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GLOBAL CREDIT RISK: WORLD, COUNTRY AND INDUSTRY FACTORS

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SUMMARY

We investigate the dynamic properties of systematic default risk conditions for firms in different countries, industries and rating groups. We use a high-dimensional nonlinear non-Gaussian state-space model to estimate common components in corporate defaults in a 41 country samples between 1980:Q1 and 2014:Q4, covering both the global financial crisis and euro area sovereign debt crisis. We find that macro and default-specific world factors are a primary source of default clustering across countries. Defaults cluster more than what shared exposures to macro factors imply, indicating that other factors also play a significant role. For all firms, deviations of systematic default risk from macro fundamentals are correlated with net tightening bank lending standards, suggesting that bank credit supply and systematic default risk are inversely related.

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Supporting information may be found in the online version of this article.

1. INTRODUCTION

Recent studies provide evidence of many cross-country links and common global dynamics in macroeconomic fluctuations and financial asset returns.[1] Simultaneously, these common movements in macroeconomic fluctuations and asset returns are known to influence the time variation in corporate default rates; see, for example, Pesaran *et al.* (2006), Koopman *et al.* (2009) and Giesecke *et al.* (2011). Given that many macro-financial phenomena are pictured best in a global perspective, we raise the question of whether the same holds true for corporate default rates. In particular, we ask ourselves whether there is a world default risk cycle. And, if so, what are its statistical properties? To what extent is the world default risk cycle different from the world business cycle, which also affects defaults? When can the default risk cycle and business cycle decouple? Is such decoupling only specific to the USA, or is it an international phenomenon? And finally, what are the implications, if any, of world default risk factors for the risk-bearing capacity of internationally active financial intermediaries?

The main objectives of this study are to quantify the share of systematic default risk that can be attributed to *world* business cycle factors and default-specific factors, infer their statistical properties, estimate their location over time, and assess to what extent the world default risk cycles can decouple from world macroeconomic conditions. Compared to previous credit risk studies that focus on the US perspective, our study provides an international perspective on default clustering. We investigate the

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[1] For example, Kose *et al.* (2003, 2008, 2012) document the presence of a world business cycle in macroeconomic variables, and analyse its statistical properties as well as its economic determinants. Ciccarelli and Mojon (2010) and Neely and Rapach (2011) find pronounced global common dynamics in international inflation rates, with international factors explaining more than half of the country variances on average. Yet other research points to global common movement in international stock returns (see, for example, Bekaert *et al.*, (2009), government bond yields (see, for example, Jotikasthira *et al.*, 2015) and term structure dynamics (see, for example, Diebold *et al.*, 2008).

credit experience of more than 20,000 firms from a 41-country sample covering four economic regions in the world over 35 years from 1980:Q1 to 2014:Q4.

In addition to the literature investigating the extent of comovements across global macroeconomic and financial market variables as mentioned above, a second strand of literature investigates why corporate defaults cluster so much over time within certain economies. For example, quarterly default probabilities for US industrial firms can be an order of magnitude higher in a bust than they are in an economic boom; see Das *et al.* (2007) and Koopman *et al.* (2011). In general, the accurate measurement of point-in-time default hazard rates is a complicated task since not all processes that determine corporate defaults can easily be observed. Recent research indicates that readily available macro-financial variables and firm-level information may not be sufficient to capture the large degree of default clustering present in corporate default data. This point is most compellingly made by Das *et al.* (2007), who apply a multitude of statistical tests, and almost always reject the joint hypothesis that their default intensities are well specified in terms of (i) easily observed firm-specific and macro-financial information and (ii) the doubly stochastic default times assumption, also known as the conditional independence assumption. In particular, there is substantial evidence for an additional dynamic unobserved 'frailty' risk factor and/or contagion dynamics; see Koopman *et al.* (2008), Duffie *et al.* (2009) and Creal *et al.* (2014).[2]

Understanding the sources of international default risk variation is crucial for developing robust risk models at internationally active financial intermediaries as well as for effective supervision by the appropriate authorities. In addition, studying a country (or region) in isolation can lead one to erroneously believe that the observed comovement is specific to that country, say the USA, when it is in fact common to a much larger group of countries. Unfortunately, data sparsity (in particular for non-US firms) as well as econometric challenges have so far limited attention to single countries. These challenges include the combination of having non-Gaussian default data on the left-hand side and unobserved risk factors on the right hand, as well as computational challenges when jointly modelling different sets of macro and default risk data from a larger number of countries.

Only a few studies provide an explicitly international perspective on portfolio credit risk as well and its main determinants. Examples include Pesaran *et al.* (2006), who study credit risk conditions in multiple countries in a unified (GVAR) framework. Aretz and Pope (2013) decompose changes in default risk estimates based on Merton's (1974) classic model into global, country and industry effects, and find that global and industry factors dominate country effects. Finally, the RMI credit risk initiative is a noteworthy attempt to build a worldwide credit risk map from the bottom up; see, for instance, Duan and van Laere (2012).[3] In their work they do not estimate multiple sets of latent default risk drivers, such as world, country and industry factors, and they do not provide a variance decomposition of default data with respect to these factors. We address these issues by employing a high-dimensional dynamic factor modelling framework to disentangle the common components in both international macro-financial variables and international default risk data. The interesting work of Aretz and Pope (2013) is based on the decomposition into global, regional and industry factors. However, our variance decomposition results are different since we consider the shared variation in non-Gaussian default counts and proprietary expected default frequencies (EDFs), and extract a more extensive set of latent global, country and industry-specific risk factors.

The econometric methodology relies on the estimation frameworks of Koopman *et al.* (2012) and Bräuning and Koopman (2014) to model a large cross-section of mixed-measurement observations that is subject to a substantial number of latent factors. Specifically, we explain how the computational difficulties can be overcome through dimensionality reduction in a preliminary first step, as in Bräuning

[2] Both 'frailty' and contagion risk can cause default dependence above and beyond what is implied by observed covariates alone. The issue of excess default clustering is actively researched; see, in addition, McNeil and Wendin (2007), Koopman and Lucas (2008), Lando and Nielsen (2010), Koopman *et al.* (2011, 2012) and Azizpour *et al.* (2015).

[3] RMI is the Risk Management Institute of National University of Singapore (http://www.rmicri.org).

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and Koopman (2014), and the use of antithetic variables in Monte Carlo maximum likelihood evaluation for a parameter-driven mixed-measurement dynamic factor model, as introduced in Koopman *et al.* (2012). As an additional contribution, we show that a one-to-one correspondence exists between our empirical mixed-measurement dynamic factor model and a CreditMetrics (2007) type multi-factor credit risk model of default dependence. This is convenient, as it allows us to establish an economic interpretation of the empirical model parameters, and to define the shares of systematic default risk variation. In our econometric framework, non-Gaussian (integer) default counts are modelled jointly with (continuous, Gaussian) macro-financial covariates and EDF data. Considering risk data based on EDFs in addition to actual defaults is crucial, since defaults are rare for most economic regions outside the USA in Moody's default and recovery database. EDF data are standard default risk measurements that are routinely used in the financial industry and credit risk literature; see, for example, Lando (2003) and Duffie *et al.* (200, 2009).

We obtain the following four main empirical findings. First, our results indicate that there is a distinct world default risk cycle that is related to, but different from, world macro-financial cycles. We find that between 18% and 26% of global default risk variation is systematic, while the remainder is idiosyncratic. The share of systematic default risk is higher (39–51%) if industry-specific variation is counted as systematic. Shared exposure to global and regional macroeconomic factors explains 2–4% of total (i.e. systematic plus idiosyncratic) default risk variation across the economic regions and industry sectors considered in this study. The remainder of the systematic global default risk variation is accounted for by global default-specific (frailty) risk factors (7–18%) and regional frailty factors (1–11%). The latter is an important source of default risk clustering in some regions, but not others. Finally, industry-specific variation (17–31%) represents a significant additional source of default clustering. Industry dynamics are most pronounced for the transportation and energy, consumer goods, and retail and distribution industries.

Second, all risk factors tend to be highly persistent, with most autoregressive parameters well above 0.8 at the quarterly frequency. The frailty and industry-specific factors are particularly persistent, with autoregressive coefficients of up to 0.98. Such values imply a half-life of a shock to default risk of approximately 5–25 quarters. As a result, default risk conditions can decouple substantially and for an extended period of time compared to what macroeconomic and financial markets data imply, before eventually returning to their long run means.

Third, we show that the decoupling of systematic default risk from macro fundamentals is strongly related to variation in bank lending standards in all four regions. This supports economic models that have provided empirical evidence of the importance of financial intermediary behaviour as a determinant of economy-wide corporate default risk; see Aoki and Nikolov (2015), Boissay *et al.* (2016) and Clerc *et al.* (2015). In our sample, unusually low physical default risk conditions almost always coincide with net falling bank lending standards. This finding is intuitive: when bad risks receive ample and easy access to credit, they can avoid, or at least delay, default. Vice versa, net tightening bank lending standards coincide with higher systematic default risk. This phenomenon is also intuitive: when credit access is tight, even solvent firms have a higher risk of becoming illiquid; compare Acharya *et al.* (2012) and He and Xiong (2012). Our global frailty factor is consistent with bank lending standards that are strongly correlated across borders, in line with correlated monetary policy cycles and 'global liquidity' conditions; see Bruno and Shin (2015) and Hoffmann *et al.* (2014).

Finally, given the key importance of global factors, we point out that—perhaps counter-intuitively—more risk diversification across borders does not necessarily decrease portfolio default risk through a reduced dependence across firms. Two effects work in opposite directions. On the one hand, expanding the portfolio across borders *decreases* risk dependence if regional macro and regional default-specific factors are imperfectly correlated. On the other hand, portfolio diversification across borders can *increase* risk dependence if it involves new credit to firms that load more heavily on the world factors. Our empirical results demonstrate that this trade-off can be a relevant concern.

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Section 2 introduces our global data and provides preliminary evidence for default clustering across borders. Section 3 formulates a financial framework in which default dependence is driven by multiple global, regional, and industry-specific risk factors. It also introduces our estimation methodology. Section 4 presents our key empirical results. Section 5 concludes. A supplementary web Appendix (supporting information) presents data plots, additional analysis, technical details concerning estimation and a small number of robustness checks.

2. RISK DATA AND INTERNATIONAL DEFAULT CLUSTERING

This section describes our global data and provides preliminary evidence of pronounced default clustering across borders. We consider data from three sources. First, we construct default and 'firms at risk' count data for firms from 41 countries. Second, we briefly discuss EDF-based risk indices at the regional/country level. Finally, we select macroeconomic and financial time series data with the aim of capturing business cycle conditions. All data are collected at a quarterly frequency.[4]

2.1. International Default Data

As a first panel dataset, we consider default and firms-at-risk count data from Moody's extensive default and recovery database (DRD). The database contains all rating transitions and default dates for all Moody's-rated firms worldwide.

We focus on 35 years of quarterly data from 1980:Q1 to 2014:Q4. We take into account data from 16,360 rated firms in the USA, 903 firms in the UK, 2087 firms in euro area countries and 1517 firms in the Asia–Pacific region. In total, we consider 20,867 firms worldwide. Most of these firms are only active during part of the sample period. The corresponding number of defaults are 1660, 64, 106 and 72, respectively, totalling 1902 default events.

We use Moody's broad industry classification to allocate firms to six broad industry sectors: banks and other financial institutions (fin); transportation, utilities, energy and environment (tre); capital goods and manufacturing (ind); technology firms (tec); retail and distribution (ret); and, finally, consumer goods (con). When counting firms at risk and the corresponding defaults, we ensure that a firm's rating withdrawal is ignored if it is later followed by a default event. In this way, we limit the impact of strategic rating withdrawals preceding a default. We apply other standard filters; for example, we consider only the first default event when there are multiple defaults for the same firm.

We refer to web Appendix A for additional details and default data plots. Web Appendix B uses our historical default and firm count data to take a preliminary look at the benefits and limits of credit risk diversification across industry sectors and national borders. For our global default data, high default losses in one region tend to coincide with high default losses in any of the other regions. In addition to the pronounced cross-country correlation, defaults also strongly cluster in the time dimension.

2.2. EDF Risk Indices

As a second set of data we consider expected default frequencies from Moody's Analytics (formerly Moody's KMV). EDFs are proprietary point-in-time forecasts of default rates, and are based on a proprietary firm value model that takes firm equity values and balance sheet information as inputs; see Crosbie and Bohn (2003) for additional details. We use 1-year-ahead EDF-based risk indices to

[4] The quarterly frequency strikes a compromise between a monthly and a yearly grid. Moving to a monthly grid would increase the number of zero values and missing values, implying that the count data become even more sparse. Moving to a yearly frequency would substantially shorten the sample, implying that risk factor dynamics would not be estimated precisely. Creal *et al.* (2014) model default and rating transition data on a monthly grid; parameter and risk factor inference does not seem to be overly sensitive to the chosen frequency.

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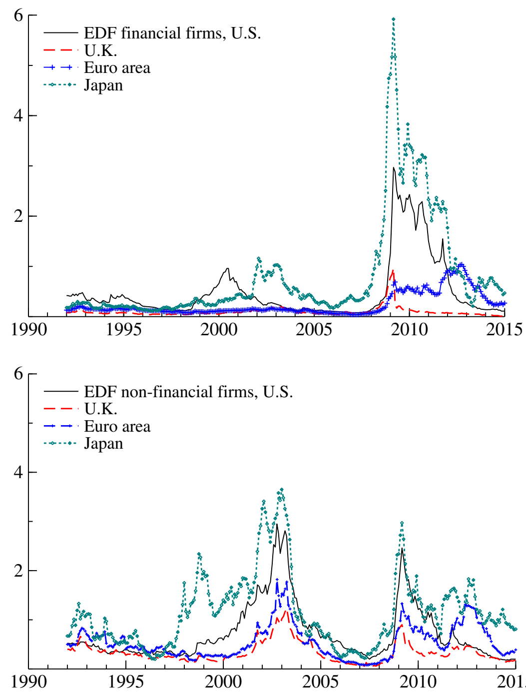

Figure 1. EDF data for financial and non-financial firms. EDF-based risk indices for financial (top) and non-financial firms (bottom). The aggregate risk measures cover firms from the USA, UK, euro area and Japan. The sample is from 1992:Q1 to 2014:Q4. [Colour figure can be viewed at wileyonlinelibrary.com]

augment our sparse data on actual defaults. This is crucial, as our worldwide credit risk analysis would be much harder to do without the additional information from the EDF measures, particularly when considering the systematic default rate variation for firms outside the USA.

Figure 1 plots the EDF-based risk indices that are used in our empirical analysis below. The figure distinguishes risk data for financial (top panel) and non-financial firms (bottom panel) located in the USA, UK, euro area and Japan. For non-financial firms, we use risk indices that are constructed as weighted averages across a large number of firms, with a firm's total assets used as weights. For financial firms, we use a risk index based on median EDF values instead, due to the particularly high concentration of total assets in that industry. While the Moody's default and recovery (DRD) database contains data on both listed and non-listed firms, our EDF data only cover listed firms.[5] Finally, we use EDF-based risk indices for Japan to approximate default risk conditions for the Asia–Pacific region as a whole because data for the rest of the region is not available to us.

The EDFs in Figure 1 reveal a striking extent of shared variation across countries, industries and time. This is similar to the pattern in actual default counts; see web Appendix A. Expected default frequencies for financial firms are high between 2001 and 2003, and in particular during the global financial crisis between 2007 and 2010. Financial EDFs continue to be elevated in the euro area between 2010 and 2013 during the euro area sovereign debt crisis. Expected default rates for non-financial corporates are peaking, in all regions, in 1992, between 2002 and 2004, and from 2008 to 2010.

[5] This implies that the EDF indexes are constructed based on a slightly different set of firms than the set of firms for which we constructed default and exposure counts. We accommodate this difference by allowing the intercept parameters of the non-Gaussian (Binomial) and Gaussian (EDF) model parts to be different.

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2.3. Macro-financial Data

Finally, we consider macro-financial time series data that are commonly considered in the empirical credit risk literature. All macroeconomic and financial time series data are taken from Thomson Reuters/Datastream. Macroeconomic time series data are routinely used as conditioning variables in supervisory stress tests; see, for example, McNeil *et al.* (2005). Important macroeconomic covariates are real GDP growth, industrial production growth and the unemployment rate. Key financial market variables are residential property prices, broad equity indices and bond yields.

For the modelling of the macro data, we distinguish leading, lagging and coincident indicators of the business cycle. We collect nine macro-financial covariates for each region. Two macro variables tend to lead the business cycle: the term structure spread (−5Q) and the change in a broad equity market index (−1Q).[6] Four coincident business cycle indicators include the real GDP growth rate, industrial production growth, the ISM[7] purchasing managers index (and a similar alternative for non-US data) and the yearly change in the unemployment rate. Three lagging indicators include the change in 10-year government bond yields (+1Q), the change in residential property prices (+2Q), and the unemployment rate (+5Q). Stacking these macro-financial time series for each region yields a total of $9 \times 4 = 36$ macro-financial time series.

The macroeconomic variables tend to be highly correlated across countries, as is well documented in the large literature on global business cycles; see, for example, Kose *et al.* (2003). A principal components analysis suggests that the first six principal components (global macro factors) account for 26%, 11%, 9.0%, 8%, 7% and 5% of the total macro data variance, and therefore collectively explain 66% of the total variation in the macro panel.

3. THE MODELLING FRAMEWORK

3.1. A Multi-factor Model of Default Risk Dependence

This section presents a multi-factor financial framework for dependent defaults. Our framework is simple but sufficiently flexible to allow us to disentangle, quantify and test which share of cross-country default dependence is due to world, regional and industry-specific risk factors. Our framework is similar to the well-known CreditMetrics (2007) model, which is a standard in the financial industry. Importantly, the financial framework presented here is closely related to a latent dynamic factor model, which we fit to the data in Section 4. The close relationship between the two models allows us to establish an economic interpretation of the model parameters and systemic default risk shares by mapping the parameters of the econometric model back to those of the financial model.

Our multivariate dynamic model extends the standard static one-factor credit risk model for dependent defaults (see, for example, Lando, 2003) to include a multi-factor version for the asset value V_{it} of firm $i = 1, \ldots, K$ at time t. The process for the asset value is given by

$$\begin{aligned} V_{it} &= a_i' f_t^{\mathrm{gm}} + b_i' f_t^{\mathrm{rm}} + c_i' f_t^{\mathrm{gd}} + d_i' f_t^{\mathrm{rd}} + e_i' f_t^{\mathrm{id}} + \sqrt{1 - a_i'a_i - b_i'b_i - c_i'c_i - d_i'd_i - e_i'e_i}\, \epsilon_{it} \\ &= w_i' f_t + \sqrt{1 - w_i' w_i}\, \epsilon_{it}; \qquad t = 1, \ldots, T, \quad i = 1, \ldots, K \end{aligned} \tag{1}$$

where **g**lobal **m**acro factors f_t^{gm}, **r**egion-specific **m**acro factors f_t^{rm}, a **g**lobal **d**efault (i.e. common frailty) factor f_t^{gd}, **r**egion-specific **d**efault factors f_t^{rd}, as well as **i**ndustry-specific **d**efault factors f_t^{id}

[6] The lead and lag relationships are based on the respective cross-correlation coefficients *vis-à-vis* the real GDP growth rate and are approximately in line with those reported in Stock and Watson (1989).

[7] ISM is the Institute for Supply Management in the USA.

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are stacked in $f_t = (f_t^{\text{gm}\prime}, f_t^{\text{rm}\prime}, f_t^{\text{gd}\prime}, f_t^{\text{rd}\prime}, f_t^{\text{id}\prime})'$. The stacked vector of loading parameters $w_i = (a_i', b_i', c_i', d_i', e_i')'$ satisfies the condition $w_i' w_i \leq 1$. The idiosyncratic disturbance ϵ_{it} has mean zero, unit variance and is serially uncorrelated for $t = 1, \ldots, T$.

Macroeconomic risk factors are either global factors and common to all countries (f_t^{gm}), or region-specific (f_t^{rm}) and thus common only to firms in a particular region. Analogously, the default specific frailty factors are either global factors and common to all firms (f_t^{gd}), or region-specific (f_t^{rd}) or industry-specific (f^{id}). Taken together, the frailty factors represent credit cycle conditions after controlling for macroeconomic developments. In other words, frailty factors capture deviations of the default risk cycle from systematic macro-financial conditions.

Without loss of generality we assume that all risk factors have zero mean and unit unconditional variance. Furthermore, we assume that the risk factors in f_t are uncorrelated at all times. These assumptions imply that $\text{E}[V_{it}] = 0$ and $\text{var}[V_{it}] = 1$ for many distributional assumptions with respect to the idiosyncratic noise component ϵ_{it} for $i = 1, \ldots, K$, such as the Gaussian or Logistic distribution.

In a firm value model, firm i defaults at time t if its asset value V_{it} drops below some exogenous default threshold τ_i; see Merton (1974) and Longstaff and Schwartz (1995). Intuitively, if the total value of the firm's assets is below the value of its debt, debt holders have an incentive to declare bankruptcy. In our framework, V_{it} in equation (1) is driven by multiple systematic risk factors, while idiosyncratic (firm-specific) risk is captured by ϵ_{it}. The default threshold τ_i may depend on the firm's current rating, headquarter location and industry sector. For firms that have not defaulted yet, a default occurs when $V_{it} < \tau_i$ or, as implied by equation (1), when

$$\epsilon_{it} < \frac{\tau_i - w_i' f_t}{\sqrt{1 - w_i' w_i}}$$

The conditional default probability is given by

$$\pi_{it} = \Pr\left(\epsilon_{it} < \frac{\tau_i - w_i' f_t}{\sqrt{1 - w_i' w_i}}\right) \tag{2}$$

Favourable credit cycle conditions are associated with a high value of $w_i' f_t$ and therefore with a low default probability π_{it} for firm i. Since only firms are considered at time t that have not defaulted yet, π_{it} can also be referred to as a discrete time default hazard rate, or default intensity under the historical probability measure; see Lando (2003, ch. 3).

Our empirical analysis considers a setting where the firms ($i = 1, \ldots, K$) are pooled into groups ($j = 1, \ldots, J$) according to headquarter location, industry sector and current rating. We assume that the firms in each group are sufficiently similar (homogeneous) such that the same risk factors and risk factor loadings apply. In this case, equations (1) and (2) imply that, conditional on f_t, the counts y_{jt} are generated as sums over independent 0–1 binary trials (no default–default). In addition, the default counts can be modelled as a binomial sequence, where y_{jt} is the total number of default 'successes' from k_{jt} independent Bernoulli trials with time-varying default probability π_{jt}. In our case, k_{jt} denotes the number of firms in cell j that are active at the beginning of period t. Our final model reads

$$y_{jt} \mid f_t \sim \text{Binomial}(k_{jt}, \pi_{jt}) \tag{3}$$

$$\pi_{jt} = [1 + \exp(-\theta_{jt})]^{-1} \tag{4}$$

$$\theta_{jt} = \lambda_j + \alpha'_j f_t^{\mathrm{gm}} + \beta'_j f_t^{\mathrm{rm}} + \gamma'_j f_t^{\mathrm{gd}} + \delta'_j f_t^{\mathrm{rd}} + \varepsilon'_j f_t^{\mathrm{id}} \tag{5}$$

where λ_j and $\vartheta_j = \left(\alpha'_j, \beta'_j, \gamma'_j, \delta'_j, \varepsilon'_j\right)'$ are loading parameters to be estimated and θ_{jt} is the log-odds ratio of the default probability π_{jt}. For more details on binomial mixture models, see Lando (2003, ch. 9), McNeil *et al.* (2005, ch. 8) and Koopman *et al.* (2011, 2012).

3.2. Quantifying Firms' Systematic Default Risk

The firm value model specification (1) allows us to rank the systematic default risk of firms from different industry sectors and economic regions, while controlling for other information such as the firm's current rating group.

Interestingly, and useful for our purposes, there is a one-to-one correspondence between the model parameters in equation (1) and the reduced-form coefficients in equation (5). If ϵ_{it} is logistically distributed, then the log-odds ratio $\theta_{jt} = \log(\pi_{jt}) - \log(1 - \pi_{jt})$ from equation (5) also denotes the canonical parameter of the binomial distribution. It can be easily verified that for any firm i that belongs to group j, we have

$$\begin{aligned} \tau_i &= \lambda_j \sqrt{1-\kappa_j}, & a_i &= -\alpha_j \sqrt{1-\kappa_j} \\ b_i &= -\beta_j \sqrt{1-\kappa_j}, & c_i &= -\gamma_j \sqrt{1-\kappa_j} \\ d_i &= -\delta_j \sqrt{1-\kappa_j}, & e_i &= -\varepsilon_j \sqrt{1-\kappa_j} \end{aligned}$$

where $\kappa_j = \tilde{\omega}_j/(1+\tilde{\omega}_j)$, and $\tilde{\omega}_j = \alpha'_j\alpha_j + \beta'_j\beta_j + \gamma'_j\gamma_j + \delta'_j\delta_j + \varepsilon'_j\varepsilon_j$. A related simpler expression is derived in Koopman and Lucas (2008) in the context of a univariate risk factor. By contrast, the current formulation allows for multiple groups of vector-valued risk factors. The restriction $w'_i w_i \leq 1$ from the firm value model (1) is always satisfied (see the expression for κ_j) and does not need to be imposed during the estimation stage.

We use the above correspondence between the firm-value model and statistical model parameters when assessing the systematic default risk of firms from different regions and industry sectors. Specifically, we define the systematic risk of firm i as the variance of its systematic risk component:

$$\mathrm{var}[V_{it} \mid \epsilon_{it}] = w'_i w_i \tag{6}$$

where $w_i = (a'_i, b'_i, c'_i, d'_i, e'_i)'$ is introduced and discussed in and below equation (1). Since $\mathrm{var}[V_{it}] = 1$, equation (6) also denotes the *share of total default risk* that is systematic, or non-diversifiable. In our empirical study below, we also report

$$\mathrm{var}\left[V_{it} \mid \epsilon_{it}, f_t^{\mathrm{id}}\right] = a'_i a_i + \ldots + d'_i d_i \tag{7}$$

which treats industry-specific variations as idiosyncratic effects that can be diversified.

3.3. Data Structure and Combination

This section explains how our high-dimensional data are combined in a mixed-measurement dynamic factor model. Our initial high-dimensional mixed-measurement data vector $\left(x'_t, y'_t, z'_t\right)'$ has three parts:

$$x_t = \left(x_{1,1,t}, \ldots, x_{1,N,t}, \ldots, x_{R,1,t}, \ldots, x_{R,N,t}\right)' \tag{8}$$

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$$y_t = \left(y_{1,1,t}, \ldots, y_{1,J,t}, \ldots, y_{R,1,t}, \ldots, y_{R,J,t}\right)' \tag{9}$$

$$z_t = \left(z_{1,t}, \ldots, z_{S,t}\right)' \tag{10}$$

where $x_{i,n,t}$ represents the nth, $n = 1, \ldots, 9$, macroeconomic or financial markets variable for region $i = 1, \ldots, 4$; $y_{i,j,t}$ is the number of defaults between times t and $t+1$ for economic region i and cross-sectional group $j = 1, \ldots, J$; and $z_{s,t}$ is the EDF at a 1-year-ahead horizon for firms $s = 1, \ldots, S$, all measured at time $t = 1, \ldots, T$. The sets of firms $1, \ldots, S$ are constructed on a somewhat ad hoc basis depending on the availability of the EDF data, as discussed in Section 2.2. The sector and region can be identified from each EDF. In other words, the cross-sectional group index $j = j(s)$ can be uniquely determined from the firm index s. The same holds for the regional index.

As a result, the model includes various 'standard' macro and EDF variables that we will consider to be conditionally normally distributed. However, the model also includes (integer) default count variables in vector y_t. The data panel consisting of (x_t, y_t, z_t), for $t = 1, \ldots, T$, is typically unbalanced. It implies that variables may not be observed for all time indices t. For example, the EDF data z_t start to become available only from 1992:Q1 onwards.

The cross-sectional dimension of the data vector implied by equations (8)–(10) is prohibitively large for any worldwide credit risk model. For example, 36 macro data series and five common macro factors would already imply 180 coefficients that need to be estimated numerically by the method of maximum likelihood. For this practical reason, we first collapse our macro panel data to smaller dimensions, and consider EDF-based risk indices at the regional level instead of firm-specific input data.

We proceed in three steps. First, we assume that the standard approximate factor analysis as used in Stock and Watson (2002) can also be adopted for our macro data as well. The static factor analysis can be based on the multivariate model representation

$$x_t = L^{\text{gm}} F_t^{\text{gm}} + u_t, \qquad t = 1, \ldots, T$$

where F_t^{gm} are global macro factors, L^{gm} are the respective factor loadings and u_t are residual terms. The dimension of the vector F_t^{gm} equals the number of global factors r. From the results in Lawley and Maxwell (1971), for example, the estimated factors can be computed as

$$\hat{F}_t^{\text{gm}} = (\hat{L}^{\text{gm}})' x_t, \text{ and } \hat{u}_t = x_t - \hat{L}^{\text{gm}} \hat{F}_t^{\text{gm}} \tag{11}$$

where F_t^{gm} are the first r principal components of all macro panel data x_t. The columns of the 'estimated' loading matrix $\hat{L}^{\text{gm}}$ consist of the first r eigenvectors that correspond to the r largest ordered eigenvalues of $X'X$, where $X' = (x_1, \ldots, x_T)$.

Second, we obtain estimates of regional macro factors from the residual variation in $\hat{u}_t$. We use the same method based on principal components as described above. We extract four regional macro factors, one for each region, from the four subsets of residuals $\hat{u}_t = \left(\hat{u}'_{1,t}, \ldots, \hat{u}'_{4,t}\right)'$, i.e.

$$\hat{u}_{i,t} = \hat{L}_i^{\text{rm}} \hat{F}_{i,t}^{\text{rm}} + v_{i,t}, \qquad i = 1, \ldots, 4 \tag{12}$$

where $F_{i,t}^{\text{rm}}$ is then interpreted as the region-specific macro factor. The principal components from this analysis are given by $\hat{F}_{i,t}^{\text{rm}} = (\hat{L}_i^{\text{rm}})' \hat{u}_{i,t}$ for $i = 1, \ldots, 4$. The four regional factors are stacked into $\hat{F}_t^{\text{rm}} = (\hat{F}_{1,t}^{\text{rm}}, \ldots, \hat{F}_{4,t}^{\text{rm}})'$. This method of estimating regional macro factors may suffer from the problem that we attribute some of the regional macro variation to the global macro factors; see Moench

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et al. (2013). For this reason we do not distinguish between world and regional macro variation when reporting the systematic default risk shares further below.

Finally, we obtain one-quarter-ahead expected default probabilities from annual EDF data as $\hat{z}_{s,t} = 1 - (1 - z_{s,t})^{1/4}$. Quarterly log-odds ratios are calculated as $\hat{\theta}^{\mathrm{EDF}}_{s,t} = \log(\hat{z}_{s,t}) - \log(1 - \hat{z}_{s,t})$ and are collected as $\hat{\theta}^{\mathrm{EDF}}_{t} = \left(\hat{\theta}^{\mathrm{EDF}}_{1,t}, \ldots, \hat{\theta}^{\mathrm{EDF}}_{S,t}\right)$. The transformed and collapsed data vector is given by

$$\mathcal{Y}_t = \left(\hat{F}^{\mathrm{gm}\prime}_t,\ \hat{F}^{\mathrm{rm}\prime}_t,\ y_t',\ \hat{\theta}^{\mathrm{EDF}}_t\right)'; \quad t = 1, \ldots, T \tag{13}$$

While the cross-sectional dimension of the original data (8)–(10) is prohibitively large, the cross-sectional dimension of collapsed data (13) is tractable.

The new measurement equation for our lower-dimensional model is given by

$$\begin{aligned}
\hat{F}^{\mathrm{gm}}_t &= f^{\mathrm{gm}}_t + e^{\mathrm{gm}}_t, \quad e^{\mathrm{gm}}_t \sim \mathrm{N}(0, \Sigma_{\mathrm{gm}}) \\
\hat{F}^{\mathrm{rm}}_t &= f^{\mathrm{rm}}_t + e^{\mathrm{rm}}_t, \quad e^{\mathrm{rm}}_t \sim \mathrm{N}(0, \Sigma_{\mathrm{rm}}) \\
p(y_{j,t} \mid f_t) &\sim \mathrm{Bin}(\theta_{j,t}, k_{j,t}) \\
\hat{\theta}^{\mathrm{EDF}}_{s,t} &= \mu_s + \theta_{j(s),t} + e^{z}_{s,t}, \quad e^{z}_{s,t} \sim \mathrm{N}(0, \Sigma_z)
\end{aligned} \tag{14}$$

where the index $j(s)$ in the last model equation can be uniquely determined from the index s. The log-odds ratio $\theta_{j,t} = \log(\pi_{j,t}) - \log(1 - \pi_{j,t})$ is also the canonical parameter of the Binomial distribution (see McCullagh and Nelder (1989)), $k_{j,t}$ is the number of firms at risk at the beginning of period t, and μ_s is the vector of unconditional means of the respective quarterly log-odds of default from EDF measures. Parameters μ_s in equation (14) and λ_j in equation (5) are different, reflecting the fact that EDF data do not cover exactly the same set of firms for which default and exposure count data are available; see Section 2.2. We collect the risk factors, including f^{gm}_t, f^{rm}_t and $\theta_{j,t}$, into the $m \times 1$ vector f_t and assume it is subject to the stationary vector autoregressive process

$$f_{t+1} = \Phi f_t + \eta_t, \qquad \eta_t \sim \mathrm{N}(0, \Sigma_\eta), \quad t = 1, \ldots, T \tag{15}$$

with the initial condition $f_1 \sim \mathrm{N}(0, \Sigma_f)$. The coefficient matrix Φ and the variance matrix Σ_η are assumed fixed and unknown. The disturbance vectors η_t are serially uncorrelated. Stationarity implies that the roots of the equation $|\mathrm{I} - \Phi z| = 0$ are outside the unit circle. Furthermore, the unconditional variance matrix Σ_f is implied by the dynamic process and is a function of Φ and Σ_η.

We stress that the measurement equation (14) treats the macro factors from equations (11) and (12) and the EDF forecasts as noisy estimates from a preliminary first step. As a result, both macro factors and EDFs are subject to measurement error; see also Bräuning and Koopman (2014). The parameters of the diagonal measurement error variance matrices Σ_{gm}, Σ_{rm}, Σ_z are estimated simultaneously with all other parameters. This feature is novel with respect to the modelling frameworks presented in Koopman *et al.* (2011, 2012) and Creal *et al.* (2014). In our present analysis, the information sets from continuous EDF data via $\hat{\theta}^{\mathrm{EDF}}_t$ and from integer default counts via the Binomial specification contribute to empirically identifying the time variation in the log-odds $\theta_{j,t}$ and in the default probabilities π_{jt}. These two datasets are relevant for our empirical analysis for which the results are reported in Section 4; web Appendix E provides more details.

3.4. Parameter and Risk Factor Estimation

The joint modelling of (discrete) default count data on the one hand and (continuous) macro-financial and EDF data on the other hand implies that a parameter-driven mixed-measurement dynamic factor model (MM-DFM) is appropriate. All estimation details are relegated to web Appendix C.

For each evaluation of the log-likelihood, we need to integrate out many latent factors from their joint density with the mixed-measurement observations. The estimation approach put forward in Koopman *et al.* (2011, 2012) is challenging within this high-dimensional setting. For example, the importance sampling weights may not have a finite variance in our empirical application, which is a necessary condition for the methodology to work and to obtain consistent and asymptotically normal parameter estimates. However, this challenge can be partly overcome by including more antithetic variables to balance the simulations for location and scale, as suggested by Durbin and Koopman (2000) and further explored in detail by Durbin and Koopman (2012, pp. 265–266). This solution has made our procedure feasible, even in this high-dimensional setting.

4. MAIN EMPIRICAL RESULTS

In our empirical study, we analyse the credit exposures of more than 20,000 firms from 41 countries in four economic regions of the world during a time period of 35 years, from 1980:Q1 to 2014:Q4. The headquarter location of the company determines the region of the firm, which is further identified by its current rating category and its industry sector. The main objective is to quantify the share of systematic default risk that can be attributed to *world* business cycle factors and default-specific factors. The analysis may assess to what extent the world default risk cycles can be decoupled from world macroeconomic conditions.

4.1. Model Specification

For the selection of the number of factors we rely on likelihood-based information criteria (IC). The panel information criteria of Bai and Ng (2002) suggest two or three common factors for the global macro data. We select five global macro-financial factors f_t^{gm} to be conservative and not to bias our results towards attributing too much variation to default-specific (frailty) factors when in fact they are due to macro factors. We also include four additional region-specific macro factors, one for each region, to ensure that we do not miss regional macroeconomic variation that may matter for the respective regional default rates.

Allowing for one default-specific frailty factor f_t^{gd} is standard in the literature; see, for example, Duffie *et al.* (2009) and Azizpour *et al.* (2015). We further include four region-specific frailty factors f_t^{rd}: one for each region. Finally, we select six additional industry-specific factors f_t^{id} that affect firms from the same industry sector. Such industry factors capture (global) industry-specific developments as well as possible contagion through upstream and downstream business links (see Lang and Stulz (1992); Acharya *et al.*, 2007), and have been included in earlier models; see, for example, Koopman *et al.* (2012).

Regarding risk factor loadings, all firms load on global factors f_t^{gm} and f_t^{gd} with region-specific factor loadings. This means that all firms are subject to these risk factors, but to different extents. Ratings affect the baseline (unconditional) default hazard rates but not the factor loadings. While somewhat restrictive, this specification is parsimonious and remains sufficiently flexible to accommodate most of the heterogeneity observed in the cross-section. In particular, it allows us to focus on the commonalities and differences in the share of systematic default risk that is explained by world, regional and industry factors.

4.2. Parameter and Risk Factor Estimates

Table I reports model parameter estimates. All sets of risk factors—macro, frailty, as well as industry-specific—contribute towards explaining corporate default clustering within and across countries. Importantly, defaults from all regions load on macro factors (in particular, the first one).

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Table I. Parameter estimates

Baseline hazard terms $\lambda_{r,j} = \bar{\lambda}_0 + \bar{\lambda}_{1,j} + \bar{\lambda}_{2,s} + \bar{\lambda}_{3,r}$

par	val	p-val
$\bar{\lambda}_0$	−4.82	0.00
$\bar{\lambda}_{1,\text{fin}}$	0.07	0.73
$\bar{\lambda}_{1,\text{tre}}$	0.07	0.80
$\bar{\lambda}_{1,\text{tec}}$	−0.23	0.39
$\bar{\lambda}_{1,\text{ret}}$	0.14	0.67
$\bar{\lambda}_{1,\text{con}}$	−0.13	0.72
$\bar{\lambda}_{2,\text{IG}}$	−3.70	0.00
$\bar{\lambda}_{3,\text{UK}}$	0.30	0.02
$\bar{\lambda}_{3,\text{EA}}$	−0.21	0.05
$\bar{\lambda}_{3,\text{AP}}$	−0.41	0.00

Global macro f_t^{gm} (ctd) $\alpha_{k,r,j} = \bar{\alpha}_{k,0} + \bar{\alpha}_{k,1,r}$

par	val	p-val
ϕ_4^g	0.83	0.00
$\bar{\alpha}_{4,0}$	0.00	0.93
$\bar{\alpha}_{4,1,\text{UK}}$	0.03	0.37
$\bar{\alpha}_{4,1,\text{EA}}$	0.07	0.04
$\bar{\alpha}_{4,1,\text{AP}}$	0.04	0.52
ϕ_5^g	0.84	0.00
$\bar{\alpha}_{5,0}$	0.03	0.37
$\bar{\alpha}_{5,1,\text{UK}}$	−0.00	0.99
$\bar{\alpha}_{5,1,\text{EA}}$	0.04	0.32
$\bar{\alpha}_{5,1,\text{AP}}$	0.06	0.29

Global frailty f_t^{gd}

par	val	p-val
ϕ^c	0.95	0.00
$\bar{\gamma}_0$	0.43	0.00
$\bar{\gamma}_{1,\text{UK}}$	0.08	0.19
$\bar{\gamma}_{1,\text{EA}}$	0.12	0.08
$\bar{\gamma}_{1,\text{AP}}$	−0.05	0.58

Regional frailty f_t^{rd}

par	val	p-val
ϕ_{US}^d	0.96	0.00
$\bar{\delta}_{0,\text{US}}$	0.43	0.01
ϕ_{UK}^d	0.96	0.00
$\bar{\delta}_{0,\text{UK}}$	0.17	0.21
ϕ_{EA}^d	0.97	0.00
$\bar{\delta}_{0,\text{EA}}$	0.21	0.13
ϕ_{AP}^d	0.87	0.00
$\bar{\delta}_{0,\text{AP}}$	0.41	0.00

Global macro f_t^{gm} $\alpha_{k,r,j} = \bar{\alpha}_{k,0} + \bar{\alpha}_{k,1,r}$

par	val	p-val
ϕ_1^g	0.90	0.00
$\bar{\alpha}_{1,0}$	0.25	0.00
$\bar{\alpha}_{1,1,\text{UK}}$	−0.00	0.90
$\bar{\alpha}_{1,1,\text{EA}}$	−0.10	0.03
$\bar{\alpha}_{1,1,\text{AP}}$	−0.06	0.43
ϕ_2^g	0.84	0.00
$\bar{\alpha}_{2,0}$	−0.02	0.65
$\bar{\alpha}_{2,1,\text{UK}}$	−0.03	0.47
$\bar{\alpha}_{2,1,\text{EA}}$	−0.06	0.08
$\bar{\alpha}_{2,1,\text{AP}}$	−0.05	0.41
ϕ_3^g	0.84	0.00
$\bar{\alpha}_{3,0}$	−0.07	0.14
$\bar{\alpha}_{3,1,\text{UK}}$	0.08	0.09
$\bar{\alpha}_{3,1,\text{EA}}$	0.08	0.08
$\bar{\alpha}_{3,1,\text{AP}}$	0.10	0.20

Regional macros f_t^{rm}

par	val	p-val
ϕ_{US}^m	0.41	0.00
$\bar{\beta}_{0,\text{US}}$	0.04	0.01
ϕ_{UK}^m	0.79	0.00
$\bar{\beta}_{0,\text{UK}}$	−0.05	0.18
ϕ_{EA}^m	0.82	0.00
$\bar{\beta}_{0,\text{EA}}$	0.01	0.52
ϕ_{AP}^m	0.87	0.00
$\bar{\beta}_{0,\text{AP}}$	−0.12	0.13

Industry factors f_t^{id}

par	val	p-val
ϕ_{fin}^i	0.97	0.00
$\bar{\epsilon}_{\text{fin}}$	0.53	0.00
ϕ_{tre}^i	0.83	0.00
$\bar{\epsilon}_{\text{tre}}$	0.78	0.00
ϕ_{ind}^i	0.84	0.00
$\bar{\epsilon}_{\text{ind}}$	0.58	0.00
ϕ_{tec}^i	0.90	0.00
$\bar{\epsilon}_{\text{tec}}$	0.55	0.00
ϕ_{ret}^i	0.93	0.00
$\bar{\epsilon}_{\text{ret}}$	0.61	0.00
ϕ_{con}^i	0.92	0.00
$\bar{\epsilon}_{\text{con}}$	0.76	0.00

Note: We report the maximum likelihood estimates of selected coefficients in the specification of the log-odds ratio (5). We use an additive parametrization for $\lambda_{r,j}$ and $\alpha_{r,j}$. Coefficients $\lambda_{r,j}$ determine baseline default rates. Factor loadings refer to global macro factors f_t^{gm}, region-specific macro factors f_t^{rm}, one global frailty factor that is common to all firms f_t^{gd}, region-specific default-specific (frailty) factors f_t^{rd}, and six industry-specific factors f_t^{id}. The global macro factors are common to all macro and default data and across all four regions. The global and regional frailty factors do not load on macro data. Industry mnemonics are financials (fin), transportation and energy (tre), industrials (ind), technology (tec), retail and distribution (red) and consumer goods (con). Estimation sample is 1980:Q1 to 2014:Q4.

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The region-specific macro factors are overall relatively less important. This is intuitive, since much of the regional macro variation is already accounted for by the global macro factors. In addition, this finding may suggest some sample selection, in that non-US firms that request to be rated by Moody's also tend to be internationally active, and more so than their US counterparts. Non-US firms from the euro area and APAC region also differ from US firms in their unconditional hazard rates $\lambda_{r,j}$; see the left-hand column in Table I. Again, this may reflect some sample selection, in that these non-US firms are sufficiently large and of a high credit quality to access capital markets rather than being forced to refinance themselves via financial intermediaries.

While the common variation in defaults implied by shared exposures to macro factors is significant and important, it is not sufficient. The global frailty factor is found to be an additional significant determinant of default rates in all regions. It tends to load slightly more strongly on non-US data than on US data (although the statistical evidence is weak). All loadings on industry-specific risk factors are significant. Industry-specific variation is most important for firms from the transportation and energy (tre) sector, probably reflecting their shared exposure to oil price developments.

Our finding of significant frailty effects, while in line with most credit risk literature, is somewhat at odds with studies that attribute less importance to such factors; see, for example, Lando and Nielsen (2010), and Duan *et al.* (2012). We stress that the importance of frailty factors depends on right-hand-side conditioning variables, in particular firm-specific information. Firm-specific covariates such as equity returns, volatility and leverage are often found to be important predictors of default; see Vassalou and Xing (2004) and Duffie *et al.* (2007, 2009). We acknowledge that ratings alone may not provide sufficient statistics for future default, and that our frailty factors may in part reflect this fact.[8] We argue in Section 4.4, however, that missing firm-specific effects are unlikely to provide a complete explanation.

All default risk factors tend to be highly persistent. Most autoregressive parameters are well above 0.8 at the quarterly frequency. The frailty and industry-specific factors are particularly persistent, with autoregressive coefficients of up to 0.98. Such values imply a half-life of a shock to default risk of approximately 5–25 quarters.

Figure 2 plots the conditional mean estimates of the global and regional frailty factors in the top panel, as well as six industry-specific factors in the bottom panel. The evolution of the world frailty risk factor (top panel) suggests that worldwide excess default clustering was most pronounced during the early 1990s, as well as between 2002 and 2003. Before the global financial crisis, default risk conditions were significantly below what was implied by macro fundamentals during 2006–2007. This pattern already suggests that the frailty factor may be related to the behaviour of financial intermediaries: non-financial firms experience higher default stress as credit access dried up following the 1991 and 2001 economic contractions. At the same time, non-financial firms appeared to have easy access to credit in the years leading up to the global financial crisis.

The world frailty risk factor (top panel) is quite different from the US frailty factor reported in Duffie *et al.* (2009) and Koopman *et al.* (2012). Indeed, US firms load significantly on their own regional frailty factor (second panel in Figure 2). World and US systematic default risk are related but do not coincide.

Some evidence of additional default clustering due to regional default-specific factors is also found for firms located in the Asia–Pacific region and in Europe following the sovereign debt crisis of 2010–2013. The loading parameters on regional frailty factors are small and insignificant for firms from the UK and the euro area. Instead, these firms load more heavily on the global frailty factor.

[8] Our modelling framework considers groups of homogeneous firms rather than individual firms, and considers data of many firms, worldwide. As a result it is hard, if not impossible, to include firm-specific information beyond rating classes, geography and industry sectors. In this regard, we again refer to the RMI credit risk initiative as a noteworthy attempt to build a worldwide credit risk map from the bottom up (see http://www.rmicri.org).

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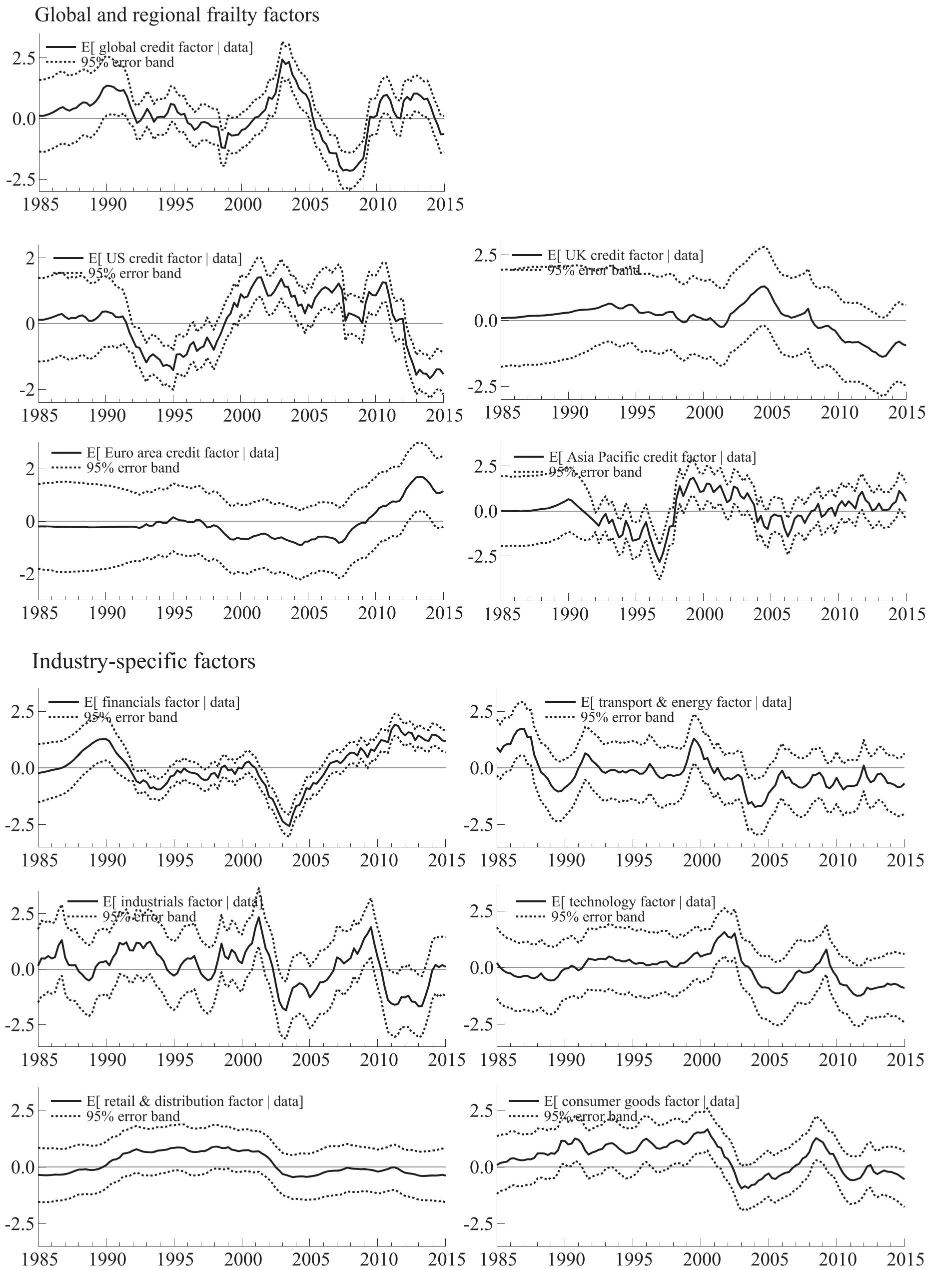

Figure 2. Global frailty and industry factors. The top panel reports the conditional mean estimates of global frailty and region-specific frailty factors. The bottom panel plots the conditional mean estimates of the six industry-specific factors

Shared exposure to volatile macroeconomic and default-specific factors implies that default hazard rates can vary substantially over time. Figure 3 plots the respective estimates of time-varying quarterly default rates for six industry sectors and four regions. Default probabilities are particularly volatile for industrial firms. US financial defaults cluster in particular during the savings and loans crisis between

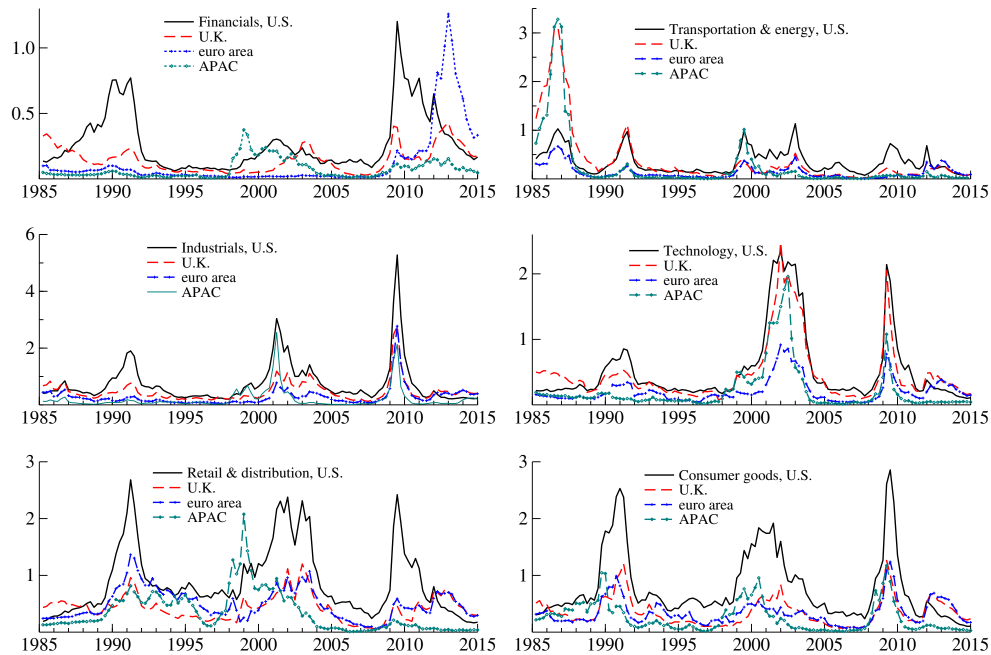

Figure 3. Global default hazard rates at the industry level. Each panel plots the model-implied time-varying default rate (one-quarter-ahead default probability in percent) for a specific industry sector. The panels refer to financial firms (top left), transportation and energy (top right), industrial (middle left), technology (middle right), retail and distribution (bottom left) and consumer goods (bottom right). Each panel distinguishes firms from the USA, UK, euro area and Asia–Pacific region. The reported hazard rates are computed from full-sample estimates of risk factors and sensitivity parameters. [Colour figure can be viewed at wileyonlinelibrary.com]

1986 and 1990 (in the USA), after the burst of the dot-com bubble between 2001 and 2002, and during the financial crisis up to the federal spending crisis between 2008 and 2013. In addition, financial sector firms located in the euro area suffered particularly during the euro area sovereign debt crisis between 2010 and 2012, when default hazard rates were substantially above their historical average. Default risk for industrial sector firms is particularly high in 1990–91, 2001–02 and 2008–09, in line with the business cycle contractions during these periods. Not surprisingly, the burst of the dot-com bubble is particularly visible for the implied default rates of technology sector firms between 2001 and 2002.

4.3. Variance Decomposition

This section attributes the time series variation in the systematic default risk of firms from different industries and countries to different sets of systematic and idiosyncratic risk drivers, using the firm-value framework from Section 3. Table II presents the estimated risk shares. We focus on three main empirical findings.

First, we find that between 18% and 26% of global default risk variation is systematic, while the remainder is idiosyncratic. The share of systematic default risk is higher (39–51%) if we count industry-specific variation as systematic. Rated firms from different countries tend to default together to some extent simply because of their shared exposure to the international business cycle and related macroeconomic conditions. An important role for global and industry factors is in line with earlier credit risk studies; see, for example, Pesaran *et al.* (2006) and Aretz and Pope (2013).

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Table II. Systematic risk and risk decomposition

Reg.	Ind.	$f_t^{\text{gm}}, f_t^{\text{rm}}$ $[a_i'a_i]$	f_t^{gd} $[c_i'c_i]$	f_t^{rd} $[d_i'd_i]$	f_t^{id} $[e_i'e_i]$	$\text{var}[V_{it} \mid \varepsilon_{it}, f_t^{\text{id}}]$ $a_i'a_i + \ldots + d_i'd_i$	$\text{var}[V_{it} \mid \varepsilon_{it}]$ $= w_i'w_i$
US	fin	4.1%	10.8%	10.7%	16.5%	25.6%	42.2%
US	tre	3.5%	9.1%	9.0%	29.8%	21.6%	51.3%
US	ind	4.0%	10.5%	10.4%	18.9%	24.9%	43.8%
US	tec	4.1%	10.7%	10.6%	17.3%	25.4%	42.7%
US	red	3.9%	10.3%	10.2%	20.3%	24.5%	44.8%
US	con	3.5%	9.3%	9.1%	28.7%	21.9%	50.6%
UK	fin	4.3%	16.0%	1.7%	17.3%	22.0%	39.3%
UK	tre	3.6%	13.4%	1.4%	31.0%	18.4%	49.4%
UK	ind	4.1%	15.6%	1.7%	19.8%	21.4%	41.1%
UK	tec	4.2%	15.9%	1.7%	18.1%	21.8%	39.9%
UK	red	4.1%	15.3%	1.6%	21.2%	21.0%	42.2%
UK	con	3.6%	13.6%	1.4%	29.9%	18.7%	48.6%
EA	fin	2.3%	18.1%	2.6%	17.1%	23.1%	40.2%
EA	tre	1.9%	15.2%	2.2%	30.6%	19.3%	49.9%
EA	ind	2.2%	17.6%	2.6%	19.5%	22.4%	41.9%
EA	tec	2.3%	18.0%	2.6%	17.8%	22.8%	40.7%
EA	red	2.2%	17.3%	2.5%	20.9%	22.0%	42.9%
EA	con	2.0%	15.4%	2.2%	29.6%	19.6%	49.2%
AP	fin	4.1%	8.7%	10.2%	17.1%	22.9%	40.1%
AP	tre	3.4%	7.3%	8.5%	30.7%	19.2%	49.9%
AP	ind	3.9%	8.5%	9.9%	19.5%	22.3%	41.8%
AP	tec	4.0%	8.6%	10.1%	17.9%	22.7%	40.6%
AP	red	3.9%	8.3%	9.7%	21.0%	21.9%	42.8%
AP	con	3.4%	7.4%	8.6%	29.6%	19.5%	49.1%

Note: We report systematic risk variation estimates for six industry sectors across four economic regions. Systematic default risk is further decomposed into variation due to subsets of systematic risk drivers. For factor mnemonics see Table I. Risk shares refer to global and region-specific macro factors f_t^{gm} and f_t^{rm}, one global frailty factor that is common to all firms f_t^{gd}, region and default-specific (frailty) factors f_t^{rd}, and six industry-specific factors f_t^{id}. Industry sectors are financials (fin), transportation and energy (tre), industrial firms (ind), technology (tec), retail and distribution (red) and consumer goods (con). We refer to the financial framework in Section 3 for a discussion of firm's systematic versus idiosyncratic risk components. Estimation sample is 1980:Q1 to 2014:Q4.

Second, the shared exposure to global and regional macroeconomic factors explains approximately 10–20% of systematic default risk, or 2–4% of total (i.e. systematic plus idiosyncratic) default risk variation. Exposure to the global frailty risk factor f_t^{gd} accounts for 7–18% of total default risk. Regional frailty factors (1–11%) are an important additional source of default risk clustering in some regions, particularly the USA and Asia–Pacific regions. As a result, the global and regional frailty factors, taken together, explain a considerably larger share of international default risk variation, by a factor of approximately five.

We conjecture that at least three effects may play a role in explaining the low macro factor shares in default risk. First, default contagion may matter at the industry, country and global level; see Azizpour *et al.* (2015). The contagion effects are likely to be captured by default-specific latent factors in our model specification.[9] Second, nonlinearities may be present, such as regime dependence in macro

[9] The simulation results reported in Koopman *et al.* (2011) apply to our setup as well. These demonstrate that our estimation method is able to differentiate fairly precisely between macro-implied default risk variation on the one hand and other effects such as contagion dynamics on the other. We refer to Azizpour *et al.* (2015), who attempt to disentangle these competing effects for a smaller set of US firms.

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factor loadings. Again, such effects would be attributed to default-specific factors in our specification. Third, the default-specific latent factors stand in for missing covariates such as the common movement in firm-specific accounting variables; see Lando and Nielsen (2010).[10]

The pronounced role of default-specific factors implies that default risk conditions can decouple substantially and for an extended period of time from what is implied by macroeconomic data, before eventually returning to their long run means. There is a distinct world default risk cycle that is related to but different from world macro-financial cycles. It is important to acknowledge the existence of such a cycle when designing a macro-prudential policy framework for the financial cycle.

Finally, industry-specific variation is a significant additional source of default clustering. Industry-specific factors explain between 17% and 31% of total default risk variation. Industry factors are most pronounced for the transportation and energy, consumer goods, and retail and distribution industries. Arguably, industry effects may be classified as non-systematic and diversifiable in a large portfolio that is sufficiently spread across industries.

The current model with frailty components can also readily be applied to study risk diversification. In line with our data analysis in web Appendix B, global diversification of the loan portfolio may not always reduce risk. On the one hand, risk is reduced by new taking new exposures to imperfectly correlated industry or region-specific frailty factors. On the other hand, however, these diversification effects may be partly offset by a larger loading of the new exposures on the common global frailty and macro factors. Such effects are harder, if not impossible, to study without the current model setup and factor decomposition.

4.4. Global Credit Risk Decoupling from Macro Fundamentals

We documented that global and regional frailty factors explain a large share of systematic default risk variation. This section demonstrates that deviations of systematic default risk from what is implied by the macro fundamentals can, to a substantial extent, be traced back to variations in international bank lending standards.

Figure 4 plots systematic default risk deviations from fundamentals. These are measured as the sum of the global, regional and industry frailty factors times their respective loadings, while ignoring the risk contribution of global and regional macro factors. The sum is standardized by the square root of its unconditional variance:

$$\mathrm{CRD}_{r,j} = \frac{\gamma_j' f_t^{\mathrm{gd}} + \delta_j' f_t^{\mathrm{rd}} + \epsilon_j' f_t^{\mathrm{id}}}{\sqrt{\gamma_j'\gamma_j + \delta_j'\delta_j + \epsilon_j'\epsilon_j}} \tag{16}$$

and is unconditionally standard normally distributed as a result. Note that the numerator of equation (16) is a special case of equation (5) with $\lambda_j = \alpha_j = \beta_j = 0$. Figure 4 focuses on financial (top) and industrial firms (bottom) in each region. Risk conditions can decouple significantly and persistently from the risk levels implied only by shared exposure to macro-financial fundamentals. Interestingly, there is a particularly large and persistent deviation of risk from fundamentals preceding the global

[10] The macro shares increase to 3–7% of total variation when the first 10 principal components from the macro data are used as global macro factors in the empirical modelling (instead of the first five). The macro factor share remains well below the share explained by frailty factors even in this case. The first 10 principal components account for approximately 82% of the total variation in the macro panel. Merely applying a different estimation sample from 2000:Q1 to 2014:Q4 leaves the risk shares approximately unchanged (see web Appendix D). We do not use vintage macro data in our study. Revised macro data is the most accurate, but can be subject to substantial revisions after initial publication. Revised data appear to be most in line with the in-sample nature of the variance decomposition.

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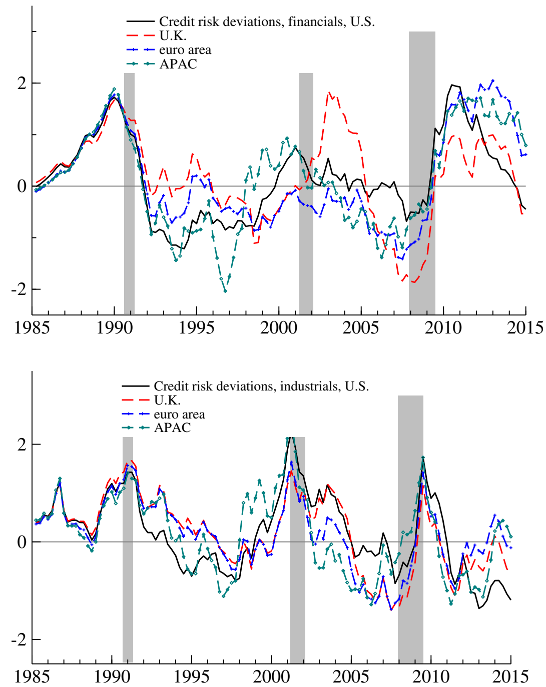

Figure 4. Credit risk deviations from fundamentals. Deviations of systematic default risk from macro-financial fundamentals for financial (top) and industrial (bottom) firms. The risk deviations are obtained according to equation (16). Shaded areas are NBER recession dates for the USA. [Colour figure can be viewed at wileyonlinelibrary.com]

financial crisis of 2007–2009 in the UK, euro area and Asia-Pacific regions. Risk conditions were then significantly and persistently below what had been suggested by fundamentals.

Figure 5 plots risk deviation estimates and the net tightening of bank lending standards for the four economic regions. The bank lending standards refer to commercial and investment loans to medium to large enterprises, and are taken from respective surveys conducted by the Federal Reserve, Bank of England, European Central Bank and Bank of Japan.[11]

We draw two main conclusions. First, physical credit risks and bank lending (credit) quantities are strongly related. In a credit boom, even bad risks have ample access to credit, and can thus postpone default. Therefore, in such a credit boom, bad risks default less frequently than what could be expected conditional on the state of the business cycle. The (too) low default rate is then not a sign of economic strength, but rather an indication of a financial boom and thus a warning signal for financial fragility and its subsequent potential unravelling. The reverse holds in a credit crunch. In a credit crunch, even financially sound firms find it hard to roll over debt, which raises their default risk due to illiquidity concerns. As a result, they default more often than what is expected conditional on the macroeconomic environment. Our results are in line with a literature on portfolio credit risk that concludes that easily observed macro-financial covariates and firm-specific information, while helpful, are not sufficient

[11] To the best of our knowledge, the connection between ease of credit access and systematic credit risk conditions (under the historical measure) was first argued informally in Das *et al.* (2007) and Duffie *et al.* (2009). The link is explored more formally in a firm value model by He and Xiong (2012), while Koopman *et al.* (2012) are, to our knowledge, the first to empirically tie unobserved credit risk deviations to the variation in (US) bank lending standards.

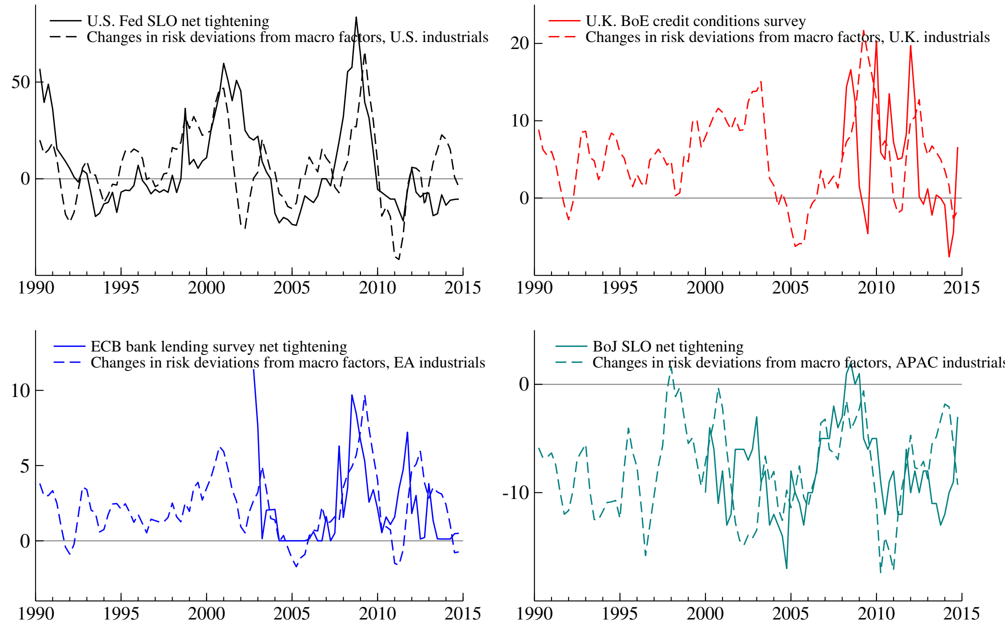

Figure 5. Credit risk deviations versus bank lending standards. Changes (year-on-year) in the credit risk deviations from fundamentals for industrial firms (see Figure 4) are associated with the net tightening of lending standards as reported in central bank surveys. Bank lending standards are from surveys by Federal Reserve for the USA (top left), Bank of England for the UK (top right), European Central Bank for the euro area (bottom left) and Bank of Japan for Japan (bottom right). Shaded areas pertain to NBER recession dates. Credit risk deviations (dashed lines) are matched in terms of means and variances to the net tightening of bank lending standards (solid lines). [Colour figure can be viewed at wileyonlinelibrary.com]

to fully explain time-varying systematic credit risk conditions; see, for example, Das *et al.* (2007), Koopman *et al.* (2008, 2009, 2011), Duffie *et al.* (2009) and Azizpour *et al.* (2015).[12]

Second, the observed comovement between bank lending standards and (excess) default risks suggest that two-way feedback effects between the health of the financial sector and the macro-economy are important. This is potentially important for predictive models that forecast default risk parameters conditional on a macro-financial stress scenario. While macro-financial stress is naturally mapped into higher default probabilities (and therefore higher bank losses and lower capital ratios), the subsequent financial tightening of bank lending standards could raise credit risk parameters even further. The tight correlation between physical default risk and financial intermediation implied by Figure 5 suggests that such second round feedback effects are substantial. It might thus be worthwhile to include bank lending standards as an additional conditioning variable in macro-prudential stress tests.

[12] The close association of bank lending standards with frailty factor dynamics observed in Figure 5 would suggest default risk model specifications which include bank lending standards directly as a separate observable factor, possibly even distinguishing its global (average) and local (region-specific deviations from that average) components. We do not do this in our current analysis, for the main reason that our estimation sample is from 1980:Q1 to 2014:Q4, while bank lending standards are only available for a fraction of that time (from 2003:Q2 onwards in the euro area, and from 2007:Q3 onwards in the UK, for example). We would expect that the need for unobserved residual factors in default risk models reduces significantly once survey-based information on bank lending practices are included as a conditioning variable.

5. CONCLUSION

We investigated the common dynamic properties of systematic default risk conditions across countries, regions and the world. For this purpose we developed a high-dimensional, partly nonlinear non-Gaussian state-space model to estimate common components in firm defaults in a 41-country sample, covering six broad industry groups and four economic regions in the world. The results indicate that common world factors are a first-order source of default risk variation and of observed default clustering, thus providing evidence for a world credit risk cycle on top of world business cycle conditions. The presence of such global macro and frailty dynamics can limit the scope for cross-border credit risk diversification in the financial industry. We also found that default clustering above business cycle variation can be linked to credit supply conditions, in particular to bank lending standards, across all global regions considered in this study. This raises an important question regarding current stress testing practices that mainly focus on stressed macro scenarios only. Accounting for subsequent credit supply effects via additional stressed default factors using the model of this study may result in more realistic stressed capital levels given the variation in bank lending standards over time.

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