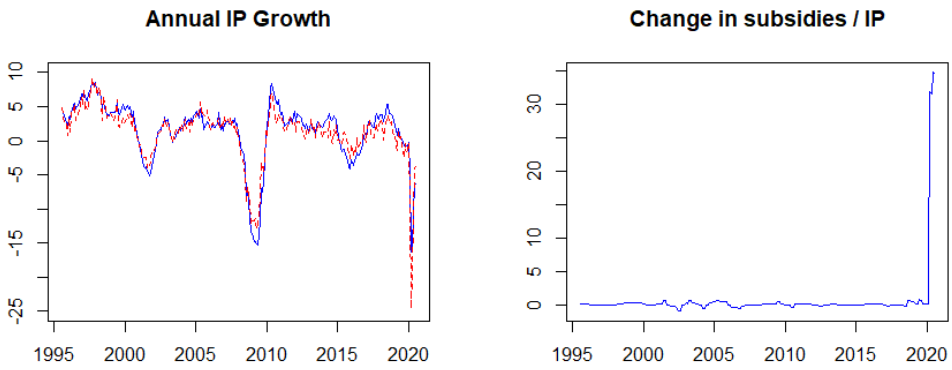


Figure 6: IP growth and government subsidies 1995–2020
Note: Left panel displays the annual growth in the industrial production expressed as an index (blue solid) and in billion dollars (red dashed) in percentages. Right panel shows a time series constructed as the annual difference in subsidies divided by annual IP growth.

sudden drops in economic activity due to the lock-down. Though the gradual decrease of IP growth is well covered by the 99.99% quantiles, this does not hold for April and June 2020. Further enhancements of the model to allow for fatter-tailed macro shocks could alleviate this issue. Overall, however, we conclude that macro-credit risk models based on unobserved components survive the initial COVID-19 stress reasonably well, not only at a one-month horizon as in Figure 4, but also at more relevant longer horizons.

4.3 COVID-19 times and government subsidies

In Section 4.1, we observed that there is a possible delinkage between the credit experience and macro fundamentals in the form of IP growth during the COVID-19 pandemic. In particular, we concluded that a model with a macro covariate tends to overestimate the NP default rate in the covid months whenever we estimate the parameters on the pre-covid sample. During the lockdown period in 2020, the government compensated the freeze of the economy by means of business support packages. Therefore, it is worthwhile to investigate whether the inclusion of government subsidies as an additional covariate in the credit risk models leads to a recovery of the macro-credit relationship.

The left panel in Figure 6 displays two series of annual IP growth. One of the series is equal to our former series based on the IP index growth (in blue). To make our subsidies variable comparable to the industrial production growth, however, we first retrieve both industrial production (GVIPT50002S) and total subsidies (B096RC1Q027SBEA) from the FRED database in billions of dollars on a seasonally adjusted basis. The red curve in the left panel of Figure 6 provides the annual growth of this new IP series in billions. We observe that the annual IP growth for the original IP index and for the new series in billions behave very similarly and only differ somewhat more at the troughs of the 2008 financial crisis and the covid lockdown period. Whereas the negative growth is smaller for the series based on billion dollars (red) during the 2008 financial crisis, we see a much larger decrease during the first months of the COVID-19 pandemic when compared to the data based on the index (blue). We put our subsidies variable on a similar scale by looking at the annual change in subsidies expressed as a fraction of last year's IP level, all in bilions. The result is presented in the right-hand panel of Figure 6. It is clear that the extent of government support in the form of subsidies is unprecedented in the sample. As a result, the variable almost acts as a level dummy for the covid months in the sample. More subtle movements become apparent if the data could be extended by further months of the covid period, which at the moment of writing are not available from the Capital IQ database. Of course, the variable includes a whole variety of packages, not all relating to cover the industrial production loss due to the lockdown. As a first attempt, however, the variable may capture the compensating government activity during covid times.

To investigate the effect of government support packages on the credit risk experience, we re-estimate models 3 up to 6 both on a pre- and post-covid sample with the growth in subsidies as an extra credit covariate. The results can be found in Table 2. We observe that the estimated μ^M is lower in the post-covid period, which is due to the severe drops in April and May 2020. These large fluctuations also lead to an increase in the σ_ε^2 estimate. Most importantly, we observe a clear sign of parameter instability for $\omega_{1,R}^{SUBS}$. The coefficients for the subsidies variable are mostly insignificant, both pre-covid and full-sample. One interesting feature is the relatively high pre-

Table 2: Estimation results including subsidies

Note: each column represents an estimated model. The top panel includes parameter estimates with corresponding heteroskedasticity-robust standard errors. The panel below displays the log-likelihood values (macro part, credit ratings part and joint) and information criteria for the different models.

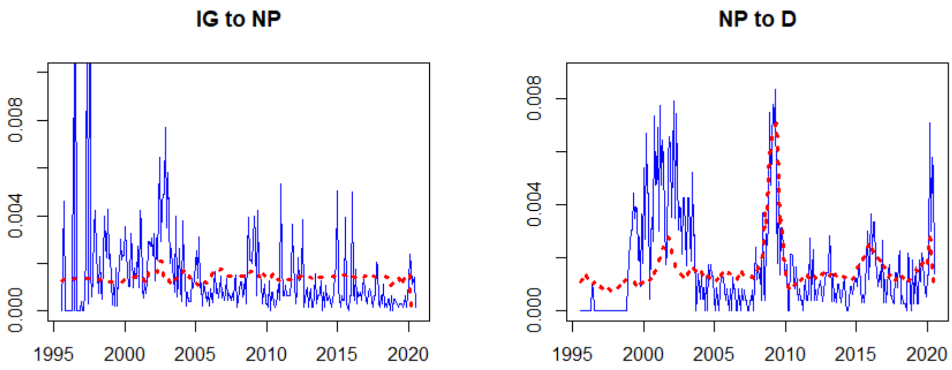
	Macro frailty in credits (model 3)		Macro frailty in credits & credit frailty (model 4)		Macro frailty with credit covariate (model 5)		Macro frailty, credit frailty & credit covariate (model 6)	
	pre	post	pre	post	pre	post	pre	post
μ^M	4.465	3.225	4.184	3.694	4.476	4.139	4.475	4.139
	(0.497)	(1.651)	(0.785)	(1.443)	(0.500)	(1.109)	(0.500)	(1.109)
σ_ε^2	0.794	1.220	0.692	1.172	0.806	1.337	0.806	1.337
	(0.105)	(0.410)	(0.104)	(0.360)	(0.107)	(0.382)	(0.107)	(0.382)
α_M	1.132	0.966	1.012	1.083	1.147	1.269	1.147	1.269
	(0.070)	(0.080)	(0.097)	(0.195)	(0.065)	(0.141)	(0.065)	(0.141)
α_R			0.205	0.207			0.176	0.178
			(0.051)	(0.065)			(0.110)	(0.098)
β_M	0.980	0.958	0.977	0.963	0.979	0.963	0.979	0.964
	(0.022)	(0.033)	(0.024)	(0.036)	(0.023)	(0.037)	(0.023)	(0.037)
β_R			0.942	0.937			0.951	0.945
			(0.034)	(0.034)			(0.031)	(0.033)
μ_{11}^R	-6.568	-6.612	-6.646	-6.622	-6.515	-6.535	-6.627	-6.629
	(0.138)	(0.094)	(0.169)	(0.146)	(0.067)	(0.064)	(0.200)	(0.178)
μ_{12}^R	-11.355	-11.426	-11.433	-11.436	-11.302	-11.349	-11.414	-11.444
	(0.293)	(0.292)	(0.315)	(0.306)	(0.287)	(0.287)	(0.326)	(0.317)
μ_{21}^R	6.104	5.903	5.850	5.953	6.189	6.196	6.184	6.196
	(0.131)	(0.170)	(0.186)	(0.186)	(0.069)	(0.067)	(0.115)	(0.108)
μ_{22}^R	-6.460	-6.630	-6.730	-6.635	-6.374	-6.391	-6.418	-6.429
	(0.114)	(0.152)	(0.154)	(0.157)	(0.057)	(0.055)	(0.138)	(0.128)
γ_1	-0.007	-0.028	-0.016	-0.007				
	(0.027)	(0.013)	(0.025)	(0.024)				
γ_2	-0.019	-0.074	-0.075	-0.050				
	(0.023)	(0.014)	(0.021)	(0.028)				
δ_1			1.172	1.052			1.602	2.574
			(0.293)	(0.206)			(2.077)	(1.927)
δ_2			1	1			1	1
			—	—			—	—
$\omega_{1,R}^{SUBS}$	-0.003	-0.016	-0.291	-0.008	-0.404	-0.012	-0.266	-0.005
	(0.032)	(0.008)	(0.216)	(0.013)	(0.240)	(0.009)	(0.235)	(0.012)
$\omega_{2,R}^{SUBS}$	-0.076	0.012	0.004	0.019	-0.032	-0.001	-0.053	0.002
	(0.025)	(0.010)	(0.173)	(0.016)	(0.156)	(0.007)	(0.172)	(0.013)
$\omega_{1,R}^{IP}$					-0.014	-0.012	-0.010	-0.007
					(0.018)	(0.017)	(0.037)	(0.034)
$\omega_{2,R}^{IP}$					-0.094	-0.093	-0.095	-0.092
					(0.011)	(0.012)	(0.032)	(0.032)
$\ell^M(\theta)$	-383.0	-527.8	-414.7	-500.6	-382.8	-469.2	-382.8	-469.2
$\ell^R(\theta)$	-38,651.3	-39,881.2	-38,427.8	-39,695.4	-38,642.4	-39,881.7	-38,419.5	-39,654.4
$\ell(\theta)$	-39,034.3	-40,408.9	-38,842.5	-40,196.0	-39,025.2	-40,350.9	-38,802.3	-40,123.7
AIC	78,092.6	80,841.9	77,715.0	80,422.0	78,074.4	80,725.8	77,634.6	80,277.3
BIC	78,136.7	80,886.3	77,770.2	80,477.6	78,118.5	80,770.3	77,689.7	80,332.9

covid magnitude of $\omega_{1,R}^{SUBS}$, though still statistically insignificant. This size is consistent in specifications 4 to 6, and negative as expected, but disappears if the covid months are added. Note that most of the other coefficients show a similar type of magnitude pre and post covid.

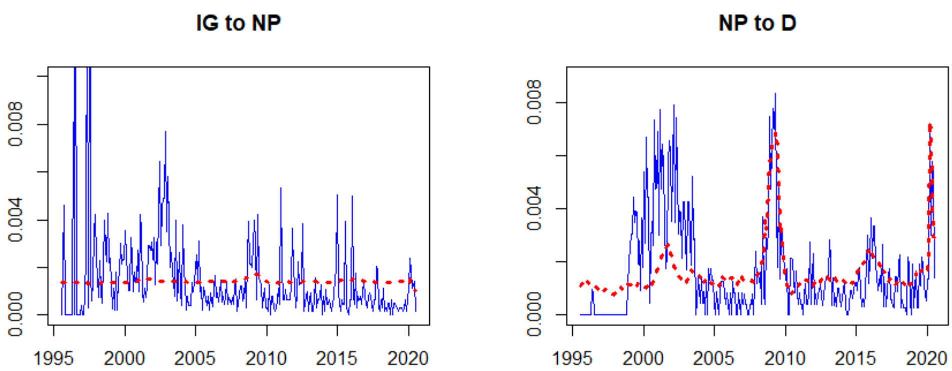
To investigate the effect of the new covariates on credit risk dynamics, Figure 7 shows the empirical rating transitions (blue) and model-induced probabilities (red) for model 5 with the new covariate included. We take model 5, as it is arguably the specification that most empiricists would like, being fully based on observables without unobserved components. The top panel shows the results when estimating all parameters on the pre-covid data only and predicting the rating transitions on the basis of those estimates. Rather than the subsidies variable repairing the macro-credit link, we observe that the predicted IG-NP downgrade probabilities now move downward during the covid months (red curve in top-left panel), whereas the realized transition rates actually move up. Also the NP-Default frequencies move much more up (blue) during covid than captured by the model with the new covariate.

To explain why this happens, we focus on the difference between $\omega_{1,R}^{SUBS}$ in the pre- and post-covid sample. In model 4 up to 6, the pre-covid estimated values are -0.291, -0.404 and -0.266 respectively. This means that an increase in subsidies leads to a rather substantial decline in the IG-NP downgrade probability and the NP-D default probability. Note, however, that this effect is clearly overstated, as the estimates for $\omega_{1,R}^{SUBS}$ drop to -0.008, -0.012 and -0.005 respectively for the full sample. The large economic effects of the COVID-19 pandemic were unprecedented and the relationship of the credit experience with the subsidies variable cannot be extrapolated from the pre-covid period into the pandemic.

In the lower panel of Figure 7, we present the fit of model 5 for the full sample. The model fits extremely poorly to the IG downgrade probability to NP, essentially producing a flat line over the entire period. For the NP to D transitions, we find that whereas the model is unable to mimic the large peak in NP defaults *ex ante*, it performs much better when estimated on the full sample. The usefulness of such a model is however limited, as it can only be constructed *ex-post*, again stressing the instability of the subsidies-rating linkage over the covid crisis. By contrast, the models with unobserved



(a) Pre-covid sample



(b) Full sample

Figure 7: Rating deteriorations based on model 5

Note: Model 5 has two credit covariates: (i) change in subsidies divided by IP and (ii) IP growth. The considered deteriorations are from IG to NP and NP to D. Panel (a) compares empirical rating transitions (solid blue) and model-induced probabilities (dashed red) on the pre-covid sample. The last 8 observations follow from applying the updating filter. Panel (b) is based on estimation on the full sample.

components and the additional covariate appear to cope much better with this transition. Their fit (not shown) actually remains good over the entire sample, with a slightly sharper peak and some overshooting during the covid months. Again, this underlines the usefulness of these models to capture unforeseen circumstances.

5 Conclusion

We investigated corporate credit risk dynamics over the early course of the COVID-19 pandemic. More specifically, we compared credit risk models based on observed macroeconomic variables as well as unobserved factors and credit frailty dynamics. Using a rating transition modeling set-up, we showed that credit risk models that are purely based on observable covariates typically suffer from instability problems from the pre-covid period to the early covid months. By contrast, models based on unobserved components and frailty dynamics appear to be better at capturing the credit dynamics, even under extreme times such as the COVID-19 pandemic. The suitability of credit risk models based on unobserved components survives if we move further out of sample and use the model for credit VaR determination.

Fixing the credit-macro link using ready-at-hand new covariates like government subsidies to capture government support packages do not result in the desired effect. The relation between subsidies and credits does not survive the transition into the covid period given the unprecedented size of the government packages. By contrast, models based on covariates only that use this additional covariate, actually perform worse than before in a 1-month out of sample context. Models based on unobserved components again fare better in this respect.

The current study into the effect of COVID-19 on corporate debt markets and credit risk models can be seen as a first step in a broader research agenda. For instance, an obvious extension is to include more months of the covid period as soon as these become available to see what their effect is on the models used. Other directions include the incorporation of more observed risk drivers, possibly including firm specific ones. As we already know, however, from for instance Duffie et al. (2009), such additional covariates do not remove the need to also include unobserved frailty factors. Finally, it might be interesting to also incorporate extremal dependence between macro and credit risk dynamics, as well as fatter-tailed scenarios for the macro evolution itself. This might lead to more prudent risk quantiles, also for the longer stretch of elevated default levels that we expect beyond our sample. We leave all of these extensions for future research.

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