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Covid-19, credit risk management modeling, and government support

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We investigate rating and default risk dynamics over the covid-19 crisis from a credit risk modeling perspective. We find that growth dynamics remain a stable and sufficient predictor of credit risk incidence over the pandemic period, despite its large, short-lived swings due to government intervention and lockdown. Unobserved component models as used in the recent credit risk literature appear mainly helpful for explaining the high-default wave in the early 2000s, but less so for default prediction above and beyond growth dynamics during the 2008 financial crisis or the early 2020 covid default peak. Government support variables do not reduce the impact of either growth proxies or unobserved components. Correlations between government support and credit risk are different, however, during the financial and the covid crisis. Using the empirical models in this paper as credit risk management tools, we show that growth factors also suffice to predict credit risk quantiles out-of-sample during covid times.

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1. Introduction

By now, a fair number of papers have investigated the impact of the covid-19 pandemic on debt markets; see for instance Augustin et al. (2022), Hawley and Wang (2021), Haddad et al. (2021), Boyarchenko et al. (2022), O’Hara and Zhou (2021), Kargar et al. (2021), and Fahlenbrach et al. (2021). Most of these earlier papers, however, concentrate on the pricing and liquidity impact of covid-19. Much less is known about the effect of covid-19 on the actual credit risk experience, i.e., on ratings and default behavior.1 To fill this gap, we study the effects of covid-19 on corporate rating migrations and defaults, with a particular focus on a risk management modeling perspective.

We address three main questions. First, we want to know whether the relationship between macroeconomic growth and rating and default dynamics has remained intact over the pre-covid and post-covid period. This follows up on Haddad et al. (2021), who find that a number of fundamental disruptions emerged in existing debt market relations and channels during the covid-19 pandemic, particularly attributable to government interventions. Second and related, we are interested whether the inclusion of government support proxies into the analysis affect our findings on the first question, and whether government interventions during the covid period succeeded in compensating for potential disruptions or breaks in the relationship between growth variables and credit risk incidence. Third, we ask ourselves whether growth factors remain useful for predicting credit risk quantiles and credit risk stress tests, given the unprecedented, short-lived fluctuations in economic growth due to the lockdown measures and freeze of the economy.

Before proceeding, we highlight why it is relevant to address the above questions for the covid-19 crisis. The covid period is not the only stressed episode in our sample, which also covers the 2008 great financial crisis and the 2000 burst of the dotcom bubble. What makes the covid period special from a risk management perspective is the fact that the severe drops in growth were government-induced. In Fig. 1 we plot annual industrial production growth. It shows two large drops of −15% early 2020 due to the lockdown of the economy. Because the drop in production was not attributable to a gradual worsening of macro fundamentals, but rather to an abrupt, short-lived intervention, the economy immediately rebounded in the months after. As such, it stands in sharp contrast to the 2008 financial crisis: though the drops in production following that crisis were as deep, they were longer-lived and more gradual. It is therefore unclear whether the relationship between economic growth variables and credit risk outcomes remains unaffected over the covid crisis. Neither is it clear

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1 An exception is Altman (2020), who focuses specifically on the role of the downgrade probability of BBB-rated bonds in the current covid-19 crisis.
ex-ante what the effect was (if any) of the substantial government aid put into the economy during covid times. This information is important for banks using credit risk models with growth related covariates, as they typically compute their capital requirements based on such models. The information is similarly important for governments and other institutions that have to design policies for dealing with future similar crisis events.

To investigate our main questions, we compare two different strands of the credit risk modeling literature: one based on observed covariates, and one based on unobserved credit risk factors. Models with unobserved credit risk components have proven useful in earlier empirical work; see for instance Duffie et al. (2007, 2009), Koopman et al. (2008, 2009, 2011) and Azizpour et al. (2018). These papers find that unobserved components can capture variables that are otherwise difficult to measure, such as the monetary climate or the variation in lending standards. Against the background of covid-19, unobserved components might also pick up unforeseen effects of the pandemic or, conversely, the effect of compensating government measures. For our analysis, we use the rating transition set-up of Creal et al. (2014) based on the methodology of Creal et al. (2013). This framework allows us to jointly study re-rating and default dynamics in relation to both observed and unobserved macro and credit factors. In the context of mortgages, Babii et al. (2019) use a similar model for defaults only without any re-rating part.

We find that models with a growth-related covariate actually fare quite well during covid times. Their main drawback is their bad performance in the early 2000s. During that period, the unobserved components in the model provide most of their value-added. The predictive relation between growth and the default experience seems to survive quite well into the covid period, implying that risk management models based on this predictive relation could still be used, despite the unusual behavior of economic growth during that period. In fact, we find that realized 12-month compound default rate forecasts over covid times fit well within the 99.9% credit quantile based on pre-covid estimates alone. It is only when the big drops in growth due to the lockdown start to enter the 12-month-ahead credit risk forecasts, that these forecasts become overly conservative, particularly when based on a stress testing paradigm.

The survival of the relation between growth and credit risk may be attributed to the particular and short-lived nature of the disruptions. The drops were due to government intervention and exogenous large shocks (the covid pandemic), and can therefore not be related to slowly deteriorating fundamental conditions like in earlier crises. This distinguishes the covid-19 period from earlier stressed times, like the 2000 burst of the dotcom bubble, or the 2008 global financial crisis. The result that the predictive relation from growth to credit risk experience survives into the covid period also affects the (un)usefulness of government support proxies in our model. Effectively, it turns out that none of these variables significantly enters the predictive relation. There are of course obvious endogeneity concerns here, as we do not observe the counterfactual of defaults and downgrades in a setting where government support was absent. Indeed, comparing the effects between the 2008 financial crisis and the covid crisis in our results suggests that further research is useful, as the predictive relations between government support and credit risk incidence appear rather different between the two episodes.

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) that we use to capture the dynamics between credit risk and the macro economy. We also provide some new intuition for the transition equation of that model. Section 4 discusses our three main empirical findings. 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 the period January 1998 to September 2021, which accounts for 285 observations. Following Creal et al. (2014), we focus on the long term entity ratings (ratingtypecode=STDLONG). We use the rating dates (rather than the creditwatch dates) for the rating transitions and concentrate on U.S. (region=USA) corporate ratings (sectorcode=CORPS) only. We regroup the original 21 rating scale into three rating classes: investment grade (IG) with the original ratings AAA to BB−, non-prime (NP) with the original ratings BB+ to C, and default (D) holding the original ratings D and SD (strategic default). Using these two broader rating categories IG and NP, 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 at the start and the end of a month. Firms that moved into the non-rated class (NR) over a month are omitted in that specific month, but still accounted for in all previous months.

Fig. 2 shows the frequencies of each of the six possible transitions. For instance, if 5010 firms are rated IG at the start of the month, and 10 moved into non-rated, 50 downgraded to NP by the end of the month, and 4950 remained IG, then the IG to NP transition rate for that month is computed as 50/(5010 – 10) × 100% = 1%. The dashed vertical 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 NP to D. Interestingly, also other transition rates such as IG to NP show increases over 2020. All of these appear smaller and shorter lived than those following the 2000 dotcom bubble or 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.

Fig. 2 also shows that jumps from IG to 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. The top left panel of Fig. 1 shows the corresponding time series. From March 2020 onwards, we observe large negative IP growth rates. In particular, we see the severe drops in April and May 2020 of below ~15%. These initial extreme decreases are related to the covid-19 lockdown and the corresponding freeze of the economy. As these were temporary, they result in a strong rebound of the economy a year later in April and May 2021 with annual growth rates exceeding ~15%.

The macroeconomic activity index 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 D frequencies in Fig. 2 appear to show a comparable pattern, except that the increase in defaults in the early 2000s is much more pronounced. The patterns reveal that it is quite challenging to relate
default and downgrade activity to macroeconomic activity across this range of crises.

Because it might be difficult to explain credit dynamics by growth dynamics alone over crisis periods, we follow two approaches. First, we introduce a class of frailty models in the next section. Such models allow credit markets to be partly predicted by their own dynamics alongside economic activity dynamics. Here one can think of unmodeled control variables such as government support packages rolled out over such periods, but also of relaxing or sharpening of lending standards, stress in the banking system, etc. By introducing latent components into the credit model, all such factors can be captured in order to better explain the credit experience over the three crisis periods in our sample.

Second, we introduce additional control variables alongside IP growth and the frailty factors. By doing this, we can explicitly try to see to what extent government support packages have been correlated to reducing credit risk. High-quality proxies for pinning down the relevant support are not directly evident, as data appear scattered across many sources. In this paper, we study three proxies in relation to credit risk. The proxies are presented in the remaining panels of Fig. 1.

The first variable is a generic federal subsidies variable, which we express as percentages of lagged IP levels to make it comparable to the IP growth percentages. Though clearly not all subsidies go into support of the corporate sector, we conjecture that the impact might work both directly via supporting firms or industries, as well as indirectly via stimulating the economy that supports firm survival. The variable clearly takes off during the covid period, while being around zero before this time. As such, it might be an important proxy for our study into the covid period, but also one whose impact can only be determined if the estimation sample includes the covid period itself.

Our second variable is the (de-seasonalized) federal surplus or deficit as a percentage of lagged IP levels. Acknowledgedly, this variable captures much more than only government support. Still, it might be a relevant and important proxy variable to pick up parts of government support, both during the 2008 financial crisis and the covid crisis. This is clearly visible in Fig. 1. The variable swings into negative territory in the aftermath of the financial crisis, and even more so during the covid period, with clear sharp troughs in the early months of the covid crisis.

Finally, we tried to gather proxies related to the Troubled Assets Relief Plan (TARP), which was implemented as a reaction to the 2008 financial crisis. The size of the TARP is massive (up to $700bn) and covers different specialized industries and markets, such as the housing market, the automobile industry, the banking industry, or even specific companies such as the American International Group (AIG). Again, data appear quite scattered across platforms, and are not always up to date. We settle in the end for the inclusion of two TARP related measures that can be directly downloaded from the official FRED database. The two variables relate to the corporate bonds issued by commercial banking under the TARP Capital Purchase Program (CPP), and the support given to AIG. Admittedly, these proxies measure only a small fraction of the TARP program (max around 0.1% for the CPP data, and around 11% for AIG). Still, given the patterns in Fig. 1 they capture the massive support dynamics in the aftermath of the crisis, both the shorter-lived and longer-lasting support. As such, and for lack of better overall measures, we use them as robustness controls in one of our final regressions to investigate the relation between support packages and the default experience. In particular, one might suspect that the inclusion of economic support measures drives out the unobserved components introduced in the modeling framework in Section 3. This would allow us to use these additional observable variables to explain a larger proportion of credit risk variation that cannot be explained by economic growth dynamics alone.

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 observable macroeconomic 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 approaches as found in for instance Koopman et al. (2008, 2009). We explain the basic model and its estimation in Section 3.1. The dynamic extension of Creal et al. (2014) is discussed 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) macrovariable(s) $Y_{t}^{M}$, as well as rating migration counts $Y_{t}^{R}$, where $t = 1, \ldots, T$, $i = 1, 2, 3$, and $j = 1, 2, 3, \ldots$ With $i = j = 1 = \text{IG}, i = j = 2 = \text{NP}$, and $j = 3 = \text{D}$. In our application, we restrict to scalar $Y_{t}^{M}$, but the model easily allows for a vector of macro variables as well. The scalar $Y_{t}^{R}$ denotes the number of firms that migrated from rating $i$ to rating $j$ between $t$ and $t+1$. We also define the number of firms that are rated in category $i$ at time $t-1$, and rated in category $j$ or higher at time $t$ as $n_{i|j} = \sum_{j=1}^{M} Y_{t}^{Rj}$, 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 $n_{i} = \sum_{j=1}^{M} n_{i|j}$. Note that $n_{i} = n_{i|t}$ 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 $Y_{t}^{Rj}$ and $n_{i}$ into vectors $Y_{t}^{R}$ and $n_{i}$, respectively.

Our general model uses observed as well as latent factors to link the dynamics of macro and credit observations. More specifically, we assume that

$$Y_{t}^{R} | F_{t-1} \sim \text{Ordered-logit} \left( \pi \left( f_{t}^{M}, f_{t}^{R}, z_{t}^{M} \right), n_{i} \right), \tag{1}$$

$$Y_{t}^{M} | F_{t-1} \sim \text{N} \left( \mu^{M} + f_{t}^{M} + \beta^{M} z_{t}^{M}, \sigma^{2}_{M} \right), \tag{2}$$

where $Z_{t}^{M}$ and $Z_{t}^{R}$ are vectors containing observed explanatory variables for the macro and credit series, respectively. $\mu^{M}$ is a fixed intercept, $f_{t}^{M}$ is a time varying intercept (around zero), and $\pi \left( f_{t}^{M}, f_{t}^{R}, z_{t}^{M} \right)$ is a ratings transition matrix from rating $i$ (row) into rating $j$ (column), which satisfies a particular structure that is explained later, and $f_{t}^{R}$ is a latent ratings-related dynamic component that drives the dynamic rating transition matrices. The information set $F_{t}$ contains all lagged values of $Y_{t}$ and $Y_{t}^{M}$, as well as the observed concurrent factors $Z_{t}^{M}$ and $Z_{t}^{R}$. Our current model uses univariate $f_{t}^{M}$ and $f_{t}^{R}$, but can be generalized to higher dimensional latent factors. These factors are not observed but are modeled as pre-determined using the methodology of Creal et al. (2013) and Harvey and Luati (2014), as opposed to the state-space approach of for instance Bangia et al. (2002), Gagnardini and Gouriéroux (2005a,b), Feng et al. (2008), and Koopman et al. (2008, 2011). A major advantage of this approach is that the likelihood is available in closed form, and therefore estimation can be done by standard maximum likelihood methods.

Our model for the rating transition probabilities is an ordered logit model, given by the rating transition matrix $\pi \left( f_{t}^{M}, f_{t}^{R}, z_{t}^{M} \right)$. To construct this matrix, we first define the cumulative probabilities

$$

t_{i|j} \left( f_{t}^{M}, f_{t}^{R}, z_{t}^{M} \right) = \pi \left( R_{k,t} \geq j \mid R_{k,t-1} = i \right) f_{t}^{M}, f_{t}^{R}, z_{t}^{M}, \tag{3}$$

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 $\bar{\pi}_{i,j,t}(f^M_t, f^R_t, z^R_t)$ are well-defined due to the ordinal nature of credit ratings and have a standard logistic specification:

$$\bar{\pi}_{i,j,t}(f^M_t, f^R_t, z^R_t) = \frac{\exp \left( \mu^M_i + \gamma^M_{j,t} f^M_t + \delta^R_{i,t} f^R_t + \beta^R_i z^R_t \right)}{1 + \exp \left( \mu^M_i + \gamma^M_{j,t} f^M_t + \delta^R_{i,t} f^R_t + \beta^R_i z^R_t \right)}, \quad (3)$$

for $i = 1, 2$ and $j = 2, 3$, and where we set $\bar{\pi}_{i,1,t} = 1$ and $\bar{\pi}_{i,4,t} = 0$ for $i = 1, 2$. The intercepts $\mu^M_i$, the factor loadings $\gamma_i$, and the regression parameters $\beta^R_i$ all need to be estimated from the data. For identification, we have to impose a restriction on one of the $\delta_i$ 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 $\gamma_i$, as the macro frailty factor will be defined from the macro data via equation (2).

Using (3), the transition probabilities follow directly as

$$\pi_{i,j,t} = \bar{\pi}_{i,j,t} - \bar{\pi}_{i,j,t+1}, \quad i = 1, 2, \quad j = 1, 2, 3, \quad (4)$$

or equivalently

$$\pi_{i,j,t} = \Lambda(\mu^M_i + \gamma^M_{j,t} f^M_t + \delta^R_{i,t} f^R_t + \beta^R_i z^R_t) - \Lambda(\mu^M_i + \gamma^M_{j,t} f^M_t + \delta^R_{i,t} f^R_t + \beta^R_i z^R_t), \quad \Lambda(x) = e^x/(1 + e^x)$$

is the logistic mapping, and the parameters $\mu^M_i$ must be ranked with respect to $j$, i.e., $\mu^M_i(l + 1) \leq \mu^M_i(l)$. Note that the dependence of $\gamma_i$ and $\delta_i$ on the initial rating $i$ and not on the output rating $j$ induces an ordered logit structure for the probability model. We can also look at this specification from a structural credit risk modeling point of view. In such a setup a firm currently rated as $i$ moves to rating $j$ if its log asset level ends between the thresholds $\mu^M_i(l) + \gamma^M_{j,t} f^M_t + \delta^R_{i,t} f^R_t + \beta^R_i z^R_t$ and $\mu^M_i(l + 1) + \gamma^M_{j,t} f^M_t + \delta^R_{i,t} f^R_t + \beta^R_i z^R_t$, where we assume the log asset level to have a logistic distribution. This brings the current modeling framework close to the original structural credit risk modeling framework of Merton (1974). The key idea in our model with both observed ($z^R_t$) and latent (f$^M_t$ and f$^R_t$) components is that the thresholds that define rating $j$ for initial rating $i$ can vary over time as long as all thresholds for $j = 1, 2, 3$ move in parallel for a given initial rating $i$ in order not to destroy the ordering structure of ratings.

The credit part of the model is accompanied by a macro part (2) containing the macro factor $f^M_t$. Apart from capturing the time-varying conditional mean of $y^M_t$, the latent macro factor also influences the ratings $y^R_t$ via equation (1). We expect positive economic conditions to correlate positively to upgrade probabilities and negatively to downgrades and default probabilities. The rating transitions $y^R_t$, however, 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 latent macroeconomic factor $f^M_t$ and the observed credit factors $z^R_t$. Such additional variation might for instance be caused by variables that are harder to quantify, such as changes in the monetary or lending climate, changes in lending standards or regulation, or stress in capital markets or in the banking system. Though proxies for such variables are sometimes available, they are typically noisy. The latent credit risk factor $f^R_t$ can then be used to describe such dynamics, which are harder to pin down otherwise.

We note that our model nests familiar specifications from the literature, such as the generalized linear model or the pure frailty model. For instance, by setting $\gamma_i = \delta_i = 0$ for all $i$, we obtain a standard static ordered logit model. Similarly, if $\beta^R$ and $\beta^M$ are zero, the model becomes a pure frailty model with only latent components; see for instance Duffie et al. (2007, 2009), Koopman et al. (2008, 2009, 2011), Azizpour et al. (2018), and Babii et al. (2019).

3.2. Modeling the dynamics of the frailty factors

The dynamic latent factors $f^M_t$ and $f^R_t$ for the macro and credit variables, respectively, are likely to exhibit substantial autocorrelation as they pick up unmodeled dynamics caused by for instance lending climate, changing credit standards, but also government aid if not included via $z^R_t$.

In this paper, we follow Creal et al. (2014) and 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 from a numerical point of view considerably easier than a set-up as in Koopman et al. (2011); see also the references below equation (1). The score-driven dynamics for the factors are given by

$$\left( \begin{array}{c} f^M_{t+1} \\ f^R_{t+1} \end{array} \right) = \left( \begin{array}{cc} b^M & 0 \\ 0 & b^R \end{array} \right) \left( \begin{array}{c} f^M_t \\ f^R_t \end{array} \right) + \left( \begin{array}{cc} 0 & 0 \\ 0 & a^R \end{array} \right) \left( \begin{array}{c} s^M_t \\ s^R_t \end{array} \right), \quad (6)$$

where $S_i$ is a scaling matrix that depends on the parameters and on the factors and observations up to time $t$. The model is called score-driven due to the updates $s^M_t$ and $s^R_t$ in (6), which modify the factors at each time point $t$ locally change the fit of the model to better accommodate the most recent observation. The model accomplishes this by a steepest ascent-type step based on the local log-likelihood, i.e., using the derivative or score of the log predictive density $\log p[y^M_t, y^R_t | f^M_t, f^R_t, z^R_t, z^M_t]$ with respect to the time-varying parameters $f^M_t$ and $f^R_t$. This results in scaled gradient-based steps as in (7), Blasques et al. (2015) show that such steps can be linked to minimizing the Kulback-Leibler divergence between the model and the data.

In our current setting and following Creal et al. (2014), we have

$$\frac{\partial \ell_t(\theta)}{\partial f^M_t} = \frac{y^M_t - \mu^M_t - \beta^M f^M_t - \frac{f^M_t}{\sigma^2}}{\sigma^2} - \sum_{i=1}^3 \gamma_i \cdot s^R_{i,t}, \quad (8)$$

and

$$\frac{\partial \ell_t(\theta)}{\partial f^R_t} = -\sum_{i=1}^3 \delta_i \cdot s^R_{i,t}, \quad (9)$$

with

$$s^R_{i,t} = \sum_{j=1}^3 \pi_{i,j,t} (1 - \pi_{i,j,t}) - \pi_{i,j,t} (1 - \pi_{i,j,t+1}) \frac{\pi_{i,j,t}}{\pi_{i,j,t+1}}$$

and

$$s^M_{i,t} = \sum_{j=1}^3 \pi_{i,j,t} (1 - \pi_{i,j,t}) - \pi_{i,j,t} (1 - \pi_{i,j,t+1}) \frac{\pi_{i,j,t}}{\pi_{i,j,t+1}} = \sum_{j=1}^3 n_{i,t} \cdot \left( \frac{n_{i,3,t}}{n_{i,t}} - \frac{n_{i,2,t}}{n_{i,t}} \right) = \sum_{j=1}^3 n_{i,t} \cdot \left( \frac{n_{i,3,t}}{n_{i,t}} - \frac{n_{i,2,t}}{n_{i,t}} \right), \quad (10)$$

where we have slightly rewritten equations (8)–(10) compared to Creal et al. (2014) to reveal the core intuition of the updates more clearly. The first term in the update for the macro factor in (8) is highly intuitive: if the observed realization $y^M_t$ is higher than its conditional expectation $\mu^M_t + f^M_t$, we update the macro factor upwards. This form of the first term in the update follows from the normality assumption in equation (2). 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 down-weighted if $y_{i,t}^M$ is a tail observation.

The second term in (8) can be best understood by looking at the updates of the credit frailty factor via equations (9)–(10). These updates seem more involved, but are again highly intuitive upon closer inspection. The updates consist of two terms. The first term in (10) measures the discrepancy between the empirical frequency $(n_{1,2,t}/n_{1,t})$ of moving from rating i at $t-1$ into rating 2 or higher at time $t$, and its theoretical counterpart, the probability $\hat{\pi}_{2,t,i}$. 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 $n_{1,t}$. Due to the ordered logit structure, there is however a further signal. This is impounded into the second term in (10). This term takes the empirical conditional frequency $(n_{1,3,t}/n_{1,t})$ of moving from rating i at $t-1$ 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 $(\hat{\pi}_{2,t,i}/\hat{\pi}_{1,t,i})$. Again, if the former is higher than the latter, the credit frailty factor is moved upwards for $\delta_i > 0$, or downwards for $\delta_i < 0$.

Finally, the signals on $f_{i,t}^M$ from the rating transitions are aggregated over all possible initial ratings i via the summation over i in (9), using the slope coefficients $\delta_i$ appropriate for each initial rating. As the macro factor $f_{i,t}^M$ also affects all rating probabilities, there is also a second set of terms in (8). Here, of course, the contributions $\gamma_{i,t}$ are weighted by the slope coefficients $\gamma_i$ of the macro factor in the credit risk part of the model. If the $\gamma_i$ 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

$$S_t = \left[ \begin{array}{ccc} 1/\sigma^2 & 0 & 0 \\ 0 & \sum_{i=1}^2 n_{i,t} \cdot c_{i,t} & \sum_{i=1}^2 n_{i,t} \\ 0 & \sum_{i=1}^2 n_{i,t} \cdot c_{i,t} & \sum_{i=1}^2 n_{i,t} \end{array} \right]^{-1}. \quad (11)$$

This scaling choice automatically assigns more weight to either (8) or (9), depending on whether the macro or credit part of the model contains most information on the current position of the unobserved factors $f_{i,t}^M$ and $f_{i,t}^R$.

Though the model may look quite daunting at first, it is easily estimated by maximum likelihood. Define a vector of parameters $\theta$ holding all static parameters in the model such as $a^M$, $a^R$, $b^M$, $b^R$, $\beta^M$, $\beta^R$, $\gamma_i$, et cetera. Next, for a given parameter vector $\theta$, we iterate equation (6) to obtain $f_{i,t}^M$ and $f_{i,t}^R$ for all $t = 1, \ldots, T$, starting from some initial values $f_{i,1}^M$ and $f_{i,1}^R$. Using $f_{i,t}^M$ and $f_{i,t}^R$ for $t = 1, \ldots, T$, we can compute the log-likelihood function

$$\ell(\theta) = \ell^M(\theta) + \ell^R(\theta) = \sum_{t=1}^T \ell_{t}^M(\theta) + \sum_{t=1}^T \ell_{t}^R(\theta), \quad (12)$$

where the macro and credit rating parts of the log-likelihood are given by

$$\ell_{t}^M(\theta) = -\frac{1}{2} \log(2\pi \sigma^2) - \frac{1}{2} \left( \frac{y_{i,t}^M - \mu_{i,t}^M}{\sigma} \right)^2, \quad \ell_{t}^R(\theta) = \frac{1}{2} \sum_{i=1}^2 \sum_{j=1}^2 y_{i,j,t}^R \log \pi_{i,j,t},$$

This allows us to use standard numerical maximization techniques to estimate the model. Using the Hessian and Outer-Product-of-Gradients at the optimum, robust (sandwich) standard errors can be easily computed. R code for estimation is provided as supplementary material to this paper.

The fact that the likelihood is available in closed form is a distinct advantage of the current set-up of the model and makes the whole approach numerically efficient compared to a non-linear state-space approach. In terms of fitted credit risk factors and predictive accuracy, our score-driven models and state-space models also behave similarly; see Koopman et al., 2008, Creal et al., 2014, and Koopman et al. (2016). Economically, the score-driven approach for credit risk forecasting is closer to a contagion interpretation than to a common factor interpretation: as a data generating process, current defaults ceteris paribus increase future probabilities of default and downgrade; see also Azizpour et al. (2018) for the importance of contagion factors compared to frailty risk, where probabilities of default dynamics are exogenously given. Empirically, however, one should remember that distinguishing these two sources of credit risk dynamics is hard at the current level of data aggregation, and that the likelihood is typically quite flat when both components are included, which provides an additional argument to not complicate the current model specification further.

An advantage of the current set-up is that a model with only latent components ($\beta^M = 0$, $\beta^R = 0$) can be used directly for forecasting credit risk scenarios. This contrasts with models that have explanatory variables $z_{i,t}^M$ or $z_{i,t}^R$. For such models, an auxiliary model is needed to forecast the explanatory variables as in Duffie et al. (2009). In equations (1)–(2), the dynamics of macro and credit variables are modeled jointly from the outset.

4. Empirical results

To investigate how the covid-19 pandemic has influenced the relationship between credit risk and macro fundamentals, we proceed in three steps. First, we estimate our models over the pre-covid period (Jan 1998 – Dec 2019, i.e. 264 observations) and evaluate the fit over both the pre-covid and covid months (i.e. including Jan 2020 - Sep 2021) using models with and without unobserved dynamic components. 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. Second, we study whether proxies for government rescue packages help drive down the latent credit risk components in the covid period and thus help in explaining credit risk variation, particularly during crisis periods. Finally, we use credit risk simulations and stress testing to assess whether models with unobserved components can be helpful for determining capital buffers over stressed periods.

4.1. Pre-covid estimation results

In this section, we estimate four relevant model specifications over the pre-covid period. The results are presented in Table 1. The first model is a standard ordered logit model with one-month-lagged annual industrial production growth, denoted ΔIndPro, as a covariate. As expected, economic growth has a clear negative relation with NP transitions, and to a lesser extent with IG transitions. The ordered logit intercepts appear reasonable: if a logistically distributed log asset return falls in the interval $(\mu_{R|D} - \mu_{R|IC})$, the resulting rating remains NP. This is in line with the structural credit risk model interpretation in Merton (1974), but then for the ordered logit introduced in Section 3. With values of $\mu_{R|D} = -5.837$ and $\mu_{R|IC} = 6.682$, current NP firms clearly have highest probability of retaining their non-prime rating. Similarly, $\mu_{R|D} = -10.482$ and $\mu_{IC|NP} = -6.087$ indicate that current IG firms are extremely unlikely to default and have a modest monthly probability of downgrading to NP. Note that all these boundaries move...
The factor (log-lik-M) increases from model 2 to model 3: as \( f_M \) no longer needs to describe both macro and rating transition data simultaneously, the macro part of the model can concentrate more on solely explaining IP growth using \( f_M \), which results in a better fit. The macro factor still significantly impacts the non-prime rating dynamics. The effect on the investment grade rating dynamics, however, is no longer significant. The new factor \( f_M \) describes the credit rating transitions better than the macro-factor \( f_M \) in model 2. Also, the coefficient of \( \delta_{IG} = 0.920 \) for \( f_M \) in the IG ratings panel indicates that the credit risk factor \( f_M \) is present both in NP (as normalized to \( \delta_{NP} = 1 \)) and IG transitions with roughly the same order of magnitude. With a coefficient of \( \beta_R = 0.965 \), the credit risk factor appears highly persistent.

We can see the precise pattern of \( f_M \) in the bottom panel of Fig. 3. It is clear that the main effect comes from better fitting the height of the NP defaults following the burst of the dotcom bubble. This is also seen in the much improved fit of the NP default rate during that period. From 2005 onwards, the frailty component is much less present. In particular, it does not seem to be very active during the great financial crisis (in-sample), nor during the current covid period (out-of-sample). This may be due to the fact that the increased default experience coincided with the economic lockdown period. As the lockdown was very short-lived and the economy picked up immediately after, the increased default experience did not proceed into the next months, but rebounded to its originally low levels from before the covid period. Compared to model 2, the inclusion of the credit factor \( f_M \) in model 3 allows the coefficient \( \gamma_{NP} \) of the macro factor \( f_M \) to grow slightly in magnitude from \(-0.083 \) to \(-0.093 \). This in turn causes an over-shooting of the NP default rate during the covid lockdown period for model 3 compared to model 2 (and 1), as seen in the top panels of Fig. 3.

It is also interesting to compare the credit frailty factor with non-prime (high-yield) bond yield spreads in the lower-right panel of Fig. 3. The patterns are vastly different. The yield spreads appear to follow the default frequencies in the upper panels more closely. Part of these dynamics, however, are already accounted for by the growth dynamics. The credit factor only captures what is left beyond these growth-related credit risk dynamics, and therefore has a different trajectory. We also see that there is a substantial difference between credit risk pricing (yield spreads) and credit risk incidence (default frequencies). During the 2008 financial crisis, we observe a peak in credit risk prices that is much sharper than the peak in default frequencies. By contrast, the peak in default frequencies in the (early) covid crisis appears larger than that in prices, at least compared to the 2000 and 2016 peaks. Differences are likely driven by a time-varying price of credit risk. Such variation can and should not be picked up by the credit risk factor \( f_M \), as it focuses on capturing credit risk incidence only.

Replacing the macro factor \( f_M \) by the macro covariate (lagged IP growth) from model 3 to 4 results in only minor changes again. The model performance deteriorates marginally, and also the coefficients and fit of the model are hardly affected. Interestingly, the fit in the out-of-sample covid period, however, appears to improve compared to model 3. More specifically, there is no longer substantial overshooting of the default rate during the lockdown period early 2020, as the coefficient for IP growth \( \beta_{IP} \) remained at its original position around \(-0.081 \). By contrast, this coefficient combined with the peak in the annual growth rate early 2021 (see Fig. 1) does result in an overshooting of the upgrade frequency from NP

Table 1: Estimation results (pre-covid sample).

| Credit factor | Model 1 | Model 2 | Model 3 | Model 4 |
|---------------|---------|---------|---------|---------|
| Macrow factor | no      | yes     | yes     | yes     |
| Macro covariate | yes   | no      | yes     | no      |

Part A1: credit frailty dynamics coefficients

| \( f_M \) | 1    |
|-----------|------|
| \( \Delta \text{Ind.Pro} \) | -0.083 |
| \( \Delta \text{Ind.Pro} \) | -0.083 |
| \( \mu_{NP} \) | -5.837 |
| \( \mu_{NP} \) | -5.837 |
| \( \mu_{IG} \) | 6.682 |
| \( \mu_{IG} \) | 6.682 |
| Part A2: Non-Prime (NP) coefficients |

| \( f_M \) | 0.920 |
|-----------|-------|
| \( f_M \) | 0.920 |

Part A3: Investment-Grade (IG) coefficients

| \( \Delta \text{Ind.Pro} \) | -0.027 |
| \( \mu_{NP} \) | -10.482 |
| \( \mu_{NP} \) | -10.482 |
| \( \mu_{IG} \) | -6.087 |
| \( \mu_{IG} \) | -6.087 |

Part B: Macro frailty dynamics coefficients

| \( \beta_R \) | 0.961 |
| \( \beta_R \) | 0.961 |
| \( \alpha^2 \) | 0.797 |
| \( \alpha^2 \) | 0.797 |
| \( \text{log-lik-M} \) | -356.37 |
| \( \text{log-lik-M} \) | -348.17 |

Note: each column represents an estimated model. The top panel includes parameter estimates with corresponding heteroskedasticity-robust standard errors. The models are estimated based on the pre-covid sample Jan 1998 - Dec 2019. The out-of-sample log-likelihood fit is given by the row log-lik-covid over the period Jan 2020 - Sep 2021.

up and down in parallel with the covariate. The values of the log-likelihood and the Akaike and Bayesian information criteria (AIC and BIC) are given at the bottom of the first column and relate to the credit part of the model, equation (1), only.

In the second model, we replace the macro covariate by an unobserved macro factor using (2). The macro factor \( f_M \) closely follows the dynamics of the covariate itself as seen in Fig. 3. This holds even during the covid period, despite the fact that the coefficients in the model have been estimated over the pre-covid period only. As a result, it is not surprising to see that the coefficients associated to \( \Delta \text{Ind.Pro} \) and \( f_M \) are highly similar between models 1 and 2 (i.e., \( \beta_{IP} = -0.082 \) and \( \gamma_{NP} = -0.083 \), respectively). The log-likelihood, AIC and BIC all slightly improve from model 1 to model 2, but the differences are mostly negligible.

A larger change occurs if we also include an unobserved credit risk component \( f_M \) in model 3. This is the first sign that the macro and credit dynamics may not always align, even in the pre-covid period, and that a single unobserved macro component cannot capture both dynamics at the same time. The likelihood increases by more than 130 points from model 2 to 3 upon adding only three parameters \( \{a_R, b_R, \delta_R\} \), causing substantial drops in both the AIC and BIC, and resulting in the best performance across the four models considered in terms of in-sample fit. The impact of macro conditions on credit risk dynamics remains rather similar: the coefficients \( \mu_{NP} \) stay stable, as do the coefficients for \( f_M \).

Note that the log-likelihood of the macro part of the model (log-lik-M) increases from model 2 to model 3: as \( f_M \) no longer needs to describe both macro and rating transition data simultaneously, the macro part of the model can concentrate more on solely explaining IP growth using \( f_M \), which results in a better fit. The macro factor still significantly impacts the non-prime rating dynamics. The effect on the investment grade rating dynamics, however, is no longer significant. The new factor \( f_M \) describes the credit rating transitions better than the macro-factor \( f_M \) in model 2. Also, the coefficient of \( \delta_{IG} = 0.920 \) for \( f_M \) in the IG ratings panel indicates that the credit risk factor \( f_M \) is present both in NP (as normalized to \( \delta_{NP} = 1 \)) and IG transitions with roughly the same order of magnitude. With a coefficient of \( \beta_R = 0.965 \), the credit risk factor appears highly persistent.

We can see the precise pattern of \( f_M \) in the bottom panel of Fig. 3. It is clear that the main effect comes from better fitting the height of the NP defaults following the burst of the dotcom bubble. This is also seen in the much improved fit of the NP default rate during that period. From 2005 onwards, the frailty component is much less present. In particular, it does not seem to be very active during the great financial crisis (in-sample), nor during the current covid period (out-of-sample). This may be due to the fact that the increased default experience coincided with the economic lockdown period. As the lockdown was very short-lived and the economy picked up immediately after, the increased default experience did not proceed into the next months, but rebounded to its originally low levels from before the covid period. Compared to model 2, the inclusion of the credit factor \( f_M \) in model 3 allows the coefficient \( \gamma_{NP} \) of the macro factor \( f_M \) to grow slightly in magnitude from \(-0.083 \) to \(-0.093 \). This in turn causes an over-shooting of the NP default rate during the covid lockdown period for model 3 compared to model 2 (and 1), as seen in the top panels of Fig. 3.

It is also interesting to compare the credit frailty factor with non-prime (high-yield) bond yield spreads in the lower-right panel of Fig. 3. The patterns are vastly different. The yield spreads appear to follow the default frequencies in the upper panels more closely. Part of these dynamics, however, are already accounted for by the growth dynamics. The credit factor only captures what is left beyond these growth-related credit risk dynamics, and therefore has a different trajectory. We also see that there is a substantial difference between credit risk pricing (yield spreads) and credit risk incidence (default frequencies). During the 2008 financial crisis, we observe a peak in credit risk prices that is much sharper than the peak in default frequencies. By contrast, the peak in default frequencies in the (early) covid crisis appears larger than that in prices, at least compared to the 2000 and 2016 peaks. Differences are likely driven by a time-varying price of credit risk. Such variation can and should not be picked up by the credit risk factor \( f_M \), as it focuses on capturing credit risk incidence only.

Replacing the macro factor \( f_M \) by the macro covariate (lagged IP growth) from model 3 to 4 results in only minor changes again. The model performance deteriorates marginally, and also the coefficients and fit of the model are hardly affected. Interestingly, the fit in the out-of-sample covid period, however, appears to improve compared to model 3. More specifically, there is no longer substantial overshooting of the default rate during the lockdown period early 2020, as the coefficient for IP growth \( \beta_{IP} \) remained at its original position around \(-0.081 \). By contrast, this coefficient combined with the peak in the annual growth rate early 2021 (see Fig. 1) does result in an overshooting of the upgrade frequency from NP.
to IG (see the peak in the lower-left panel of Fig. 2). The lack of overshooting the default rate in the covid period appears a generic result in our analysis: over the (out-of-sample) covid period the models with covariates fare slightly better than the models with the filtered macro and credit factors, even though both use the same data: models 1 and 4 use the 1-month lagged IP growth as a covariate $z_{i,t}$, whereas models 2 and 3 use it via $f_{i,t}$ which is based on the same lagged IP growth given the score-driven nature of the model.

The results are further corroborated if we look at the log-likelihood values in the “log-lik-covid” row of Table 1. These contain the fit of the models over the 21 months in the covid period (Jan 2020 – Sep 2021). Interestingly, models 1 and 4 perform somewhat better than models 2 and 3, respectively. In particular, they do not appear to overshoot the default peak in the lockdown, whereas the unobserved components models (2 and 3) do. More specifically, the overshooting of model 3 is so large that it results in the worst out-of-sample log-likelihood performance at a value of $-1257.27$.

Fig. 3 also suggests that IP growth alone can already capture most of the default rate dynamics over the covid period, though a credit risk factor $f_{i,t}$ may be needed to capture the height of the recession in the early 2000s. We investigate this in more detail in the next section using a number of proxies for the government rescue packages put in place during the different high-default times.

4.2. Covid-19 times and support packages

In Section 4.1, we observed that there can be periods where credit experience de-links from macro fundamentals in the form of IP growth. Such a de-linkage could be corrected for by including unobserved credit factors into the model. The results thus far, however, suggest that such de-linkage was particularly present during the 2000 burst of the dotcom bubble. The unobserved components did not appear particularly helpful, neither during the (in-sample) 2008 great financial crisis nor during the (out-of-sample) covid crisis. Conditioning on growth dynamics as a covariate was found to perform better. In this section, we look at the Jan 2020 – Sep 2021 covid period in more detail. In particular, we investigate the effect of the initiatives of different authorities to support the economy during stressed times, thus possibly avoiding or delaying defaults and downgrades. The covid period, however, is not the only period where active and substantial interventions occurred. Another prime example is the great financial crisis, which can therefore serve as a benchmark period.

As explained in Section 2, finding appropriate proxies for government support is non-trivial. Our prime candidate is the amount of federal subsidies as a fraction of (lagged) IP levels, which is displayed in Fig. 1. The other three proxies that we consider are arguably noisier, and are therefore mainly used in a robustness analysis. The results of our first set of regressions can be found in Table 2. We concentrate on three models: model 2, which has no unobserved credit factor, and models 3 and 4, which have a credit risk factor, but treat IP growth as a covariate (model 4) or as an unobserved macro factor (model 3). To save space, we leave out the macro part of the model (i.e., there is no Part B as in Table 1). We estimate all models both pre-covid and over the full sample.

We again note that the models with an unobserved credit component fit the data better in-sample, both for the pre-covid sample (left-hand column for each model) and the full sample (right-hand columns). We also see that the coefficient for $\Delta$Ind.Pro decreases slightly in magnitude when fitted over the full sample. This holds both for models with IP growth as a covariate (models 4) and as an unobserved macro factor ($f_{i,t}$ coefficients in models 2 and 3) and seems in line with our results from Table 1: growth dynamics alone already provide a reasonably good fit for the covid credit risk experience. It would be interesting to investigate how the reduced magnitude (around $-0.065$ rather than $-0.085$) of the IP growth coefficient as estimated over the full sample would underestimate the predictive relation between growth and the ratings and default experience after the covid period. One reason for the reduction in the magnitude of this coefficient over the full-sample may be the incidental nature of the large swings in IP growth due to the lockdown: if not properly corrected for, this could underestimate the relationship between growth and credit risk for subsequent observations. We leave this for future research.

To see whether rescue packages are correlated with the credit risk experience, we consider the coefficient of the subsidy to lagged IP ratio. Looking at the results, we see a clear discontinuity between the pre-covid and covid period. Whereas coefficients are between roughly $-0.5$ and $-1.5$ for the NP ratings, they are extremely large with values between $-3.8$ and $-4.7$ for IG ratings. Given the pattern in Fig. 1, such magnitudes hardly make sense, as there were no sizeable subsidies in the pre-covid compared to the covid period: the full sample is therefore needed to reliably estimate its relation to credit risk.

The result can be seen in Fig. 4. The red curves in the top panels indicate the result for the pre-covid estimates: the unobserved
credit risk factor $f^R$ increases sharply to off-set the exaggerated effect of the subsidy ratio on rating transition rates and defaults. Despite this, the model only succeeds in bringing back the covid NP-D rates to reasonable values after some time, leaving predicted NP default rates at unrealistically low levels early 2020 compared to the covid experience.

The structural break in the behavior of the subsidy ratio impedes its use as a forecasting variable. We can still, however, consider its relation to credit risk as estimated over the full sample (right columns for each model). We see that the size of the coefficient for the subsidy ratio roughly collapses to zero for the full-sample estimates, being statistically insignificant, and for some models of the wrong sign. There is an obvious endogeneity concern here: rescue packages might have prevented the counterfactual of even larger drops in IP growth and higher default rates to occur at all. We revisit this problem at the end of this subsection.

In Fig. 4, the green curves display the unobserved credit risk component based on full sample estimates. We see that these now behave much more in line with their behavior over the previous ten years: they no longer have to correct for the large impact of the subsidy ratio as a covariate and no longer spike upwards. Similarly, we see in the lower panels that the peak of defaults in Spring is captured much better again: we no longer have a period of zero predicted defaults early 2020 (see the red curve).

We can also compare the in-sample plus out-of-sample log-likelihood from Table 1 with the full-sample log-likelihood values from the models by comparing the log-lik and log-lik-Tab1 entries for the different models in Table 2. The increase in likelihood by fitting over the full sample plus adding the subsidy ratio as an additional explanatory variable is very modest given the size of the variation in the subsidy variable: from a meager $-15767.67$ to $-15777.01 = 3.34$ likelihood points for model 3, to 8.23 points for model 2. Therefore, we conclude once again that simple growth dynamics already provide a good prediction of aggregate credit risk dynamics: the relation between the two does not appear to break, despite substantially higher fluctuations due to government measures such as the lockdown during the covid period.

As mentioned, the coefficient of the subsidy ratio may suffer from an endogeneity problem. Also, as discussed in Section 2, the subsidy ratio is just one out of several possible proxies to capture government support. It is inadequate as a proxy during for instance the 2008 financial crisis, as it was mostly hovering around zero during that period. Instead, in 2008 the TARP was most prevalent and responsible for a total support package of up to around $700$ billion. To ensure that we capture government support adequately over the full sample, we include Table 3 which consists of estimation results for a 'kitchen-sink' type approach including all of our models.
proxies introduced in Section 2. The incorporation of TARP proxies, which are mostly effective in the aftermath of the 2008 crisis, also allow us to benchmark, to some degree, the endogeneity bias of the subsidies variable during the covid period.

The estimation results including all support package proxies show clear similarities with the results in Table 2, but also some important differences. The vanishing importance of the subsidy ratio when estimated over the full sample compared to the pre-covid sample is the same as before. We also see that most of the other proxies for government support are insignificant, both when estimated on the full and the pre-covid sample. The main difference with the previous results is the large size of the coefficient for the TARP-AIG variable. The coefficients are stable (as expected) across the pre-covid period and full sample, as the variable was only effective in the pre-covid sample. As for the subsidy ratio in our previous analysis, there is an obvious endogeneity concern for the TARP variables during the financial crisis that we cannot resolve given the current data. It manifests itself in for instance the positive coefficient for TARP-AIG for non-prime ratings, as increases in support are likely to go hand-in-hand with a worsening of the economic outlook due to a simultaneity problem. Coming back to the results for our subsidy ratio, we might therefore be more surprised that we do not see a similar phenomenon for the subsidy ratio during the covid period as we see for the TARP-AIG during the financial crisis. Instead, the impact of the subsidy ratio collapsed to zero, whereas that of TARP-AIG appeared to be positively biased. In the end for the current data, we cannot rule out that subsidies truly had no impact on credit experience, nor that subsidies prevented a worse counterfactual of more defaults and downgrades from appearing. Interestingly, the off-setting subsidies during the lockdown IP collapse (see Fig. 1) could not prevent the sharp temporary surge in the default and downgrade rate around that time, as visualized in the lower-right and upper-middle panel of Fig. 2, respectively. As a result, macro growth dynamics appear to retain their predictive relation to default dynamics quite well, and government support proxies appear to add little to that. Given the granularity of the current dataset and the quality of the proxies, it will be difficult to get around the endogeneity concerns for government support. Also given the global impact of both the 2008 financial crisis and the covid pandemic it might be challenging to find good instrumental variables. A possible avenue might be to exploit the international cross-section and different timings and types of lockdowns and government support. That would, however, also require high-quality international default and rating series, which are typically scarce. We leave this for future research.

4.3. Covid-19, frailty models, and credit risk management

In the previous subsections, we discussed all models as estimated over the pre-covid and the full sample. In this section, we reflect on some of the consequences of our findings for credit risk management based on unobserved component models as introduced in Section 3.

First, our findings suggest that from a predictive perspective, the simple models based on growth dynamics alone appear to work reasonably well out-of-sample over the covid period in terms of point forecasts. For risk forecasts, however, one is more interested in forecasting (extreme) credit quantities rather than the mean only. Models without any covariates, like models 2 and 3, can easily produce such forecasts. For instance, for a 12-month-ahead forecasting horizon we can use the model to simulate compound transition frequencies over the coming 12 months. The algorithm for this is straightforward. Using $f_{t-s}^1$ and $f_{t-s}^2$ we obtain the next factor values $f_{t+1}^1$ and $f_{t+1}^2$ via the transition equations (8)–(10), which result in the transition matrix $\pi((f_{t+1}^1, f_{t+1}^2))$. This new transition matrix is used to simulate realizations of $y_{T+1}^M$ and $y_{T+1}^H$, which in turn be used to update the unobserved factors to $f_{t+2}^1$ and $f_{t+2}^2$ via (8)–(10). The process can be repeated up to the forecast horizon $T + H$. Using the simulated credit data $y_{t+h}^H$ for $h = 1, \ldots, H$, we can compute the compounded 12-month default and downgrade rates and their distribution over repeated samples. This distribution can be used to compute credit risk quantiles.

Fig. 5 shows the results for models 2 and 3, respectively. The black curve gives the compound 12-month NP-D frequency. For instance, for Sep 2021 we compound the 12 monthly empirical transition frequency matrices for Oct 2020 until Sep 2021 and compare the result to its model-implied counterpart. This is the relevant perspective for a risk manager in Sep 2020, who wants to look 12 months ahead. The dark blue band provides the 0.1%–99.9% band across 10,000 simulations for the 12-month-ahead compound non-prime default rate. We see that throughout the covid period, the 99.9% credit risk quantile (i.e., the upper line of this band) covers the realized 12-month compound default frequencies. The band is even (highly) conservative from early 2021 onwards. Note that this is due to the lockdown measures one year before (in early 2020). The big drops in realized IP growth during that period start affecting the 12-month-ahead simulated credit risk quantiles exactly a year later, but their effect slowly dissipates in the period after, still

\[ \text{Note the absence of } \chi^2 \text{ in the rating transition matrix, as we use models without covariates.} \]
leaving the credit risk quantile at the conservative side compared to the realized credit risk.

Despite the fact that the 99.9% credit risk quantile seems to capture the realized credit risk well even during the covid lockdown, one may argue that simulation approaches like this are inappropriate to capture ‘black swan’ events like the covid pandemic. One alternative might be to change the macro model \((2)\) into something that can generate more outliers, such as a Student’s \(t\) distribution. It is unlikely, however, that the estimated fat-tailedness of such a model would suffice to describe the large \(-15\%\) drops in IP growth in 2020. We therefore opt for an alternative approach inspired by stress testing. When running the previously described simulations to obtain the out-of-sample distribution of credit risk, we administer two extra \(-10\%\) point shocks to \(y_{T,h}^m\) in months 3 and 4 \((h = 3, 4)\) of the 12-month forecasting period. This is more modest than the \(-15\%\) actually realized. The results are presented by the upper bound of the light-blue region in Fig. 5b.

As expected, the stressed scenarios provide even more conservative bounds on credit risk. The bounds become arguably unrealistic if they are mounted on the twice \(-15\%\) IP growth over the lockdown. Interestingly, we see that the stressed bounds for model 3 are slightly less conservative, except when forecasting 12 months ahead during Spring 2020, corresponding to Spring 2021 forecast horizons in the graph. This is due to the fact that the unobserved credit risk component not only allows the credit risk experience to grow higher than in model 3 due to the additional risk, but can also drive it lower. This is clearly seen in Fig. 2,
where we see lower (and thus better) fitted values for model 3 compared to 2 at for instance 2006 or 2014. By and large, however, our simulations and stress tests confirm that growth dynamics also appear sufficient for credit risk quantiles, and that the credit risk factors appear to contribute less during the recent covid crisis.

5. Conclusion

We investigated corporate credit risk dynamics over the covid-19 pandemic. More specifically, we studied whether unobserved components helped in explaining credit risk in stressed periods, and whether the importance of such components could be taken over by observed variables capturing government support to the economy. Using a dynamic rating transitions model, we showed that unobserved credit risk components were very helpful to increase the model’s in-sample fit, mainly capturing the large swings in defaults during the early 2000s. The factors appeared less helpful to capture the peak in defaults during either the financial crisis, or the smaller surge in defaults in the early months of the covid pandemic: for both of these periods industrial production growth appeared to be a sufficient predictor of credit risk dynamics.

We also investigated whether government support variables helped in explaining credit risk incidence and drive out unobserved components from the model. We found no clear effects of this over neither the pre-covid nor the full sample. We stress that the data did not allow us to do a causal analysis of government rescue packages on re-ratings and defaults. Still, the results for the financial crisis and covid crisis appeared to be different in the sense that for the former non-zero correlations (subject to endogeneity biases) were found, whereas no such correlations were detected over the covid period. More research is needed to resolve the endogeneity issues, for instance using the international cross-sectional dimension and differences in the timing and type of government interventions, as well as cross-sectional variations across industries in terms of how badly they were hit by the pandemic.

Finally, we showed that credit risk quantiles based on relatively simple score-driven dynamic unobserved components models produced quantiles that covered the realized credit risk over the covid period. Augmenting the credit risk simulations with further stress tests made the risk quantiles very conservative compared to the realized risk, even during stressed times as the covid pandemic. This suggests that the unobserved components models as studied in this paper remain useful tools for credit risk management, also during times of turmoil such as the covid crisis. In particular, also from a credit risk management perspective models with growth dynamics only appeared to suffice, whereas additional unobserved credit risk components added little over the covid crisis.

Credit Author Statement

Sean Telg: empirical analyses for original submission and revision; coding; gathering macro data; writing of first version and revision.

Anna Dubinova: initial research ideas (for MSc thesis work) and preliminary analyses for master thesis, gathering and processing rating data for original submission, original manuscript correction.

Andra Lucas: empirical analyses, coding, gathering and processing ratings data for revision, writing of first version and revision.

Declaration of Competing Interest

The authors declare they have no conflict of interest.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2022.106638.

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