Credit risk around the world:

Inference on world, country and industry factors*

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Inference on world, country and industry factors

B. Schwaab, S. J. Koopman, A. Lucas

Abstract

This paper investigates the dynamic properties of systematic default risk conditions for firms from different countries, industries, and rating groups. We use a high-dimensional non-linear non-Gaussian state space model to estimate common components in corporate defaults in a 41 country sample between 1980Q1-2014Q4, encompassing both the global financial and euro area debt crises. We find that macro and default-specific world factors are a first order source of default clustering across countries. Defaults cluster more than what is implied by shared exposure to macro factors, indicating that other factors are of first-order importance. For all firms, deviations of systematic default risk from macro fundamentals are correlated with net tightening bank lending standards, strongly suggesting that bank credit supply and systematic default risk are inversely related.

Keywords: systematic default risk; credit portfolio models; frailty-correlated defaults; international default risk cycles; state-space methods.

JEL classification: G21, C33
1 Introduction

Is there a world default risk cycle? Recent studies provide evidence that there are many cross-country links and common global dynamics in macroeconomic fluctuations and financial asset returns. At the same time, these macroeconomic fluctuations and asset returns are also well known to influence the time variation in corporate default rates, see, for example, Pesaran, Schuermann, Treutler, and Weiner (2006), Koopman, Kräussl, Lucas, and Monteiro (2009), and Giesecke, Longstaff, Schaefer, and Strebulaev (2011). Given that many macro-financial observations are best thought of as global phenomena, we ask whether the same is true for corporate default rates. Thus, is there a world default risk cycle? If so, what are its statistical properties? How different is the world default risk cycle from the world business cycle that also affect defaults? When may the two be decoupled? Is such default risk decoupling U.S. specific, or an international phenomenon? Finally, what are the implications of world factors for the risk bearing capacity of internationally active financial intermediaries?

Just as an important first strand of literature investigates the extent of co-movement across global macroeconomic and financial market variables, a second strand of literature investigates why corporate defaults cluster so much over time within certain economies. For example, quarterly default probabilities for U.S. industrial firms can be up to an order of magnitude higher in a bust than they are in an economic boom, see Das, Duffie, Kapadia, and Saita (2007) and Koopman, Lucas, and Schwaab (2011). In general, the accurate measurement of point-in-time default hazard rates is a complicated task since not all processes that determine corporate default are easily 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

1For example, Kose, Otrok and Whiteman (2003, 2008), and Kose, Otrok, and Prasad (2012) document the presence of a world business cycle, 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 influences explaining more than half of the country variances on average. Yet other research points to global common movement in international stock returns (see e.g. Bekaert, Hodrick, and Zhang (2009)), government bond yields (see e.g. Jotikasthira, Le, and Lundblad (2011)), and term structure dynamics (see e.g. Diebold, Li, and Yue (2008)).
most forcefully made by Das, Duffie, Kapadia, and Saita (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, or conditional independence, assumption. In particular, there is substantial evidence for an additional dynamic unobserved ‘frailty’ risk factor or contagion dynamics, see McNeil and Wendin (2007), Koopman, Lucas, and Monteiro (2008), Koopman and Lucas (2008), Duffie et al. (2009), Lando and Nielsen (2010), Koopman, Lucas, and Schwaab (2011, 2012), Azizpour, Giesecke, and Schwenkler (2014), and Creal, Schwaab, Koopman, and Lucas (2014).

The main objective of this paper is to quantify the share of systematic default risk that can be attributed to world business cycle and default-specific factors, to infer their statistical properties, estimate their location over time, and to assess to which extent the world default risk cycles can be decoupled from world macroeconomic conditions. Compared to the above credit risk studies, our current paper takes an international perspective on default clustering across borders rather than a U.S.-only perspective. We investigate firms from a 41-country sample covering four economic regions of the world. In addition to their headquarter location, firms differ in terms of their industry sectors and current rating categories.

Understanding the sources of international default risk variation is important for developing robust risk models at internationally active financial intermediaries as well as for their effective supervision by the appropriate authorities. In addition, studying a country (or region) in isolation can lead one to erroneously believe that the observed co-movement is particular to that country, say the U.S., when it is in fact common to a much larger group of countries. Unfortunately, data sparsity (in particular for the non-U.S. data) as well as econometric difficulties (due to the combination of having non-Gaussian default data on the left hand side and unobserved risk factors on the right hand side; but also due to computational challenges when jointly modeling different sets of macro and default risk data pertaining to a larger number of countries) have heretofore limited attention to single countries. To our knowledge there has not been a detailed study of whether fluctuations in systematic de-
fault risk are associated with worldwide, country/regional, or industry-specific risk drivers. We address these issues by employing a high-dimensional dynamic factor modeling framework to disentangle common components in both international macro-financial variables and international default risk data.\(^2\)

From a methodological viewpoint, we here extend the estimation framework of Koopman, Lucas, and Schwaab (2012) to a substantially larger cross-section of mixed measurement observations. In our setting, non-Gaussian (integer) default counts are modelled jointly with (continuous, Gaussian) macro-financial covariates and expected default frequencies (EDF) data in one integrated framework. All unobserved risk factors and model parameters are estimated in a single step. Considering data on expected default frequencies (EDF) in addition to actual defaults is crucial since defaults are rare for most economic regions outside of the U.S. EDF data are standard default risk measurements and routinely used in the financial industry and credit risk literature, see for example Lando (2003), Duffie et al. (2007) and Duffie et al. (2009).

We report three main empirical findings. First, our results indicate that there is a distinct world default risk cycle that is related to but distinct from world macro-financial cycles. We find that between 10-28% of global default risk variation is systematic, while the remainder is idiosyncratic. Shared exposure to global macroeconomic factors explains 1-6% of total (i.e., systematic plus idiosyncratic) default risk variation across the economic regions and industry sectors considered in this paper. Regional macro factors (0-1%) are relatively less important for default risk. A global default-specific (frailty) risk factor accounts for an additional 7-20% of total risk. Regional frailty factors (1-15%) are also important source of default risk clustering. Overall, 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

\(^2\)To our knowledge, only Pesaran, Schüermann, Treutler, and Weiner (2006) study credit risk conditions in multiple countries in a unified (GVAR) framework. These authors, however, do not distinguish between different sets of latent default risk drivers, such as world, country, and industry factors, and do not provide a variance decomposition of default data with respect to these components.
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 from what is implied by macroeconomic data, before eventually returning to their long run means.

Second, 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 argue that the behavior of financial intermediaries is an important determinant of economy-wide corporate default risk (He and Xiong (2012), Aoki and Nikolov (2014), Clerc et al. (2014)). In our sample, unusually low physical default risk conditions almost always coincide with net falling bank lending standards. This is intuitive: when even bad risks receive ample and easy access to credit, they find it possible to avoid, or at least delay, default. Vice versa, net tightening bank lending standards coincide with higher systematic default risk. This is also intuitive: when credit access is tight, even solvent firms have a higher risk of becoming illiquid. Our global frailty factor is consistent with bank lending standards that are strongly correlated across borders, in line with synchronized monetary policy cycles and global liquidity conditions (Bruno and Shin (2012)).

Finally, given the key importance of world factors, we conclude that – perhaps counter-intuitively – more risk diversification across border 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 is a relevant concern. As a corollary, our empirical results suggest that the risk bearing capacity of global lenders is not necessarily vastly superior to that of a more regionally constrained lender, as long as the latter firm’s credit portfolio is diversified across industry sectors and rating groups (Wheelock and Wilson (2012), Richter and Euffinger (2014)).

The remainder of this paper is organized as follows. Section 2 introduces our global data
and provides first visual 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.

2 Risk data and international default clustering

This section describes our global data and provides first evidence of pronounced default clustering across borders. We consider data from three sources. First, we consider default and firm count data of firms from 41 countries. Second, we consider EDF-based risk indexes at the country level. Finally, we chose macroeconomic and financial time series data with the aim to capture business cycle conditions. All data are collected at a quarterly frequency.

2.1 International default data

As a first panel data set, we consider default and firm count data from Moody’s default and recovery database (DRD). The database contains rating transitions and default dates for all rated firms, worldwide, from 1980Q1 to 2013Q3. From these data, we construct quarterly values of defaults and firms at risk. Moody’s broad industry classification allows us to pool firms into six broad industry sectors: banks and other financial institutions such as insurers, trusts, and real estate (fin); transportation, utilities, and energy & environment (tre); capital industries and manufacturing (ind); technology firms (tec); retail & distribution (ret); and, finally, consumer industry firms (con). When counting firms at risk and the corresponding defaults, a previous rating withdrawal is ignored if it is followed by a later default. In this way, we limit the impact of strategic rating withdrawals preceding a default. If there are multiple defaults per firm, we consider only the first event.

Figure 2 plots aggregate default counts, exposures, and observed fractions over time for each economic region. The top panel reports the total number of defaults, the total number of firms at risk, and the respective default fractions (all per economic region). The panel
We consider default and firm count data from 41 countries in our empirical analysis.

We group countries into four regions as follows.

<table>
<thead>
<tr>
<th>Region 1: U.S.</th>
<th>Region 3: Euro area</th>
<th>Region 4: Asia-Pacific</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S.</td>
<td>Austria</td>
<td>Australia</td>
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<tr>
<td>U.S. Territories</td>
<td>Latvia</td>
<td>Cambodia</td>
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<td>Belgium</td>
<td>China</td>
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<td>Finland</td>
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<td>Portugal</td>
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<tr>
<td>Region 2: U.K.</td>
<td>Germany</td>
<td>Japan</td>
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<tr>
<td>United Kingdom</td>
<td>Slovakia</td>
<td>Sri Lanka</td>
</tr>
<tr>
<td>British Virgin Islands</td>
<td>Greece</td>
<td>Japan</td>
</tr>
<tr>
<td>Isle of Man</td>
<td>Slovenia</td>
<td>Taiwan</td>
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<td></td>
<td>Ireland</td>
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<td>Spain</td>
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<td>Malaysia</td>
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<td></td>
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<td>Vietnam</td>
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</table>
Figure 2: Historical default and firm counts

The first panel plots time series data of the total default counts $\sum_j y_{r,j,t}$ aggregated to a univariate series (top), the total number of firms at risk $\sum_j k_{r,j,t}$ (middle), as well as the aggregate default fractions $\sum_j y_{r,j,t} / \sum_j k_{r,j,t}$ over time (bottom). The second panel plots observed default fractions at the industry level for four different economic regions, distinguishing firms from the United States, the United Kingdom, the euro area, and the Asia-Pacific region. Light-shaded areas are NBER recession times for the United States for comparison.
Figure 3: EDF data for financial and non-financial firms

EDF panel data for financial (left) and non-financial firms (right). The aggregate risk measures cover firms from the U.S., the U.K., the euro area, and Japan. EDF data are from Moody’s KMV. The sample is from 1992Q1 to 2014Q4.

strongly suggests that defaults tend to cluster both in time and across economic regions. The highest default fractions are observed during (U.S.) recession years such as 1990-91, 2001-02, and 2007-2009. The bottom panel confirms that times around U.S. NBER recession dates are periods of high default fractions within and across all four regions considered in this paper.

2.2 EDF risk indexes

As a second set of panel data we consider expected default frequencies from Moody’s Analytics (formerly Moody’s KMV). EDFs are forecasts of default rates on year ahead, and are based on a proprietary firm value model that takes equity values and balance sheet information as inputs. We use the EDFs to augment our sparse data on actual defaults. The EDF data sample ranges from 1992Q1 to 2013Q3. Our worldwide credit risk analysis would be hard, or impossible, to do without the additional information from the EDF measures, in particular when considering the systematic default rate variation for firms outside the U.S.

Figure 3 plots aggregated EDFs. Aggregated EDFs are obtained as averages across firms, weighted by the respective total assets. The four panels distinguish financial (dashed lines) and non-financial (solid lines) firms in the U.S., U.K., euro area, and Japan. High default
probabilities for non-financial firms are observed during 1992 (the beginning of the sample), between 2001-2002, and the great recession between 2007-2009. Default probabilities are highly volatile over time, and up to an order of magnitude higher in a bust than in an economic boom. Default risk probabilities for financial firms are particularly high at the end of our sample, during the financial crisis from 2008-2010 and the euro area sovereign debt crisis from 2010-2012. Figure 3 reveals a striking amount of common variation across borders as well. This common variation is entirely in line with the observed international default clustering in Figure 2.

2.3 Macro-financial data

Finally, we consider macro-financial time series data that are commonly considered in the relevant credit risk literature. Such time series data are routinely stressed in supervisory macro stress tests, see Figlewski, Frydman, and Liang (2008), Tarullo (2010), and Koopman et al. (2011). Such conditioning variables are, for example, real GDP growth, the industrial production growth rate, the unemployment rate, and key asset prices such as house price indexes, equity prices, and bond yields. We consider nine macro-financial measurements for each economic region. When modeling the macro data it is appropriate to distinguish leading, lagging, and coincident indicators of the business cycle. Two macro variables tend to lead the business cycle: the term structure spread (-5Q) and the change in a broad equity market index (-1Q)).\textsuperscript{3} Four coincident indicators are the real GDP growth rate, industrial production growth, the ISM purchasing managers index (or a similar alternative), and the yearly change in the unemployment rate. Three lagging indicators are the change in 10 year government bond yields (+1Q), 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. All macroeconomic and financial time series data are taken from Thomson Reuters/Datastream.

\textsuperscript{3}The lead and lag relationships are based on the respective cross-correlation coefficients viz-a-viz the real GDP growth rate and are approximately in line with those reported in Stock and Watson (1989).
In line with a separate literature on global business cycles, all macroeconomic variables are clearly correlated across countries. A principal components analysis suggest that the first three principal components (global macro factors) explain 24.9%, 14.7%, and 11.0% of the total macro data variance, and thus explain approximately half of the total variation in the macro panel. The remaining variation exhibits some residual regional correlation. The first principal component extracted from the (four, regional) sub-panels of the remaining macro variation explains 25.5%, 27.2%, 24.8%, and 24.3% in the U.S., U.K., euro area, and Asia-Pacific macro data, respectively.

2.4 Observed default clustering in international credit portfolios

This section uses the historical default rates as discussed in Section 2.1 to study the benefits (and limits) of credit risk diversification across borders. If, as suggested by Figures 2 and 3, world factors are important determinants of national default rates, we would expect to see this feature reflected in realized portfolio losses. To check this intuition, we turn to a study of the realized risks of successively more diversified credit portfolios, holding marginal risks (the ratings) constant.

We distinguish four credit portfolios. Each portfolio is of equal size (1000$). For simplicity, all loans have a maturity of one quarter. Loans are extended to firms that are active in the beginning of each quarter during our sample. At all times, loans are split equally between investment and speculative grade firms. The rating profiles of firms (as measures of firm-specific risk) are held constant and are the same across portfolios. As a result, differences in portfolio risk are only due to changes in the default dependence (systematic risk) across firms. Portfolio $a$) contains 1000 loans of 1$ each to 1000 U.S. industrial firms. Thus, portfolio $a$) is concentrated in terms of geography (only the U.S.) and industry sector (only industrial firms). Portfolio $b$) contains 200 loans of 1$ each to U.S. firms from five non-financial industry sectors (transportation, industrials, technology, retail and distribution, consumer goods). As a result, this portfolio remains concentrated in the U.S., but is now diversified across industries. Portfolio $c$) contains 250 loans of 1$ each to industrial firms in
Figure 4: Unconditional portfolio loss densities

The figure reports unconditional (historical) loss densities for portfolios a) to d) as discussed in the main text. The red line is a kernel density estimate of the loss rate distribution. The blue dashed line indicates the unconditional loss distribution as implied by the full model estimated in Section 4.

Table 1: Portfolio risk measures

The table reports portfolio risk measures for losses from four portfolios a) to d) as discussed in the main text. The risk measures are based on observed default rates. The VaR at 95% is the 95% quantile of the observed losses. The expected shortfall is calculated as the unweighted average over the 95% to 99% empirical quantile of the observed losses. Sample data is 1980Q1 to 2014Q4.

<table>
<thead>
<tr>
<th>Observed losses</th>
<th>mean loss</th>
<th>Var 95%</th>
<th>ES 95%</th>
<th>max loss</th>
</tr>
</thead>
<tbody>
<tr>
<td>PF1 [most concentrated]</td>
<td>0.58%</td>
<td>1.74%</td>
<td>2.47%</td>
<td>4.09%</td>
</tr>
<tr>
<td>PF2 [country concentration]</td>
<td>0.57%</td>
<td>1.45%</td>
<td>1.75%</td>
<td>2.32%</td>
</tr>
<tr>
<td>PF3 [industry concentration]</td>
<td>0.27%</td>
<td>0.97%</td>
<td>1.73%</td>
<td>3.49%</td>
</tr>
<tr>
<td>PF4 [fully diversified]</td>
<td>0.39%</td>
<td>1.51%</td>
<td>2.00%</td>
<td>2.78%</td>
</tr>
</tbody>
</table>
each of our four regions (U.S., U.K., the euro area, and Asia-Pacific). Thus, portfolio c) is diversified geographically, but concentrated in one industry. Finally, portfolio d) contains 50 loans a 1$ each to firms in each of our four regions and five non-financial industries. It is diversified across both industry sectors and regions as a result.

Based on our simple backtest of credit portfolios based on historical default rates, we observe that, perhaps counter-intuitively, more credit risk diversification across borders does not necessarily decrease portfolio risk. Figure 4 plots the historical loss rates for portfolios a) to d). Table 1 reports portfolio risk measures for these four loan portfolios. The respective 95% expected shortfall as reported in Table 1 is indicated in each panel of Figure 4 as a vertical line. Based on the 95% expected shortfall, successively reducing the portfolio concentrations moves the quarterly portfolio risk from 2.47% to 1.75% to 1.73%, and then up again to 2.00%. The pattern is similar (first down, then up again) when portfolio risk is measured as the 95% Value-at-Risk statistic, or as the mean portfolio loss.

We conclude that cross-border risk diversification is not necessarily beneficial if the initial portfolio is already somewhat diversified, e.g. across industries in a single country, or across countries in a single industry. Why is that? In a setting where world factors are a first order source of international default clustering, two effects work in opposite directions. First, expanding the credit portfolio across borders decreases dependence across firms, and therefore portfolio credit risk, if country-specific (regional) macro-financial and other factors are imperfectly correlated. Conversely, however, portfolio diversification across borders can increase dependence if it leads to risk exposures that load relatively more heavily on the world factors, such as for example global macro and global default-specific factors. Figure 4 suggests that the first effect dominates when moving from portfolio a) to portfolios b), c), and d). The second effect dominates when moving from portfolios b) and c) to portfolio d).
3 The modeling framework

3.1 A multi-factor model of default risk dependence

This section develops a simple multi-factor financial framework for dependent defaults. The financial framework is similar to the well-known CreditMetrics (2007) model, an industry standard. The framework allows for cross-border default dependence due to shared global macroeconomic, default-, and industry-specific factors, as well as regional macro and frailty factors. We demonstrate that the financial framework is closely related to a latent dynamic factor model. Interestingly, we can establish a semi-structural economic interpretation of the parameters by relating the parameters of the statistical model to those of the financial model.

In the special case of a standard static one-factor credit risk model for dependent defaults, the values of the borrowers’ assets, $V_i$, are driven by a common random factor $f$, and an idiosyncratic disturbance $\epsilon_i$. More specifically, the asset value of firm $i$, $V_i$, is modeled as

$$V_i = \sqrt{\rho_i} f + \sqrt{1 - \rho_i} \epsilon_i,$$

where scalar $0 < \rho_i < 1$ weights the dependence of firm $i$ on the general economic condition factor $f$ in relation to the idiosyncratic factor $\epsilon_i$, for $i = 1, \ldots, K$, where $K$ is the number of firms, and where $(f, \epsilon_i)'$ has mean zero and variance matrix $I_2$. The conditions in this framework imply that

$$E(V_i) = 0, \quad Var(V_i) = 1, \quad Cov(V_i V_j) = \sqrt{\rho_i \rho_j},$$

for $i, j = 1, \ldots, K$. In our multivariate dynamic model, the framework is extended into a more elaborate version for the asset value $V_{it}$ of firm $i$ at time $t$ and is given by

$$V_{it} = a_i' f^g_t + b_i' f^m_t + c_i' f^c_t + d_i' f^d_t + e_i' f^i_t + \sqrt{1 - a_i' a_i - b_i' b_i - c_i' c_i - d_i' d_i - e_i' e_i} \epsilon_{it},$$

$$V_{it} = w_i' f_t + \sqrt{1 - w_i' w_i} \epsilon_{it}, \quad t = 1, \ldots, T,$$

where global macro factors $f^g_t$, region-specific macro factors $f^m_t$, a global default-specific (frailty) factor $f^c_t$, region-specific frailty factors $f^d_t$, as well as industry-specific factors $f^i_t$.
are stacked in \( f_t = (f_t^g, f_t^m, f_t^c, f_t^d, f_t^i)' \). 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 \( \epsilon_{it} \) is serially uncorrelated for \( t = 1, \ldots, T \).

Macroeconomic risk factors are common to all countries \( (f_t^g) \) or country/region-specific \( (f_t^m) \). Analogously, the frailty factors are common to firms from all regions \( (f_t^c) \), or region-specific \( (f_t^d) \). 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. Industry-specific risk factors \( f_t^i \) are common to firms from the same industry sector, regardless of their geographical location. 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 with each other at all times. These assumptions imply that \( E[V_{it}] = 0 \) and \( \text{Var}[V_{it}] = 1 \) for many distributional assumptions with respect to the idiosyncratic noise component \( \epsilon_{it} \) for \( i = 1, \ldots, I \), 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 default threshold \( \bar{\lambda}_i \), see Merton (1974) and Black and Cox (1976). Intuitively, if the total value of the firm’s assets is below the value of its debt to be repaid, equity holders with limited liability have an incentive to walk away and to declare bankruptcy. In our framework, \( V_{it} \) in (1) is driven by multiple latent systematic factors, while idiosyncratic risk is captured by \( \epsilon_{it} \). The threshold \( \bar{\lambda}_i \) may depend on headquarters location, the firm’s current rating category, and possibly its industry sector. For firms which have not defaulted yet, a default occurs when \( V_{it} < \bar{\lambda}_i \) or, as implied by (1), when

\[
\epsilon_{it} < \frac{\bar{\lambda}_i - w_i'f_t}{\sqrt{1 - w_i'w_i}}.
\]

The conditional default probability is given by

\[
\pi_{it} = \Pr \left( \epsilon_{it} < \frac{\bar{\lambda}_i - w_i'f_t}{\sqrt{1 - w_i'w_i}} \right). \tag{2}
\]

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

Our empirical analysis considers a setting where the firms \((i = 1, \ldots, I)\) are pooled into groups \((j = 1, \ldots, J)\) according to geography (headquarter location), industry sector, and current rating class. We assume that the same risk factor loadings apply to each firm in the same group. In this case, (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 \( \pi_{jt} \). In our case, \( k_{jt} \) denotes the number of firms in cell \( j \) that are active at the beginning of period \( t \).

\[
y_{jt} | f_t \sim \text{Binomial}(k_{jt}, \pi_{jt}), \quad \text{(3)}
\]
\[
\pi_{jt} = [1 + \exp(-\theta_{jt})]^{-1}, \quad \text{(4)}
\]
\[
\theta_{jt} = \chi_j + \omega_j f_t^q + \beta_j f_t^m + \gamma_j f_t^c + \delta_j f_t^{id} + \varepsilon_j f_t^i, \quad \text{(5)}
\]

where \( \chi_j \) and \( \lambda_j = (\omega_j, \beta_j, \gamma_j, \delta_j, \varepsilon_j)' \) are loading parameters to be estimated, and \( \theta_{jt} \) is the log-odds ratio of the default probability \( \pi_{jt} \). For more details on binomial mixture models, see Lando (2003, Chapter 9), McNeil, Frey, and Embrechts (2005, Chapter 8), and Koopman, Lucas, and Schwaab (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 category (marginal risk).

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

$$\bar{\lambda}_i = \chi_j \sqrt{1 - \kappa_j}, \quad a_i = -\alpha_j \sqrt{1 - \kappa_j},$$
$$b_i = -\beta_j \sqrt{1 - \kappa_j}, \quad c_i = -\gamma_j \sqrt{1 - \kappa_j},$$
$$d_i = -\delta_j \sqrt{1 - \kappa_j}, \quad e_i = -\varepsilon_j \sqrt{1 - \kappa_j},$$

where $\kappa_j = \bar{\omega}_j/(1 + \bar{\omega}_j)$, and $\bar{\omega}_j = \alpha_j' \alpha_j + \beta_j' \beta_j + \gamma_j' \gamma_j + \delta_j' \delta_j + \varepsilon_j' \varepsilon_j$. A related simpler expression is derived in Koopman and Lucas (2008) in the context of a univariate unobserved risk factor. By contrast, the current formulation allows for multiple groups of (vector-valued) risk factors.

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,

$$\text{Var}[V_{it}] = w_i' w_i,$$

where $w_i = (a_i', b_i', c_i', d_i', e_i')'$, see (1). Since $\text{Var}[V_{it}] = 1$, (6) also denotes the share of total default risk that is systematic, or non-diversifiable. We also report $\text{Var}[V_{it}|\epsilon_{it}, f_t^i] = a_i' a_i + \ldots + d_i' d_i$ in our empirical study below. The latter expression treats industry-specific variation as idiosyncratic (diversifiable).

### 3.3 Data structure and combination

This section explains how our high-dimensional data are combined in a mixed-measurement dynamic factor model.

We initially consider high-dimensional mixed measurement data $\tilde{Y}_t = (x_t', y_t', z_t')'$ which follows a tri-part data structure

$$x_t = (x_{1,1,t}, \ldots, x_{1,N,t}, \ldots, x_{R,1,t}, \ldots, x_{1,N,t})',$$  
$$y_t = (y_{1,1,t}, \ldots, y_{1,J,t}, \ldots, y_{R,1,t}, \ldots, y_{R,J,t})',$$  
$$z_t = (z_{1,1,t}, \ldots, z_{1,S,t}, \ldots, z_{R,1,t}, \ldots, z_{R,S,t})'',$$
where $x_{r,n,t}$ represents the $n$th, $n = 1, \ldots, 9$, macroeconomic or financial markets variable for region $r = 1, \ldots, 4$ measured at time $t = 1, \ldots, T$, and $y_{r,j,t}$ is the number of defaults between times $t$ and $t+1$ for economic region $r$ and cross section $j = 1, \ldots, J$ which denotes different categories of firms. The expected default frequency $z_{r,s,t}$ is at a one year ahead horizon and refers to a set of firms $s = 1, \ldots, S$ located in a given country (or region) $r$ at time $t$. As a result, the model includes more ‘standard’ (conditionally normally distributed) macro and EDF variables, but also (integer) count variables $y_t$. The panel $(x_t, y_t, z_t)$ is typically unbalanced, such that variables may not be observed at all times.

The cross-sectional dimension of the tri-part data (7) to (9) is prohibitively large for our multi-country credit risk model. For example, 36 macro data series and 4 common macro factors would already imply 144 coefficients to be estimated by maximum likelihood. For this reason we first collapse some subsets of our macro panel data to smaller dimensions. We proceed in three steps.

First, we first assume that a standard approximate dynamic factor model (Stock and Watson (2002)) applies to our macro data,

$$x_t = \Lambda_g F_{g,t} + u_t,$$

where $F_{g,t}$ are global macro factors, $\Lambda_g$ are the respective factor loadings, and $u_t$ are residual terms. We obtain

$$\hat{F}_{g,t} = \hat{\Lambda}_g' x_t, \quad \text{and} \quad \hat{u}_t = x_t - \hat{\Lambda}_g \hat{F}_{g,t},$$

where $\hat{F}_{g,t}$ are the first $r$ principal components of all macro panel data $x_t$. The loading matrix $\Lambda_g = U = (U_1, \ldots, U_r)$, where $U_r$ is the eigenvector corresponding 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 again use the method of principal components. We extract four regional macro factors, one for each region, from the residuals $u_t = (u'_1, \ldots, u'_R)'$.

$$u_{r,t} = \Lambda_r F_{r,t} + v_{r,t},$$

17
where \( F_{r,t} \) is a region-specific macro factor. We obtain \( \hat{F}_r = \hat{A}_r u_{r,t} \), for \( r = 1, \ldots, R \). Regional factors are stacked in \( \hat{F}_{m,t} = (\hat{F}_{1,t}, \ldots, \hat{F}_{R,t})' \). All macro factors are stacked into \( \hat{F}_{x,t} = (\hat{F}_{g,t}', \hat{F}_{m,t}')' \).

Finally, we obtain alternative measures of default risk variation from EDF data. We obtain quarterly default probabilities from the annual EDFs of active firms as \( \hat{z}_{s,t} = 1 - (1 - \hat{z}_{s,t})^{\frac{1}{4}} \). Quarterly log-odds ratios are obtained as \( \hat{\theta}_{s,t}^{\text{EDF}} = \log(\hat{z}_{s,t}) - \log(1 - \hat{z}_{s,t}) \). Log-odds of default probabilities are stacked as \( \hat{\theta}_{t}^{\text{EDF}} = (\hat{\theta}_{1,t}^{\text{EDF}}, \ldots, \hat{\theta}_{S,t}^{\text{EDF}}) \).

The transformed data is given by
\[
\gamma_t = \left( \hat{F}_{g,t}', \hat{F}_{m,t}', y_t', \hat{\theta}_{t}^{\text{EDF}} \right)'.
\]

While the cross-sectional dimension of the original data (7) — (9) is prohibitively large, the cross-sectional dimension of collapsed data (12) is tractable.

The new measurement equation is given by
\[
\hat{F}_{g,t} = f_{t}^g + e_{t}^g, \quad e_{t}^g \sim N(0, \Sigma_g),
\]
\[
\hat{F}_{m,t} = f_{t}^m + e_{t}^m, \quad e_{t}^m \sim N(0, \Sigma_m),
\]
\[
p(y_{j,t} | f_t) \sim \text{Bin}(\theta_{j,t}, k_{j,t}),
\]
\[
\hat{\theta}_{j,t}^{\text{EDF}} = \mu_j + \theta_{j,t} + e_{t}^s, \quad e_{t}^s \sim N(0, \Sigma_s),
\]
where \( \theta_{j,t} = \log(\pi_{j,t}) - \log(1 - \pi_{j,t}) \) is the canonical, or natural, parameter of the Binomial distribution, see McCullagh and Nelder (1989), \( k_{j,t} \) are the number of firms at risk at the beginning of period \( t \), and \( \mu_j \) is the vector of unconditional means of the respective quarterly log-odds of default from EDF measures. The state equation (14) and initial conditions remain unchanged.

We stress that all estimated macro factors (principal components) and EDF risk data are treated as noisy estimates from a preliminary first step. They are therefore both subject to measurement error, see Jungbacker et al. (2011) and Brauning and Koopman (2013). The parameters of the diagonal measurement error variance matrices \( \Sigma_g, \Sigma_m, \Sigma_s \) are estimated. As a result, all data is used simultaneously to determine just how informative (or noisy) the
principal component and EDF estimates are. Both the information from (continuous) EDF data - via \( \hat{\theta}_{t}^{\text{EDF}} \) - as well as the (integer, non-Gaussian) default counts - via the Binomial specification - contribute towards estimating the time variation in the (log-odds of) default probabilities \( \theta_{j,t} \) and \( \pi_{j,t} \).

### 3.4 Parameter and risk factor estimation

The joint modeling of (discrete, non-negative) 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. As a result, our estimation framework is most closely related to Koopman et al. (2012). We consider available data

\[
Y_{t} = (Y_{1t}, \ldots, Y_{Nt})' , \quad t = 1, \ldots, T ,
\]

where each row \( Y_{i} = (Y_{i1}, \ldots, Y_{iT}) \), \( i = 1, \ldots, N \), is time series data from a potentially different family of parametric distributions.

All observations depend on a set of \( m \) dynamic factors which are generated from a dynamic Gaussian process. We collect the risk factors into the \( m \times 1 \) vector \( f_{t} \) and assume a stationary vector autoregressive process,

\[
f_{t+1} = \Phi f_{t} + \eta_{t} , \quad \eta_{t} \sim N(0, \Sigma_{\eta}) , \quad t = 1, 2, \ldots,
\]

with the initial condition \( f_{1} \sim N(0, \Sigma_{f}) \). The \( m \times 1 \) mean vector \( \mu_{f} \), the \( m \times m \) coefficient matrix \( \Phi \) and the \( m \times m \) variance matrix \( \Sigma_{\eta} \) are assumed fixed and unknown. Stationarity implies that the \( m \) roots of the equation \( |I - \Phi z| = 0 \) are outside the unit circle and that \( \Sigma_{\eta} \) is positive definite. The \( m \times 1 \) disturbance vectors \( \eta_{t} \) are serially uncorrelated. The variance matrix \( \Sigma_{f} \) is a function of \( \Phi \) and \( \Sigma_{\eta} \) or, more specifically, \( \Sigma_{f} \) is the solution of \( \Sigma_{f} = \Phi \Sigma_{f} \Phi' + \Sigma_{\eta} \).

Conditional on a factor path \( F_{t} = \{ f_{1}, f_{2}, \ldots, f_{t} \} \), the observation \( Y_{i,t} \) of the \( i \)th variable
at time $t$ is assumed to come from a certain density given by

$$
\mathcal{Y}_{i,t} | \mathcal{F}_t \sim p_i(\mathcal{Y}_{i,t}; \theta_{i,t}, \psi), \quad i = 1, \ldots, N,
$$

with a time-varying parameter defined by $\theta_{i,t} = \chi_i + \lambda_i f_t$, where $\chi_i$ is an unknown constant and $\lambda_i$ is the $m \times 1$ loading vector with unknown coefficients. The conditional (on $\mathcal{F}_t$) independence of all observations implies that the density of the $N \times 1$ observation vector $\mathcal{Y}_t = (\mathcal{Y}_{1,t}, \ldots, \mathcal{Y}_{N,t})'$ is given by

$$
p(\mathcal{Y}_t | \mathcal{F}_t, \psi) = \prod_{i=1}^{N} p_i(\mathcal{Y}_{i,t} | \mathcal{F}_t, \psi).
$$

The parameter vector $\psi$ contains all unknown coefficients in the model specification including those in $\Phi$, $\chi_i$ and $\lambda_i$ for $i = 1, \ldots, N$. To enable the identification of all entries in $\psi$, we assume standardized factors in (14) which we enforce by the restriction $\Sigma_f = I$ implying that $\Sigma_\eta = I - \Phi \Phi'$. The estimation of parameters $\psi$ and risk factors $f_t$ via maximum likelihood is non-standard because an analytical expression for the maximum likelihood (ML) estimate of parameter vector $\psi$ for the MM-DFM is not available. Let $\mathcal{Y} = (\mathcal{Y}_1', \ldots, \mathcal{Y}_T')'$ and $f = (f_1', \ldots, f_T')'$ denote the vector of all the observations and factors, respectively. Let $p(\mathcal{Y}|f; \psi)$ be the density of $\mathcal{Y}$ conditional on $f$ and let $p(f; \psi)$ be the density of $f$. The log-likelihood function is only available in the form of an integral

$$
p(\mathcal{Y}; \psi) = \int p(\mathcal{Y}, f; \psi) \, df = \int p(\mathcal{Y}|f; \psi)p(f; \psi) \, df,
$$

where $f$ is integrated out. A feasible approach to computing this integral is provided by importance sampling; see, e.g. Kloek and van Dijk (1978), Geweke (1989) and Durbin and Koopman (2001). Upon computing the integral, the maximum likelihood estimator of $\psi$ is obtained by direct maximization of the likelihood function using Newton-Raphson methods.

For each evaluation of the log-likelihood, we need to integrate out many (18) latent factors from their joint density with the mixed measurement observations. This causes the estimation approach put forward in Koopman, Lucas, and Schwaab (2011, 2012) to break
down. Specifically, the importance sampling weights do not appear to have a finite variance, which is a necessary conditions for obtaining consistent and asymptotically normal parameter estimates. We overcome this challenge by using four antithetic variables for location and scale as suggested in Durbin and Koopman (1997). We leave the suggestion that employing antithetic variables can stabilise the importance sampling weights substantially if large dimensional vectors of stacked factors need to be integrated out for likelihood evaluation.

4 Main empirical results

4.1 Model specification

This section discusses issues related to model specification such as the number of factors and pooling over parameters. 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 either two or three common factors for the global macro data. We select three global macro-financial factors $f_{gt}$ to be conservative and not to bias our results towards attributing too much variation to default-specific (frailty) factors. We also select four region-specific macro factors, one for each region. The global macro factors are common to all mixed measurement data (all macro-financial covariates and all default data), capturing in particular the positive correlation between business cycle conditions across regions. Global and regional macro factors are stacked in $f_{gt}$ and $f_{mt}$, respectively.

Allowing for one default-specific frailty factor $f_{ct}$ is standard in the literature, see for example Duffie et al. (2009) and Azizpour et al. (2014). Indeed, one (global) frailty factor is often sufficient to capture pronounced deviations of systematic default risk from observed macro-financial conditions. We further include four region-specific frailty factors $f_{dt}$, one for each region. Finally, we consider six additional industry-specific factors $f_{it}$. These factors load only on firms from the respective industry sector, regardless of the economic region. International default data loads on global macro factors $f_{gt}$ and the global frailty factor $f_{ct}$.
with region-specific factor loading coefficients.

For all risk factors, we pool risk factor loadings across rating classes. This allows us to focus on differences in systematic risk across corporates from different industries and different regions. While somewhat restrictive, this specification remains sufficiently flexible to accommodate most of the heterogeneity observed in the cross section and allows us to test the key economic hypotheses at hand.

4.2 Parameter and risk factor estimates

This section discusses our main parameter and risk factor estimates.

All five sets of risk factors - global and regional macro, global and regional frailty, as well as industry-specific - play a role in explaining corporate default clusters within each country and across countries. Table 2 reports model parameter estimates. The estimates of $\alpha_{k,r}$ and $\beta_{k,r}$ correspond to global and regional factors, respectively. Defaults from all regions load on the global macro factors.

Overall, the region-specific macro factors are relatively less relevant than the global macro factors. This is probably a consequence of how the regional macro factors are constructed, i.e., as principal components of the respective residuals after the global factors were extracted.

The common variation in defaults implied by shared exposure to macro data is important but not sufficient. The estimates of $\gamma_{k,r}$ and $\delta_{k,r}$ in Table 2 correspond to global and regional default-specific (frailty) factors, respectively. The global frailty factor is found to be important for defaults in all regions. The global frailty component loads slightly more strongly on non-U.S. data than on U.S. data. Finally, industry-specific factors are also significant.

Figure 5 reports location estimates of the global and three regional frailty factors (top panel), as well as six industry-specific factors (bottom panel). The world frailty risk factor (top left) resembles the U.S. frailty factor reported in Duffie, Eckner, Horel, and Saita (2009) and Koopman, Lucas, and Schwaab (2012). This suggests that the (excess) default clustering as experienced by U.S. firms is not specific to that country, but in fact common to a much wider set of countries. Turning to the regional frailty factors, significant excess clustering is
Table 2: Parameter estimates

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 $f_t^g$, region-specific macro factors $f_t^m$, one global frailty factor $f_t^c$, region-specific frailty factors $f_t^d$, and six industry-specific factors $f_t^i$. 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 & energy (tre), industrials (ind), technology (tec), retail & distribution (red), and consumer goods (con). Estimation sample is 1980Q1 to 2014Q4.

<table>
<thead>
<tr>
<th>Intercept terms</th>
<th>Regional macro $f_t^m$</th>
<th>Industry factors $f_t^i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lambda_{r,j} = \lambda_0 + \lambda_{1,j} + \lambda_{2,r} + \lambda_{3,r}$</td>
<td>$\phi_{g,US}^0$</td>
<td>$\phi_{fin}^0$</td>
</tr>
<tr>
<td>$\lambda_0$</td>
<td>-3.48</td>
<td>0.00</td>
</tr>
<tr>
<td>$\lambda_{1,fin}$</td>
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<td>0.00</td>
</tr>
<tr>
<td>$\lambda_{1,tre}$</td>
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<td>0.00</td>
</tr>
<tr>
<td>$\lambda_{1,tec}$</td>
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<td>0.00</td>
</tr>
<tr>
<td>$\lambda_{1,ret}$</td>
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<td>0.00</td>
</tr>
<tr>
<td>$\lambda_{1,con}$</td>
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<td>0.11</td>
</tr>
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<td>$\lambda_{2,IG}$</td>
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</tr>
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<td>0.00</td>
</tr>
<tr>
<td>$\lambda_{3,EA}$</td>
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<td>0.75</td>
</tr>
<tr>
<td>$\lambda_{3,AP}$</td>
<td>-0.62</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Global macro factors $f_t^g$

<table>
<thead>
<tr>
<th>Global frailty $f_t^c$</th>
<th>Regional frailty $f_t^d$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_{k,r} = \alpha_{k,0} + \alpha_{k,1,r}$</td>
<td>$\phi^c$</td>
</tr>
<tr>
<td>$\phi_1^g$</td>
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<tr>
<td>$\alpha_{1,0}$</td>
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<td>$\alpha_{1,UK}$</td>
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<tr>
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</tr>
<tr>
<td>$\alpha_{1,AP}$</td>
<td>0.02</td>
</tr>
<tr>
<td>$\phi_{2,0}$</td>
<td>0.84</td>
</tr>
<tr>
<td>$\alpha_{2,0}$</td>
<td>-0.02</td>
</tr>
<tr>
<td>$\alpha_{2,UK}$</td>
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</tr>
<tr>
<td>$\alpha_{2,EA}$</td>
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<td>$\phi_{3,0}$</td>
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<td>$\alpha_{3,0}$</td>
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<td>0.04</td>
</tr>
<tr>
<td>$\alpha_{3,AP}$</td>
<td>0.04</td>
</tr>
</tbody>
</table>

$\phi_{US}$, $\phi_{UK}$, $\phi_{EA}$, $\phi_{AP}$, $\phi_{fin}$, $\phi_{tec}$, $\phi_{con}$, $\gamma_0$, $\gamma_{1,UK}$, $\gamma_{1,EA}$, $\gamma_{1,AP}$, $\delta_{US}$, $\delta_{UK}$, $\delta_{EA}$, $\delta_{AP}$.
Figure 5: Global frailty and industry factors
The top panel reports the conditional mean estimates of the global frailty and region-specific frailty factors. The bottom panel plots the conditional mean estimates of the six industry-specific factors.

[Graph showing time series plots for different factors over the years 1985 to 2015, with 95% error bands.]
Figure 6: Global default hazard rates at the industry level

Each panel plots the model-implied time-varying default rate (one quarter ahead default probability) for a specific industry sector. The panels refer to financial firms (top left), transportation & energy (top right), industrial (middle left), technology (middle right), retail & distribution (bottom left), and consumer goods (bottom right). Each panel distinguishes firms from the U.S., U.K., euro area, and Asia-Pacific region.

Hazard rates vary widely over time and across sectors, often by an order of magnitude. Figure 6 plots the respective estimates of time-varying quarterly default rates for six industry sectors and four regions. The default rates are functions of the estimated risk factors as well as of the estimated loading coefficients. Implied probabilities of default are particularly volatile for financial firms. The top left panel of Figure 6 suggests that financial firm defaults cluster in particular during the savings and loans crisis between 1986-1990 in the U.S., the dot-com bubble in 2001-02, and the financial crisis between 2007-10, and the euro area sovereign debt crisis between 2010-2012. Default risk for industrial sector firms is particularly
high between 1990-91, 2001-02, and 2008-09, in line with business cycle contraction periods. The dot-com bubble is particularly visible for default rates of technology firms between 2001-02, in each region of the world.

4.3 Variance decomposition

This section decompose the systematic default risk variation of firms from different industry sectors and countries into its underlying systematic and idiosyncratic risk drivers. We use the firm-value framework as introduced in Section 3 to this purpose. Table 3 presents the estimated risk shares. We focus on three main empirical findings.

First, the global macro-financial factors are relatively more relevant than the regional macro factors. This is the case for all combinations of industry sector and geographic location in our sample. Rated firms from different countries tend to default together to some extent simply because of their shared exposure to global macroeconomic factors.

Second, our (global and regional) frailty factors explain more default risk variation than the (global and regional) macro factors. This is the case for firms from the U.S. as well as the U.K., euro area and the Asia-Pacific. Shared exposure to global frailty factors implies significant additional default dependence across borders, above and beyond what is implied by macro-financial factors. In short, excess default clustering is an international phenomenon. Credit risk cycles can significantly and persistently be decoupled from macro-financial fundamentals.

Finally, industry-specific variation is a significant additional source of default clustering. Industry-specific dynamics are the most relevant for the transportation and energy-related sectors, for which industry-specific variation is the most important driving force of default risk. In addition, the consumer goods, technology, and financial sectors also exhibit strong industry dynamics.
Table 3: Systematic risk and risk decomposition
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. 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. Sample is 1980Q1 to 2013Q3.

| Reg. | Ind. | $f_t^0$ | $f_t^m$ | $f_t^f$ | $f_t^q$ | $f_t^1$ | $\text{Var}[V_{it} | \varepsilon_{it}, f_t]$ | $\text{Var}[V_{it} | \varepsilon_{it}]$ |
|------|------|---------|---------|---------|---------|---------|---------------------------------|---------------------------------|
| US   | fin  | 3.6%   | 0.1%   | 10.1%  | 12.4%  | 15.4%  | 26.2%                          | 41.6%                          |
| US   | tre  | 3.0%   | 0.1%   | 8.3%   | 10.2%  | 30.2%  | 21.7%                          | 51.8%                          |
| US   | ind  | 2.6%   | 0.1%   | 7.2%   | 8.8%   | 39.9%  | 18.7%                          | 58.5%                          |
| US   | tec  | 3.6%   | 0.1%   | 9.9%   | 12.2%  | 16.9%  | 25.8%                          | 42.7%                          |
| US   | red  | 3.4%   | 0.1%   | 9.5%   | 11.7%  | 20.2%  | 24.8%                          | 44.9%                          |
| US   | con  | 2.6%   | 0.1%   | 7.2%   | 8.8%   | 39.9%  | 18.7%                          | 58.5%                          |
| UK   | fin  | 6.3%   | 0.3%   | 19.8%  | 1.5%   | 1.4%   | 27.7%                          | 29.1%                          |
| UK   | tre  | 2.7%   | 0.1%   | 8.6%   | 0.6%   | 57.1%  | 12.1%                          | 69.2%                          |
| UK   | ind  | 2.3%   | 0.1%   | 7.3%   | 0.5%   | 63.3%  | 10.3%                          | 73.6%                          |
| UK   | tec  | 3.4%   | 0.1%   | 10.6%  | 0.8%   | 47.1%  | 14.9%                          | 62.0%                          |
| UK   | red  | 3.2%   | 0.1%   | 10.1%  | 0.7%   | 49.8%  | 14.1%                          | 63.9%                          |
| UK   | con  | 2.3%   | 0.1%   | 7.3%   | 0.5%   | 63.3%  | 10.3%                          | 73.6%                          |
| EA   | fin  | 2.5%   | 0.2%   | 19.0%  | 1.5%   | 18.0%  | 23.2%                          | 41.2%                          |
| EA   | tre  | 1.5%   | 0.1%   | 11.5%  | 0.9%   | 50.3%  | 14.1%                          | 64.3%                          |
| EA   | ind  | 1.3%   | 0.1%   | 9.8%   | 0.8%   | 57.6%  | 12.0%                          | 69.6%                          |
| EA   | tec  | 1.8%   | 0.2%   | 14.2%  | 1.2%   | 38.7%  | 17.3%                          | 56.1%                          |
| EA   | red  | 1.7%   | 0.2%   | 13.5%  | 1.1%   | 41.8%  | 16.5%                          | 58.3%                          |
| EA   | con  | 1.3%   | 0.1%   | 9.8%   | 0.8%   | 57.6%  | 12.0%                          | 69.6%                          |
| AP   | fin  | 3.0%   | 0.4%   | 8.4%   | 12.9%  | 14.2%  | 24.7%                          | 38.9%                          |
| AP   | tre  | 3.1%   | 0.4%   | 8.7%   | 13.4%  | 10.6%  | 25.7%                          | 36.3%                          |
| AP   | ind  | 2.8%   | 0.4%   | 7.8%   | 12.0%  | 20.2%  | 23.0%                          | 43.1%                          |
| AP   | tec  | 3.4%   | 0.5%   | 9.6%   | 14.8%  | 1.8%   | 28.3%                          | 30.0%                          |
| AP   | red  | 3.4%   | 0.5%   | 9.4%   | 14.5%  | 3.4%   | 27.8%                          | 31.2%                          |
| AP   | con  | 2.8%   | 0.4%   | 7.8%   | 12.0%  | 20.2%  | 23.0%                          | 43.1%                          |
Figure 7: Credit risk deviations from fundamentals

Deviations of systematic default risk from macro-financial fundamentals for financial (left) and industrial (right) firms. The risk deviations are obtained as CRD_{r,j} = \gamma_j f_j^t + \delta_j f_j^t + \epsilon_j f_j^t \sqrt{\gamma_j^2 + \delta_j^2 + \epsilon_j^2} and are unconditionally standard normally distributed. Shaded areas are NBER recession dates for the U.S.

4.4 Global credit risk decoupling from macro fundamentals

This section demonstrates that deviations of systematic default risk conditions from macro fundamentals can be traced back to a significant degree to the behaviour of financial intermediaries, and in particular to variation in international bank lending standards.

Risk conditions can decouple significantly and persistently from the risk levels implied only by shared exposure to macro-financial fundamentals. Figure 4.4 reports systematic default risk deviations from fundamentals, focusing on firms from the capital goods industry in each region. While risk conditions have decoupled before, there is a particularly large and persistent deviation of risk from fundamentals preceding the global financial crisis of 2007-2009. Risk conditions were then significantly and persistently below what was suggested by fundamentals. We argue that such a risk decoupling is indicative of a lending bubble, in particular if credit quantity growth is unusually high as well and bank lending standards are generous.

Finally, our risk deviation estimates in Figure 4.4 are highly correlated with the net tightening of bank lending standards as taken from surveys undertaken by the respective central bank. Figure 8 plots risk deviation estimates and the net tightening of bank lending
Figure 8: Credit risk deviations vs. bank lending standards
Changes (yoy) in the credit risk deviations from fundamentals for industrial firms (see Figure 4.4) are associated with the net tightening of lending standards as reported in central bank surveys. Bank lending standards are from surveys by the Federal Reserve for the U.S. (top left), the Bank of England for the U.K. (top right), the European Central Bank for the euro area (bottom left), and the Bank of Japan for Japan (bottom right). Shaded areas pertain to NBER recession dates.

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. A significantly “too low” default rate is then not a sign of economic strength, and to be welcomed, but could instead be indicative of a boom and thus a warning signal of impending weakness. The reverse holds in a credit crunch. In a credit crunch, even financially sound corporates 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.4

Second, the observed co-movement 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 particularly crucial for predictive models that forecast credit risk 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 sector tightening of lending standards subsequently raises credit risk measures even further. The tight correlation between physical default risk and financial intermediation implied by Figure 8 suggests that such second round feedback effects may be substantial. We leave the suggestion to include bank lending standards as an additional conditioning variable in macro-prudential stress tests.

4To 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, Duffie, Kapadia, and Saita (2007) and Duffie, Eckner, Horel, and Saita (2009). The link is explored more formally in a firm value model by He and Xiong (2012), while Koopman, Lucas, and Schwaab (2012) are the first to empirically tie unobserved credit risk deviations to U.S. bank lending standards. These results are much 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 to fully explain time-varying systematic credit risk conditions, see for example Das et al. (2007), Koopman, Lucas, and Monteiro (2008), Duffie et al. (2009), Koopman, Kräussl, Lucas, and Monteiro (2009), Azizpour, Giesecke, and Schwenkler (2014), and Koopman, Lucas, and Schwaab (2011).
5 Conclusion

We investigated the common dynamic properties of systematic default risk conditions across countries, regions, and the world. To this purpose we developed a high-dimensional, partly non-linear non-Gaussian state space model to estimate common components in firm defaults in a 22-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 observed default clustering, thus providing evidence for a world credit risk cycle. Global macro and frailty dynamics naturally limit the scope for cross-border credit risk diversification and, as a result, negatively affect the risk bearing capacity of globally active lenders.

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