The Global Latent Risk Factor in Corporate Debt Distress: Frailty and Spillover Effects*

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Abstract

This paper provides strong evidence of a common global latent risk (frailty) factor that impacts corporate debt distress risk worldwide by employing a dataset with international coverage of corporate default events. The global latent risk factor identifies substantial common variation among separately estimated dynamic latent risk (frailty) factors of firms at the country level. Estimations of country frailty factors control for observable firm fundamentals capturing systemic risk and omitted macroeconomic factors. Commonalities among country frailty factors highlight global systemic risk. Observable global factors and financing variables can only explain up to 25% of global frailty, indicating the vulnerability of global corporate credit markets to common latent systemic risk. The findings also detect cross-country corporate default risk spillovers, underscoring the international interconnectedness of corporate distress risk.

Keywords: Corporate Default Clustering, Frailty, International Spillover, Global Risk
JEL Classifications: F3, G15, G33, C40

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1 Introduction

Global non-financial corporate debt has doubled from \$45.6 trillion in 2008 to over \$90 trillion in 2023. A record wave of \$15 trillion corporate debt will mature from 2024 – 2026 (IMF, 2023), raising concerns about the ability of firms to fulfill their debt repayment obligations in the next few years. Interest rate hikes by central banks worldwide and the commitment to maintain a higher for longer rate regime further compound these concerns. Rising interest rates adversely impact debt servicing costs and the cost of raising new debt, elevating firm exposure to financial distress risk.[1]

Figure 1 shows the rising worldwide trend of non-financial corporate leverage corresponding to the low-interest rate environment and favorable lending conditions post the global financial crisis and the unprecedented COVID-19 pandemic shock in 2020. The global trend of rising corporate leverage poses an increasing threat to international financial stability. Compounded with rising interest rates, default action by a critical firm (or firms) can spill over to other firms due to financial linkages and other interconnections across firms, elevating the risk of surviving firms falling into financial distress. Giesecke and Kim (2011), Azizpour et al. (2018), and others provide empirical evidence supporting these concerns - Defaulted firms with higher liabilities trigger a more destabilizing financial contagion effect.[2]

This paper examines the vulnerability of firms worldwide to a dynamic latent risk (frailty) factor that goes beyond the information reflected in observable variables. The paper makes two main contributions. First, adopting a more computationally efficient method of estimating the frailty factor, I show that incorporating the frailty factor provides a more accurate and realistic assessment of corporate default risk exposure. The result is robust both in- and out-of-sample, controlling for a comprehensive set of firm fundamentals. Second, I show a substantial common variation among separately estimated country frailty factors. The findings raise concerns about firm vulnerability to a global dynamic latent risk factor.

The economic case for firm vulnerability to a frailty factor is intuitive. Systemic risk in the corporate credit market can arise through several channels. Giesecke and Kim (2011) and Azizpour et al. (2018) point out that credit portfolios are vulnerable to systemic risk – coordinated failure among firms. Default action by critical firms with large debt adversely increases the financial distress risk of surviving firms in an economy and beyond, triggering financial contagion. Direct firm interlinkages via production networks and global value

[1] Correspondingly, global corporate leverage rose from 76.8% to a peak of 98.7% in 2022, standing at one of the highest points of all time.

[2] In response to the recent and ongoing real estate debt crisis in China, the Federal Reserve warned that financial stress in China's real estate sector could increasingly expose the global financial markets to systemic risk through direct trade linkages and worsening of risk sentiment due to the systemic importance of China in the global economy. (Federal Reserve, 2022)

chains highlight real interlinkages,[3] suggesting that default action by key firms can directly impact other firms. Information contagion is another channel. The revelation of adverse news about a critical firm can strain global financial markets through risk sentiment, affecting lending conditions and triggering destabilizing capital flows worldwide.

Consequently, surviving firms face greater challenges in raising funds, increasing their financial distress risk exposure. Systemic risk may not be reflected in observable firm fundamentals and systematic variables. Thus, its omission can lead to underestimating corporate financial distress risk exposure.

The endogenous nature of corporate default actions provides further justification for incorporating the frailty factor or latent systemic risk in corporate default risk assessment. Structural corporate default risk literature, such as Bhamra et al. (2010a) and Bhamra et al. (2010b), highlight that adverse macroeconomics backdrops or financial crisis distort the value of firms' collateral and the present value of their future earnings payoff. With the option to default on their issued debt and equity, firms have fewer incentives to fulfill their financial obligations during crisis periods due to the depressed valuation of their financial assets. Consequently, corporate default risk models estimated with data from benign periods may have overlooked the time-varying incentives of firms to default, thus underestimating default risk exposure during crisis periods.

This paper employs a novel dataset that contains a global coverage of corporate default events. The dataset is from the CRI database,[4] containing a comprehensive description of default events,[5] accounting and market data for over 70,000 exchange-listed firms in 133 countries from 1990 to 2021. It is critical to have extensive coverage of corporate default events worldwide to holistically explore the significance of the frailty factor across countries, particularly during adverse periods of default clustering. Several key episodes with severe clustering of corporate default events include the Asian Financial Crisis, the Global Macroeconomic Recession in the early 2000s, the Global Financial Crisis in 2008, the Eurozone Sovereign Debt Crisis, and, to some extent, the COVID-19 pandemic.

I begin by estimating a binary logit model that measures firms' probability of default separately by country. I select explanatory variables based on Campbell et al. (2008), comprising a comprehensive set of firm accounting and market-based variables. The approach provides a holistic assessment of a firm's distress risk exposure across multiple observables, such as profitability, liquidity, and leverage.[6] Overall, the corporate default risk models

[3] Refer to Acemoglu et al. (2012) and Antràs and Chor (2013) for key literature on production networks and global value chains respectively.

[4] CRI (or NUS CRI) stands for Credit Research Initiative at the National University of Singapore.

[5] The dataset is novel for its detailed description and accounting of corporate default events worldwide. It accounts for variations in bankruptcy laws, corporate default actions, and indicators of financial distress across countries worldwide. Refer to Section 4.3 for further details on the coverage of the default events in the NUS CRI database.

[6] The selected variables are standard and widely employed in macroeconomic and finance literature to assess firms' financial distress risk exposure across countries worldwide.

generally provide a relatively accurate assessment of aggregate corporate default risk exposure under benign periods for all countries. However, the default risk models vastly underestimate overall aggregate corporate default risk exposure during severe macroeconomic recessions or financial crises. To capture the omitted factor that can impact distress risk in corporate debt portfolios but excluded from the econometrics specification, I incorporate a frailty factor, i.e., a dynamic latent variable. The frailty factor is estimated using a non-standard Generalized Autoregressive Score (GAS) method, modified based on Babii et al. (2019).[7] A key feature of this approach is the dynamic updating of the frailty factor with the generalized residuals - the empirical difference between estimated and actual default risk exposure. Intuitively, the generalized residuals capture systemic risk and other omitted systematic factors that impact corporate debt distress risk.

My approach for estimating the frailty factor is distinct from the prior corporate default clustering literature (e.g., Duffie et al. (2009), Koopman et al. (2011), Creal et al. (2014), etc.), which focuses on a dataset of modest size – of either industry aggregated data or a constrained selection of explanatory variables at firm-level. Instead, I estimate the frailty factor in a relatively big data setting. My dataset contains millions of observations at the firm level and an extensive selection of explanatory variables.[8] Employing big datasets based on firm-level data allows a more detailed accounting of firm heterogeneity across multiple components of firm fundamentals.

A feature of critical importance for this paper is to take into account that firms in different countries are more vulnerable to different risk factors due to distinct structural characteristics. Notably, econometrics models with variables selected based on U.S. firm-level or industry-aggregated data cannot account for variations in firm-level heterogeneity across countries,[9] and generally lead to poorer predictive performance when applied on firms in other countries.[10]

Based on the non-standard GAS method of estimating the frailty factors, I find strong evidence of a frailty factor that impacts corporate debt distress risk. The finding holds universally across countries worldwide, controlling for firm fundamentals. Specifically, the frailty factors are highly significant across different countries and better explain the clustering of corporate default events during crises. The findings confirm that exclusive reliance on firm fundamentals is inadequate in providing a holistic assessment of firms'

[7] My application of the GAS econometrics model is modified from Babii et al. (2019) to account for the financial risk issues I am addressing in this paper. A similar GAS econometrics specification is employed in Hansen and Schmidtblaicher (2021) to allow the model's parameters to vary over time. Their paper studies vaccine compliance with a binomially distributed dependent variable.

[8] Prior corporate default clustering literature estimates the frailty factor with simulation or other computationally intensive methods.

[9] Existing research in corporate default clustering literature largely estimates the frailty factor with industry or economy-aggregated data due to the computationally intensive nature of estimating the frailty factor using firm-level data

[10] Asis et al. (2020), Asis et al. (2021) and NUS Credit Research Initiative (2021) provide empirical results that support these findings based on an international firm-level data.

default risk exposure. Marginal effects analysis shows that a standard deviation increase of the frailty factor, across countries on average, captures 47.7% variations of the corporate default risk exposure for different countries in the data sample. Applying the likelihood ratio test and AUC out-of-sample analysis confirms the relevance of the frailty factor in explaining aggregate corporate default risk exposure without compromising the default risk models' discriminatory power based on firm-by-firm default risk assessment.

Subsequently, I show that incorporating the frailty factor can provide a more realistic prediction of corporate default events in an out-of-sample setting. I show that excluding the frailty factor severely underestimates corporate default risk exposure during crises, even at the extreme 99% quantile prediction. Incorporating the frailty factor provides a more realistic forecast of corporate default risk exposure – in terms of mean bias estimation and potentially accounting for extreme realizations of default events under severe macroeconomic recessions or financial crises.

Using the separately estimated frailty factors across different economic regions worldwide, I identify a common global latent risk factor that explains a substantial share of the variation among these countries' frailty factors. Standard observable global factors and financing variables can only explain up to 25% of the risk inherent in the global frailty factor, indicating strong evidence that a substantial proportion of the global risk is latent, capturing firm exposure to global systemic risk. Based on this finding, I orthogonalize the global frailty factors with a comprehensive set of measurable global factors and financing variables to construct a latent global systemic risk factor[11] that impacts corporate debt distress risk worldwide but is not explained by observable characteristics. After controlling for firm fundamentals, marginal analysis of the global systemic risk factor shows that one standard deviation increase in this factor, on average, explains 19.3% of the default events in the data sample across countries worldwide.

Finally, I show substantial evidence of cross-country corporate default risk spillovers. The spillover effect is measured based on the country frailty factor, which captures aggregate financial distress risk information not reflected in firm fundamentals and measurable global factors. I study the severity of corporate default risk spillover across different countries and time periods. The empirical tests show a highly significant degree of causal relations among frailty factors of different countries, suggesting substantial evidence of cross-country corporate default contagion that is not captured with measurable, observable explanatory variables. I next employ Han et al. (2016) cross-quantilogram method to study the severity of quantile dependence among the frailty factors. These tests also support a substantial degree of dynamic dependence among frailty factors at the extreme

[11]The global latent risk factor captures common factor that impacts international corporate credit markets. Firm fundamentals and the standard set of global factors cannot explain the risk contained in the global latent risk factor, suggesting that the global latent factor captures common systemic risk that impacts international corporate credit markets. Subsequently, I will interchange the terms global latent risk factor and global systemic risk factor to illustrate the latent nature of global systemic risk.

quantiles, further supporting evidence of international distress risk spillovers as a channel that underlies the global dynamic latent risk factor.

Literature Review: This paper contributes to three key strands of literature in corporate default risk and international finance. First, I contribute to the strand on corporate default risk assessment. Early research in corporate bankruptcy by Beaver (1966) and Altman (1968) identify a comprehensive list of accounting variables that significantly predict firms' bankruptcy risk. Subsequent research by Shumway (2001), Chava and Jarrow (2004), Campbell et al. (2008), and numerous others study different constructions of market-based variables that provide useful information on corporate distress risk exposure. Besides firm-specific variables, external macroeconomic conditions also impact corporate default risk. Duffie et al. (2007), Lando and Nielsen (2010), Duan et al. (2012), and many others identify a wide range of domestic macro-financial variables that impact corporate debt distress risk. Asis et al. (2021) shows that global financing variables impact corporate default risk. Across firms in different countries worldwide, my paper shows that firms are vulnerable to a frailty factor, even with a comprehensive selection of explanatory variables. Marginal analysis of the frailty factor shows the economic significance of this factor. The finding highlights that existing explanatory variables identified in corporate default risk literature cannot provide a comprehensive assessment of firm financial vulnerability, highlighting the importance of a latent or contagion factor in corporate default risk assessment.

Second, this paper contributes to the literature on corporate default clustering. Das et al. (2007) show that four key explanatory variables cannot adequately explain the clustering of corporate default events exhibited in the U.S. economy. The corporate default clustering literature proposes two key approaches to account for this phenomenon - dynamic latent variable (frailty) and contagion. Duffie et al. (2009) and Koopman et al. (2011) uses simulation methods to estimate the frailty factors. They show that incorporating the frailty factor in the econometric corporate default risk model provides a more realistic assessment of aggregate default risk exposure during crises. Predicting corporate default risk exposure without the frailty factor may lead to underestimating default risk even at the extreme quantile interval. Creal et al. (2014) also identify a similar finding with a standard GAS approach to estimate the frailty factor. After controlling for the frailty factor and systematic variables, Azizpour et al. (2018) show that corporate default events are 'contagious.' Default events elevate surviving firms' exposure to financial distress risk over multiple periods. This paper employs a more computationally efficient method of estimating the frailty factor compared to prior corporate default clustering literature. The frailty factor can be flexibly estimated based on firm-level data with a comprehensive selection of explanatory variables. With this approach, I separately show that firms across different countries worldwide are vulnerable to an economically significant frailty factor that provides a more realistic assessment of corporate default risk under crisis.

Finally, this paper contributes to a recent and growing body of research on the global financial cycle in international finance. This field of study identifies a global risk factor that drives common comovement of financial assets across different financial markets worldwide, such as commodities, equities, and bonds (Rey (2015)). Miranda-Agrippino and Rey (2020) identify evidence for a common global factor that accounts for considerable correlation among risky assets worldwide. In currency markets, Lustig et al. (2011) identify evidence of a common global risk factor that impacts variation in currency risk exposure. In the capital flows literature, Forbes and Warnock (2012), Habib and Venditti (2019), Chari et al. (2020), Chari et al. (2022), among others, identifies proxies for global risk measures that account for international cross-border capital flows. This paper identifies a substantial degree of common variation among frailty factors across different countries, indicating strong evidence of a global dynamic latent risk factor that drives corporate debt distress risk worldwide. The global latent factor cannot be explained with observable global risk factors and financial conditions, indicating the vulnerability of the corporate credit markets to a latent global systemic risk.

The paper proceeds as follows. Section 2 outlines the baseline specification for estimating the frailty factor in an economy and the economic justification for incorporating a common global frailty factor. Section 3 describes the data and the selection of the explanatory variables. Section 4 presents the empirical results to show the relevance of the frailty factor in forecasting corporate default risk. Section 5 estimates the global systemic risk factor and underscores the economic significance of this factor. Section 6 presents evidence on international corporate default risk spillovers and contagion based on the estimated frailty factors. Section 7 concludes.

2 Firm frailty and global systemic risk

The international economics literature highlights corporate debt vulnerability to adverse movements in global factors and financing conditions. Global financial cycle literature identifies substantial evidence of a common international risk factor that drives joint movements in the valuations of financial assets worldwide (e.g. Rey (2015), Habib and Venditti (2019), Miranda-Agrippino and Rey (2020), etc). The international risk factor co-moves with global factors and financial conditions, such as U.S. monetary policy or global liquidity conditions. Depressed valuation of firms' financial assets precipitates more expensive refinancing and borrowing costs, raising concerns that adverse movements in global factors elevate firms' exposure to financial distress risk.

Asis et al. (2021) shows that global financing conditions impact firms' market value and, correspondingly, their financial distress risk exposure. With a comprehensive set of observable global financing conditions, they construct a composite measure of corporations' exposure to global financing conditions – the Global Variable Z. The factor measures corporate debt vulnerabilities to the broader global financing conditions. This finding motivates the following hypothesis:

Hypothesis 1: Firms worldwide are vulnerable to a common global frailty risk factor.

If the econometrics model excludes observable global factors, such as U.S. monetary policy or global liquidity measures, then hypothesis 1 suggests that the global frailty risk factor can capture these international risk factors and other omitted variables. Correspondingly, separately estimated country frailty factors should display a substantial degree of common variations – capturing the risk of the omitted global factors. However, the frailty corporate default risk literature such as Das et al. (2007), Duffie et al. (2009), Creal et al. (2014), Azizpour et al. (2018) and others, point out that economists inevitably omit the pertinent variables that impact corporate default risk, even with a rigorous selection of explanatory variables. This finding raises concerns that the corporate default risk econometrics model estimated solely based on observable explanatory variables underestimates vulnerabilities in corporate debt portfolios. The insight motivates the following hypothesis:

Hypothesis 2: A common global latent risk factor impacts firm financial distress risk worldwide. Observable global factors and financing variables cannot adequately explain the risk of the latent global risk factor.

Evidence from macroeconomics and corporate finance literature raises concerns about firms' vulnerability to global systemic risk. For instance, network models in Acemoglu et al. (2015), Eisenberg and Noe (2001), Elliott et al. (2014) highlight that firm failure to fulfill their financial obligations increases default risks of surviving firms due to firm interlinkages. Global value chain literature, such as Antràs and Chor (2013), Antras et al. (2017), and others, illustrate that firms source for input materials internationally rather than operate within an economy in isolation. Bankruptcy or financial distress of a critical firm (or firms) in the global value chain triggers domino effects of disproportionate disruption of business activities along the supply chain, harming profitability and exposing firms worldwide to greater financial distress risk. Firm fundamentals and macroeconomic explanatory variables overlook firm interlinkages; thus, sole reliance on these variables underestimates firms' systemic risk exposure. Likewise, quantifying the link between disruptions in the global value chain and corporate default risk worldwide is often infeasible due to the confidentiality of corporate financial relations data and limited granular data on international firm-level supply chains. Firm fragility due to international firm interlinkages but limited granular data capturing this information justifies the incorporation of a global latent risk factor in studying firm vulnerability.

Apart from direct economic linkages, corporate financial distress risk is also contagious through the informational channel. Oh (2013) uses the global games method to show that default by a critical firm (or firms) reveals harmful information on surviving firms, exposing them to greater financial distress risk due to financial contagion. Financial distress of a critical firm raises concerns that remaining firms are also exposed to the same risk, worsening sentiments in global financial markets. Creditors consequently impose tighter lending conditions, elevating other firms' costs of refinancing and borrowing. Surviving firms face greater financial distress risk, even without changes in firm fundamentals. Giesecke (2004) raises a similar finding with a structural model of multi-firm default.

Endogenous corporate default actions expose the global corporate credit markets to systemic risk. Hackbarth et al. (2006), Bhamra et al. (2010b), Bhamra et al. (2010a), Bhamra et al. (2021), and others, highlight that firms have disproportionately greater incentives to default under crisis periods, triggering the clustering of corporate default events. Severe global macroeconomic recessions or financial crises trigger adverse declines in the valuation of firms' financial assets and their present value of future payoff. With a less valuable default option, firms have greater incentives to default on their financial obligations. In compounding this issue, Leary and Roberts (2014) shows that firms mimic corporate financing decisions of peer firms within an industry due to common omitted risk factors, indicating that the default action of a firm adversely elevates the default risk of surviving firms. These findings raise concerns that explanatory variables cannot adequately account for endogenous corporate default actions, leading to underestimating corporate default risk.

Corporate financial fragility further highlights firm vulnerability to the global latent risk factor. Gabaix (2011) points out that large firms are systemically important as they disproportionately dominate the economic activity in an economy. Consequently, adverse shocks to large firms impact aggregate output in the economy, exposing firms in the broader economy to greater financial distress risk due to minimal diversification of shocks in the economy. Alfaro et al. (2019) identify a similar finding from an international perspective. They show that idiosyncratic shocks to large firms significantly correlate with economic growth in emerging markets and that adverse shocks to a large firm in emerging markets transmit risk to other firms in this region. Their findings raise concerns that elevating large firms' (or several critical firms') exposure to financial distress risk increases the vulnerabilities of broader firms in emerging markets and beyond. Based on systemic risk and the financial fragility literature, this motivates the third hypothesis:

Hypothesis 3: Adverse shocks to a country's frailty factor transmit financial distress risk to firms worldwide. The risk transmission is reflected in other countries' frailty factors, with the joint financial distress risk spillover giving rise to the global latent risk factor.

In order to assess firm vulnerability to the latent global risk factor, my empirical approach takes three key steps. First, I separately estimate a country frailty factor for firms worldwide. Second, I conduct a principal component analysis of the countries' frailty factors. The first principal component captures the global frailty risk factor that jointly drives firm distress risk across different countries worldwide. Third, I orthogonalize the global frailty risk factor with a comprehensive set of global factors and financing variables to construct corporate exposure to global systemic risk – this factor captures a latent global risk factor that observable global factors and financing conditions cannot explain.

3 Reduced-form Model Specification

This section outlines the econometrics specification for measuring corporate distress risk with frailty factor. This factor is estimated with a non-standard GAS paradigm approach, which is notably more computationally efficient than prior methods in corporate default clustering literature.

3.1 Benchmark Model Specification: Binary Logit Model

My benchmark corporate default risk measure is based on a binary logit model. This econometrics specification is widely used in corporate default risk estimation; see Shumway (2001), Campbell et al. (2008), Aretz et al. (2018), Asis et al. (2021), and many others. Compared to other econometrics models in existing corporate default risk literature, this approach is superior for its computational efficiency in utilizing past and present information to assess corporate default risk. The model assumes that the firm's marginal probability of default over the next period follows a logistic distribution, which is given by:

$$\pi_{it} = \frac{\exp(\beta_0 + X_{i,t-1}^T \beta)}{1 + \exp(\beta_0 + X_{i,t-1}^T \beta)} \tag{1}$$

where $\pi_{it} = P(Y_{i,t} = 1 | I_{t-1})$. I_{t-1} is the information set based on available information in period t-1. $Y_{i,t}$ is an indicator variable equal to 1 if the firm defaults in period t. Based on period t as the benchmark period, $X_{i,t-1}$ is the vector of explanatory variables known at the end of the previous period. $X_{i,t-1}$ encompasses firm-specific variables and may include additional systematic variables. Intuitively, the default risk model assesses the firm's risk of default in period t based on available information in t - 1. A numerically larger $\beta_0 + X_{i,t-1}^T \beta$ indicates higher probability of default.

Firms exit from the data sample if they default.[12] Besides a default event, firms may exit the data sample due to other conditions, such as privatization, merger, or acquisition. The default indicator remains at $Y_{i,t} = 0$ if the firms do not default, including the month

[12] Refer to section 4 for a detailed description of corporate default events

that firms exit the data sample not due to a default event. β_0 is the standard constant intercept term in the binary logit model without the frailty factor.

3.2 Binary Logit Model with Frailty

In assessing firm latent vulnerability, my construction of the frailty factor is modified based on Babii et al. (2019). The corporate default risk model with the frailty factor can correspondingly be written as:[13]

$$\pi_{it} = \frac{\exp(f_t + X_{i,t-1}^T \beta)}{1 + \exp(f_t + X_{i,t-1}^T \beta)} \tag{2}$$

After controlling for explanatory variables, the term f_t relates to the frailty factor, an estimated time-varying latent variable. (2) suggests that a common latent variable (frailty) broadly impacts firms within the same time period. Following the GAS model paradigm, the frailty factor follows an autoregressive specification written as:

$$f_t = \delta + \theta f_{t-1} + \alpha s_{t-1} \tag{3}$$

The innovation term (s_{t-1}) is computed as:

$$s_{t-1} = \bar{y}_{t-1} - \hat{y}_{t-1} \tag{4}$$

where the terms $\bar{y}_{t-1}$ and $\hat{y}_{t-1}$ relates to:

$$\bar{y}_{t-1} = \frac{1}{n_{t-1}} \sum_{i=1}^{n_{t-1}} y_{i,t-1} \tag{5}$$

$$\hat{y}_{t-1} = \frac{1}{n_{t-1}} \sum_{i=1}^{n_{t-1}} \hat{\pi}_{i,t-1} \tag{6}$$

Based on (3) and (4), the innovation (s_t) of the frailty factor is dynamically updated with the generalized residuals. In the case of a binary logit model, generalized residuals is computed as the difference between the empirical default rate and model predicted default rate, defined in (5) and (6), respectively.[14] This approach indicates that higher (lower) realization of default events will dynamically increase (decrease) the next period frailty factor based on higher (lower) innovations, which correspondingly dynamically updates the corporate default risk exposure. Given the stylized observation of worldwide clustering in corporate default events during crises, incorporating the frailty factor in the reduced-form model can more adequately explain corporate default risk exposure beyond information

[13] Note that the frailty factor replaces the constant intercept term in (1).

[14] Refer to Gourieroux et al. (1987) for more details on the description of generalized residuals

contained in observable firm fundamentals and systematic variables.[15]

Notably, the dynamics of updating the frailty factor deviates from standard GAS econometrics literature, which scales the score function by its standard deviation. Instead, the frailty factors are driven by generalized residuals. This approach is aligned with Babii et al. (2019), which also focuses on discontinuous binary dependent variables.[16]

My estimation of the log-likelihood function for the dynamic logit model with the frailty factor is standard. Based on equations (1) – (6) and rewriting the corresponding parameters as a vector $\psi = (\alpha, \beta, \delta, \theta)$, the logistic quasi log-likelihood is written as:

$$L_T(\psi) = \frac{1}{\sum_{i=1}^{T} n_i} \sum_{t=1}^{T} \sum_{i=1}^{n} [y_{it} \ln(\frac{\exp(f_t + X_{i,t-1}^T \beta)}{1 + \exp(f_t + X_{i,t-1}^T \beta)}) + (1 - y_{it}) \ln(\frac{1}{1 + \exp(f_t + X_{i,t-1}^T \beta)})] \tag{7}$$

In (7), the frailty factor (f_t) replaces the constant intercept under the standard estimation of a binary logit model without the frailty factor.

Importantly, my approach to estimating the frailty factor is more computationally efficient than prior frailty corporate default risk literature – due to avoiding using simulations or handling multiple complicated equations that require numerical derivatives to solve the parameters. In this case, my econometrics model can assess a firm latent vulnerability while flexibly incorporating an extensive coverage of firm-level explanatory variables.

It is possible to incorporate additional frailty factors to account for firm heterogeneity with a richer set of data that contains more default events, such as estimating extra frailty factors at the sectoral level. However, the rare nature of corporate default events hinders gaining further economic or statistical insights from incorporating additional frailty factors that account for differences in firm characteristics. Therefore, this paper does not consider the extension with multiple frailty factors.

4 Data and Methodology

4.1 Firm Fundamentals and Global Factors Selection

Selecting the pertinent explanatory variables is critical in measuring firms' distress risk exposure. This section outlines my approach to selecting the relevant firm fundamentals and global factors in assessing firms' financial distress risk exposure.

I select and construct the firm fundamentals explanatory variables based on Campbell et al. (2008). This approach systematically measures firms' distress risk exposure across

[15] Table A.1 shows the massive clustering of corporate default events worldwide during the early 2000s macroeconomic recession and 2008 Global Financial Crisis. Refer to section 4.3 for more details.

[16] See Babii et al. (2019) for more details on the theoretical results justifying the usage the generalized residuals approach for the computation of innovation term with binary dependent variable.

multiple dimensions, such as profitability, leverage, and market-based information. Campbell et al. (2008) firm explanatory variables build upon multiple generations of corporate default risk literature, such as Altman (1968), Ohlson (1980), Shumway (2001), among many others. Notably, Campbell et al. (2008) approach of measuring distress risk is widely adopted across macroeconomics and finance research, encompassing international coverage of data including the U.S., other developed countries, and emerging market economies.[17]

In quantifying the proportion of risk that standard observable global factors can explain in the global frailty factor, the following global factors and financing variables are selected: (i) U.S. three-month Treasury bill yield, (ii) U.S. spread between the ten-year Treasury note and the one-year Treasury bill, (iii) Global Growth Rate (Growth rate for G7 economy), (iv) Oil Price (West Texas Intermediate), (v) VIX, (vi) TED Spread, (vii) Credit spread between the Moody's BAA and AAA corporate yields, (viii) Changes in the real broad US$ exchange rate index. Broadly, the selected global factors can be classified into four main categories: (1) U.S. Monetary Policy, (2) Global Risk Aversion, (3) Global liquidity, (4) Global Macroeconomic Conditions, and (5) Exchange Rate Conditions. The identified global factors are also widely employed in corporate default risk and global financial cycle literature such as Azizpour et al. (2018), Asis et al. (2021), Miranda-Agrippino and Rey (2020), Chari et al. (2021), among others.[18]

The case for corporate vulnerability to global factors is easily made. Global financial cycle literature and related studies, such as Miranda-Agrippino and Rey (2020) and Chari et al. (2021), point out that tightening U.S. monetary policy correlates with low asset prices, triggering more expensive corporate financing costs and elevating firm financial distress risk exposure. A rise in the U.S. interest rate also facilitates appreciation of the U.S. dollar, which is harmful to firms worldwide, primarily if their debt is largely denominated in the U.S. dollar.

A robust global economic growth rate facilitates a favorable corporate financing environment and promising business prospects, reducing corporate financial distress risk worldwide (Giesecke et al. (2011)). A decline in oil price, a key global commodity, reflects poor global economic conditions. Consequently, firms worldwide face poorer business prospects and a greater risk of financial distress. Moreover, the oil price also reflects the global inflation rate. Depressed oil price reflects a low global inflation rate, increasing the incentives for firms to default on their financial obligations due to the lower present value of their future payoff (Bhamra et al. (2010b)).

VIX is a proxy measure of global investors' risk appetite. A higher VIX generally denotes a larger risk premium, which increases firms' borrowing costs worldwide. Global

[17]For instance, Aretz et al. (2018) and Asis et al. (2021) employ Campbell et al. (2008) explanatory variables to study the corporate distress risk premium puzzle in the advanced economies, excluding U.S. and emerging markets, respectively.

[18]As a robustness check, I subsequently consider a broader selection of global factors and indices employed in macroeconomics and international finance literature.

financing variables, such as TED spread and credit spread between BAA-AAA corporate yield, reflect global liquidity. Adverse movements in these global financing conditions signal increasing challenges for firms' worldwide access to financial funding, translating to higher distress risk exposure.

4.2 Model Performance

Corporate default risk literature has employed multiple statistical measures to assess and compare the predictive performance of default risk models. As most measures largely provide an equivalent assessment of default risk models' performance, I employ two key measures widely used across corporate default risk studies. The first measure is the Receiver Operating Characteristics (ROC) score, also known as "area under the curve" (AUC), a commonly used measure for assessing distress risk model predictive performance (e.g. Chava and Jarrow (2004), Tian et al. (2015), Asis et al. (2021), etc). The measure evaluates the default risk models' ability to distinguish between default and non-defaulted firms with a cumulative fraction of defaulted firms as a function of the models' estimated default risk, ranked from highest to lowest. For the AUC measure, a value of 1 suggests that the model has perfect discriminatory power. The model's capability to identify distressed firms declines as the numerical value of the AUC decreases. An AUC of 0.5 is equivalent to a random prediction.

I use McFadden's pseudo-R^2 to measure the goodness of fit of the econometrics models, computed as 1 - $\frac{L}{L_0}$. (L) is the estimated default risk model's likelihood compared to the alternative model that only contains the intercept parameter (L_0).

4.3 The Data

My dataset covers worldwide firm-level data across different countries and regions. The data contains detailed information on firm default events and comprehensive coverage of firm-specific and systematic variables.

My key data source is from the CRI database, the Credit Research Initiative at the National University of Singapore (NUS CRI), accessed on July 1, 2021. The NUS CRI database provides information on corporate default events, accounting, and market data for over 70,000 publicly listed firms in 133 countries/economies from 1990 onwards. However, data coverage for firms before 1995 is limited for most economies, and data on emerging and developing economies is limited. As such, my main analysis focuses on data from January 1995 to December 2020 and covers 21 economies across North America, Europe, and the Asia Pacific region.[19] Notably, corporate default is rare. The dataset shows

[19] While the NUS CRI database may contain data for a large number of countries worldwide, data in most countries are sparse. To ensure sufficient data for data analysis, I only consider countries with an average of 100

that the average corporate default rate for most countries or regions comprises less than 0.05% each year. Numerous countries lack sufficient data on corporate default events, which hinders meaningful statistical analysis if I solely focus on firm-level data at the country level. To mitigate this issue, I group several countries with limited corporate default events at a regional level based on similarities in structural characteristics and geographical proximity. Based on data availability, I focus the default risk analysis on eight countries or regions: The United States, Canada, United Kingdom, Germany, Other Europe, Japan, Australia, and Advanced Asia (Singapore, Hong Kong, Taiwan, and South Korea). Panel A of Table 1 presents the details of countries in each region.

The dataset contains detailed background information for each corporate default event. Panel B of Table 1 shows that each corporate default event is broadly classified into three main categories: (1) Bankruptcy, (2) Default, and (3) Debt Restructuring - with further classification into subcategories with a description of the background information on each corporate default event. This information is helpful as countries have different bankruptcy laws and may differ in recognizing firm financial distress. To be consistent with previous corporate default risk literature and the classification of financial distress across countries, I do not classify delayed payments made within a grace period as an indicator of financial distress.

To estimate a binary logit model, every firm-month observation requires data for all explanatory variables. Observations with missing values in the explanatory variables are excluded, mainly occurring in the data sample's earlier period. Table A.1 in Appendix A presents the number of firm-month observations per year, the respective default events, and the default rate for each country or region in the benchmark specification after excluding the missing data. Based on my aggregated data sample, the average default rate comprises less than 0.05%, reflecting the rare nature of corporate default events. Notably, corporate default events do not occur uniformly over time - they tend to cluster under crises, such as during the early 2000s global macroeconomic recession and the 2008 Global Financial Crisis.

Table A.1 also shows a notable distinction in corporate default rates across different regions. Unlike corporate default rates in the U.S., some countries, such as Japan, exhibit lower default rates. This observation is unsurprising due to differences in firms' structural characteristics across countries. For instance, Japan and most other European countries have lower default rates, mainly due to prolonged low interest rates, which supports a favorable environment of easy borrowing and refinancing of debt.

As highlighted in section 3.1, the firm fundamentals explanatory variables are classified into two main categories: firm-specific accounting ratio and market-based variables. The

firms yearly and at least one default event throughout the data sample. As an additional robustness analysis, I also study firms' default risk from emerging markets.

accounting ratios are net income to market value of total assets (NIMTA), cash to market value of total assets (CASHMTA), leverage (LEV), and market to book ratio (MB). Accounting variables are available at a quarterly frequency. Market-based variables are available at a monthly frequency. These include volatility of returns (SIGMA), log excess stock returns relative to domestic economy main stock indices (EXRET), log of stock price (PRICE), log ratio of the market cap relative to total market cap of all listed firms in the economy (RELSIZE). Based on the data convention from the NUS CRI database, the firm-level data for European countries are expressed in Euro; the rest are expressed in U.S. dollars.

Following Campbell et al. (2008), I winsorized the firm-specific variables at the 5th and 95th percentiles. This approach controls for potential data errors and eliminates unusual balance sheet and market data outliers. Accounting Ratios (NIMTA, CASHMTA, and MB) are lagged by two months to ensure that accounting information is available for predicting firms' default risk.

As discussed in Section 3.1, the global factors considered are the U.S. three-month Treasury bill yield (Yield), the U.S. spread between the ten-year Treasury note and the three-month Treasury bill (Slope), Global Growth Rate (Growth rate for G7 economy), Oil Price (West Texas Intermediate), VIX, TED Spread, Credit spread between the Moody's BAA and AAA corporate yields, U.S., US$ nominal broad effective exchange rate index. Oil price is based on the West Texas Intermediate (WTI) and is retrieved from World Bank Commodity Price Data. U.S. three-month Treasury bill yield, U.S. yield slope, VIX, Moody's BAA and AAA corporate credit spread, and TED Spread are collected from the FRED, Federal Reserve Bank of St. Louis, Federal Reserve Bank of New York. The global Growth Rate is based on the GDP growth rate of the G7 economies and is collected from the OECD. The U.S. nominal broad effective exchange rate index is collected from the Bank of International Settlements (BIS). This is the geometric weighted average of the exchange rate. The global growth rate is available quarterly; the rest of the global variables are available monthly and are common to all firms in the data sample. Unlike firm-specific variables, I do not winsorize systematic variables. Appendix Table A.2 presents additional details on the construction and the data source of the explanatory variables.

4.4 Summary Statistics

Table 2 reports the descriptive statistics for the firms' explanatory variables of the eight countries and regions. The table presents the summary statistics for the full sample and a subset sample that only includes defaulted firms. My summary statistics include the mean and a t-test analysis that assesses if there is a statistically significant difference in means between the full sample and defaulted firms. The defaulted firms' indicator is measured the month before the default event (t-1). Table A.3 reports the summary statistics of the key global factors and financing variables employed in the paper.

Panel A of table 2 reports that defaulted firms generally show the following structural features: less profitable (NIMTA), less capable of covering short-term financial obligations (CASHMTA), higher market-to-book ratio (MB), and higher leverage (LEV). Firms in financial distress also tend to have lower excess returns (EXRET), lower stock price (PRICE), and have a smaller market cap relative to economy stock indices (RELSIZE). The results universally hold for different economic regions worldwide. These summary statistics are largely consistent with economic intuition and empirical results in Campbell et al. (2008), Aretz et al. (2018), Asis et al. (2021), and others, with a similar set of explanatory variables.

5 Empirical Results

This section evaluates the significance and relevance of the frailty factor in explaining corporate default risk exposure worldwide, especially during episodes of severe default clustering. Section 2 points out that corporate debt is systemically vulnerable, and corporate default actions may be endogenous. In this case, firm fundamentals and external macroeconomic conditions, including domestic macroeconomic and global financing variables, may not provide a comprehensive assessment of corporate default risk exposure.

To measure firms' default risk exposure, I first construct logit models with accounting and market-based variables across countries worldwide. Subsequently, I incorporate the frailty factor into the logit models to assess firm vulnerability to systemic risk and omitted macroeconomic variables on corporate debt distress risk.

5.1 Firm Fundamentals

Following Campbell et al. (2008) and Asis et al. (2021), I first estimate a logistic regression that studies firms' distress risk exposure with only accounting variables. The binary logit models are separately estimated for the eight different countries and regions. This step builds upon the estimation of the later baseline logit models that includes both accounting and market-based variables.

Panel A of Table A.4 reports the logit model estimates that only include the firms' accounting variables. Across all eight countries and regions, the table shows that corporate default risk is universally negatively correlated with profitability (NIMTA) and positively correlated with leverage (LEV). The findings are statistically significant at the 1% level for all eight economic regions. Table A.4 also shows that corporate default risk is mostly negatively correlated with liquidity (CASH) and positively correlated with market-to-book (MB). However, the parameter estimates for these variables are insignificant or display counterintuitive signs for some regions. In instances with counterintuitive signs, the parameter estimates are not statistically significant. For example, the parameter estimate of the market-to-book ratio for Germany is -0.054 but is statistically insignificant. This finding is not a concern as it may arise from omitted variables due to the exclusion of market-based variables in the logit model.

Panel A of Table 3 reports the estimates of the logit model that incorporates both firms' balance sheet and market-based variables. In accordance with the findings in A.4, Table 3 shows that profitability and leverage are largely still highly significant at the 1% level and display the correct signs for all regions.

Additionally, across all eight economic regions, Table 3 shows that corporate default risk is positively correlated with volatility of returns (Sigma) and relative size (RELSIZE). The parameter estimates for these variables are largely statistically significant at the 1% level. In contrast, corporate default risk is negatively correlated with excess return (EXRET), and stock price (PRICE). The parameter estimates for these variables are also mostly statistically significant at the 1% level.[20] Overall, the parameter estimates for all eight economic regions display economically intuitive signs and are consistent with findings in the previous literature (e.g. Campbell et al. (2008), Aretz et al. (2018), Asis et al. (2021), etc.).[21]

For each economic region, the loglikelihood, pseudo-R^2, and AUC is considerably higher in Table 3 as compared to Table A.4. The finding confirms that incorporating market-based variables provide a universal better explanation of corporate default risk exposure across different economic regions worldwide.

5.2 GAS Frailty Specification

In this subsection, I present the empirical results of the binary logit model that incorporates the frailty factor while controlling for the full set of accounting and market-based variables identified in the previous section.

Panel B of Table 3 reports the results for the parameter estimates of the econometrics model based on (2) - (7). Across all economic regions, the results show that the parameters corresponding to the lagged factor (α) and innovation term (θ) of the frailty factor are universally significant at the 1% level. These results are estimated based on controlling

[20]It seems counterintuitive for RELSIZE to be positively correlated with corporate default risk. Nonetheless, this observation is not a concern considering its weak positive coefficient and its relatively minor marginal impact as compared to the negative effect of the PRICE variable. This finding is consistent with Campbell et al. (2008) and Asis et al. (2021), which employ the same explanatory variables.

[21]Sectoral fixed effects and other forms of fixed effects are excluded from the econometrics model due to the rare nature of corporate default events. Incorporating fixed effects may force us to give up a substantial number of observations and default events, which ultimately leads to the underestimation on the severity of default clustering. This approach is consistent with other corporate default risk literature, such as Campbell et al. (2008), Duffie et al. (2009), Aretz et al. (2018), Asis et al. (2021), among others.

for the firm-specific variables described in Table 3. Intuitively, the significant Alpha (α) parameter indicates that the next period default risk is highly receptive to the deviation between the logit model predicted default rate and occurrences of default events. The α parameter allows the frailty factor to adjust and account for systemic risk and other adverse shocks that impact corporate distress risk but are not reflected in observable variables in the model. The significant Theta (θ) parameter reflects the persistency of the frailty factor. The persistent frailty factor reflects the clustering nature of corporate default events exhibited in the real world data. As discussed previously, Delta (δ) corresponds to the intercept term. Separately, I also conduct Augmented Dickey-Fuller tests on the frailty factor of all regions. The results confirm that the frailty factors are stationary, and the specification of the frailty factor in the default risk model is appropriate.[22]

The comparison of results in both panels of table 3 shows that the parameter estimates for all firm fundamentals remain statistically significant and display similar magnitude, even after incorporating the frailty factor. The results indicate that the frailty factor does not substitute the observable explanatory variables.

A comparison of loglikelihood and pseudo-R^2 in both Panels of Table 3 strongly suggests that including the frailty factors in the econometrics models provide a better explanation of corporate default risk exposure. Specifically, incorporating frailty factors lead to a noticeable improvement in loglikelihood and pseudo-R^2. In-sample AUC mostly remains the same. I conduct the likelihood ratio tests to confirm that including the frailty factor provides a better explanation of corporate default risk exposure. The test measures the degree of improvement in the goodness-of-fit when additional factors are added to the restricted model. Appendix Table A.5 reports the results for the likelihood ratio tests across all economic regions. Relative to the corporate default risk model that contains accounting and market-based variables, the likelihood ratio tests are all statistically significant at the 0.01% level. These results universally show that including the frailty factor significantly improves model fit in terms of corporate default risk assessment.

The key justification of including the frailty factor lies in explaining the clustering of corporate default events during crisis period. For the three key economic regions, U.S., Europe and Asia Pacific,[23] Figure 2 plots the actual number of default events in comparison with the model predicted corporate default risk based on explanatory variables in Table 3, with and without the frailty factor for each quarter. Figure 2 shows that exclusion of frailty factor provides generally reasonable estimation of corporate default risk during benign period. However, the corporate default risk prediction largely underestimates corporate default risk exposure during crisis period. The findings mostly hold for the three key economic regions for the case of early 2000 and 2008 global financial crisis. These

[22] Autocorrelation plots of generalized residuals also show no significant evidence of correlation at the 5% level.

[23] Due to the rare nature of corporate default events, corporate default risk estimate and actual default events are compiled at a broad regional level based on Panel A of Table 1

results indicate the presence of additional systemic risk and systematic factors that drives corporate default events, but are not accounted in the firm fundamentals.

I have also conducted an Out-of-Sample (OOS) AUC analysis comparing the benchmark default risk model with the counterpart model, including the frailty factor. To conduct the OOS analysis, I first estimate the parameters of the default risk models from 1995 - 2005. Subsequently, I estimate firms' default risk exposure in year t + 1 based on parameters estimated up to year t in a recursive approach. The OOS analysis shows that including the frailty factor does not compromise the corporate default risk models' capability in identifying financially distressed firms. These results hold for all regions. For instance, in the U.S., the OOS AUC for the default risk model with and without frailty is 0.973. In the case of Japan, the AUC for the corporate default risk model with frailty is 0.917, in contrast to the model without the frailty factor at 0.914. The remaining results for other countries are reported in Table A.6 in the Internet Appendix A. Nonetheless, the critical contribution of the frailty factors lies in providing a more realistic aggregate estimation of corporate default risk in terms of mean default risk prediction and potentially accounting for extreme realizations of corporate default events. These analyses will be discussed in Section 4.3.

To provide a more intuitive insight into the parameter estimate of the country frailty factor, I compute the economic significance of the country frailty factor by measuring the marginal increment of corporate default events due to one standard deviation increase in the country frailty factor.[24] Panel A of Table 7 reports the key empirical results of the marginal analysis of the country frailty factor specific.[25] Column 1 presents the standard deviation of the frailty factor. Columns 2 and 3 present the MEM and AME, respectively. Column 4 presents the average increase in default events **in a year** with a standard deviation increase in the frailty factor, computed using AME estimates. The table suggests that one standard deviation increase in the frailty factor leads to an average increase of 4 corporate default events in a year, constituting, on average, almost 48% of the overall default events in the data sample each year.

Panel A of Table 7 provides a quantitative measure of firms' vulnerability to a dynamic latent factor after controlling for firms' fundamentals. The empirical results provide an intuitive estimate of firms' vulnerability to systemic risk and macroeconomic conditions that were omitted from the corporate default risk model, providing additional insight into corporate debt vulnerability that may be used as a form of stress testing or assessment of capital adequacy requirements.[26]

[24]Section 6.1 presents further elaboration on the computation and interpretation of the marginal analysis

[25]It is challenging to compute to the marginal impact of the frailty factor based on the parameter estimates of the frailty component in Table 3. To mitigate this issue, I separately run a separate logit regression based on the frailty factor that is synthetically estimated in Table 3 after controlling for the same explanatory variables. Based on the parameter estimates and the standard error of the frailty factor, I can compute the marginal analysis of the frailty factor.

[26]Given the relative computational efficient approach to estimating the frailty factor as compared to prior

5.3 Out-of-Sample Analysis and Tail Risk Prediction

Apart from identifying the relevant risk factors that reveal vulnerabilities in corporate debt portfolios in-sample, it is also crucial to assess if these factors provide a reliable assessment of corporate default risk out-of-sample. A reliable forecast of corporate default risk is critical for portfolio management, capital allocation, and assessing risk exposure in corporate debt portfolios.

Across key economic regions worldwide, this subsection studies if incorporating frailty factors provides a more reliable assessment of corporate default risk out-of-sample - forecasting the mean and distribution of default events in year t + 1, based on the explanatory variables and parameters estimated recursively up to year t. The forecasted default events are compared with actual default events.[27]

Figure 3 depicts the forecast distribution of default risk compared to the realized number of default events. The top three charts show the distributional forecast of default risk at the 99th percent confidence interval for the three key economic regions based on a dynamic logit model without the frailty factor. The bottom three charts depict the corresponding counterpart with the frailty factor. Based on (3), illustrating the dynamic update of the frailty factor based on generalized residuals, I construct the distributional forecast of default risk (with frailty factor) by conducting bootstrap sampling of past realized generalized residuals in each economic region.[28]

Across all three economic regions, Figure 3 shows the corporate default risk model without frailty, vastly underestimates corporate default risk exposure during crises. For instance, coinciding with the recent U.S. economic recessions, the realized default events in the U.S. economy in 2016 and 2020 are 50 and 54, respectively. However, the corresponding 99th percentile default events predictions are only 32 and 37, respectively. In the same period, the extreme forecast distribution of the default risk model with the frailty factor is 66 and 65, respectively. A similar finding holds for the Europe and Asia Pacific region, albeit to a less severe degree.[29] Overall, the econometrics model without the frailty factor generally underestimates clustered corporate default risk, especially during crises.

Apart from underestimating clustered corporate default risk during crises, Figure 3

corporate default clustering literature, I can flexibly incorporate additional macroeconomic or global factor into the econometric model and separately estimate firms' vulnerability to the frailty factor. This extension will be discussed in Section 5.4.

[27] For example, based on the explanatory variables and parameters estimated up to 2023, I forecast the mean and distribution of corporate default risk exposure in 2024.

[28] I begin with sampling 1,000 bootstrap samples of generalized residuals at a monthly interval. Subsequently, I extract the 90th quantile of the set of bootstrap samples. This data is used to update (3) to forecast the extreme confidence interval of the frailty factor.

[29] For the case of Europe during part of the European Sovereign Debt Crisis, the 99th percentile default events prediction in 2012 and 2015 are 37 and 37. The realized default events are 36 and 35, respectively. The counterpart default risk model with the frailty factor provides a more realistic assessment of default risk by forecasting the extreme distribution at 50 and 52, respectively.

also shows that incorporating the frailty factor provides a more accurate mean estimate of corporate default events across all three economic regions, especially under crisis periods. Specifically, compared to the counterpart without the frailty factor, the econometrics models with the frailty factor consistently produce a mean estimate closer to the realized default events across the entire data sample.

Across all three economic regions, additional econometrics analysis also supports the observation in Figure 3. Table 4 presents the results of the econometric analysis. Based on the 99% value at risk (VaR) backtesting approach, a standard measure of portfolio corporate credit risk, I employ the unconditional coverage and independence tests. The unconditional coverage test assesses if the actual realization of corporate default events at the extreme interval is consistent with the econometric model prediction. The independence test assesses if the breach in corporate default events is independent. The p-value of the tests confirms that excluding the frailty factor in default risk assessment severely underestimates actual default risk exposure. In contrast, the counterpart econometrics model with the frailty factor can more realistically assess corporate default risk exposure by potentially accounting for the extreme realization of default events during crises.

I also calculate the relative absolute error and root mean square error. The former measures the absolute difference between the mean estimate and realized default events, scaled by the realized number of default events in each year and the total sample. The latter calculates the root mean square of the counterpart. Table 4 shows that including the frailty factor provides a smaller absolute error and root mean square relative bias measure for all three economic regions, illustrating that incorporating the frailty factor produces a more accurate forecast of default risk.

Overall, the econometrics tests show that incorporating the frailty factor provides a more accurate mean prediction of corporate default events and a realistic forecast of clustered corporate default risk in terms of potentially accounting for severe clustering of corporate default events during crises.

5.4 Incorporating systematic factors

Thus far, my corporate default risk analysis mostly employs firms' accounting and market-based variables. While market-based and other firm fundamentals explanatory variables capture risk information in macroeconomic and global factors (e.g. Azizpour et al. (2018), Asis et al. (2021), etc.), excluding systematic variables from the econometrics corporate default risk model naturally raises concerns over whether alternatively selecting key macroeconomic and global factors can replace the frailty factor.

To address the above concerns, and as a form of robustness check, I consider a set of key macroeconomic and global factors commonly employed in corporate default risk literature. The selected global variables are global growth rate, oil price, U.S. yield slope, TED spread, and Moody's BAA and AAA corporate yields. I also consider domestic macroeconomic variables, such as the three-month interest rate and industrial production. Jointly across research in corporate default risk literature, which includes Campbell et al. (2008), Duffie et al. (2009), Lando and Nielsen (2010), Duan et al. (2012), Azizpour et al. (2018), Asis et al. (2021), among others have identified most of the selected explanatory variables to be significant predictors of corporate default risk worldwide.[30]

With the additional systematic variables, I repeat the primary econometrics analysis in the previous sections. The main results are broadly similar. The frailty factors are still highly significant across different countries worldwide. The likelihood ratio tests highlight that incorporating frailty factors can better explain firms' default risk exposure. The out-of-sample analysis also shows similar results. Even with additional systematic variables, excluding frailty factors still underestimates clustered default risk exposure, especially during crisis periods. For brevity, only the out-of-sample comparison of default risk prediction with and without the frailty factor is reported in Appendix Figure A.1. The additional empirical analysis detailed in this subsection is available upon request.

Overall, the above findings highlight firm vulnerability to the frailty factor, even after considering the key systematic factors employed in corporate default risk literature. These findings are mainly consistent with prior frailty corporate default risk literature, such as Duffie et al. (2009), Koopman et al. (2011), Creal et al. (2014), Azizpour et al. (2018); albeit with the exclusion of firm-specific default risk variables from their models.

6 Global Systemic Risk

In this section, I show substantial evidence of firm vulnerability to a common global systemic risk, explaining the common simultaneous waves of corporate default events worldwide. To construct the global systemic risk measurement, I first identify common variations across country frailty factors to create a global latent risk factor. I then orthogonalize the global latent risk factor against a comprehensive set of global factors to construct a measurement of global systemic risk. Notably, the global systemic risk factor cannot be explained with observable global factors and financing conditions.

Before investigating the static correlation among the country frailty factors worldwide, I first study the time series dynamics of individual country frailty factors. Figure 4 plots the country frailty factors estimated based on the binary logit model of Table 3, Panel B. The frailty factors are also orthogonalized based on global factors and financing conditions in Table.[31] To reiterate, the frailty factor captures corporate distress risk information

[30] NUS Credit Research Initiative (2021) employs a subset of the above systematic variables in the evaluation of corporate default risk, leveraging a firm-level dataset with international coverage.

[31] The countries in are based on Panel A of Table 1. The frailty factors are separately estimated among different regions and are standardized to allow for convenient comparison across countries.

not explained in firm fundamentals and global factors. Figure 4 may not show obvious evidence of comovement among frailty factors during the benign period. However, common adverse comovements among the frailty factors during crisis periods are evident. For instance, the frailty factors across all countries largely peaked around the early 2000s and to some extent during the 2008 period, highlighting adverse movements in frailty factors worldwide during severe crisis periods. These observations motivate further investigation into potential common variations across country frailty factors and firms' vulnerability to a common global systemic risk.

I next conduct the Principal Component Analysis (PCA) among the frailty factors to assess degree of common variations across these factors. Table 6 presents the results for the PCA analysis, showing each frailty factor's loading on the principal component and the fraction of the total variance of the frailty factor attributed to each principal component.[32].The first Principal Component explains above 45% of the common variations among all the frailty factors. Additionally, all frailty factors load almost equally on the first PC factor, with an average of 0.35. These findings indicate substantial evidence of a common systemic risk factor impacting firms worldwide.[33]

I next investigate the proportion of variations that observable global factors can account for in the global latent risk factor. To do so, I conduct a multivariate regression of the global latent risk factor[34] as the dependent variable and observable global factors as the independent variable. Column (1) of Table 5 depicts the multivariate regression of the global latent risk factor against observable global factors based on table a. Column (1) shows that key global factors can only explain about 10% of the variations in the global latent risk factor, as represented by the adjusted R^2.

Nonetheless, my previous analysis raises concerns about omitted global factors that could have captured a larger variations of the global latent risk factor. To address this concern, I consider a broader set of global factors and financing conditions in the global financial cycle and international finance literature. These global variables are listed in Appendix Table, which includes measures of major central banks' monetary policy based on three-month rate[35], global indices, to name a few.

[32]The frailty factors are estimated based on Table 3 and orthogonalized with global factors based on Table

[33]I also conducted a similar PCA for frailty factors that are estimated based on Table A.4, without market-based variables. Figure A.2 depicts the plot of frailty factors. Panel A of Table A.9 shows the empirical results of the PCA analysis, showing stronger evidence of firm vulnerability to a global risk factor, as the first principal component explains over 50% of the variations among country frailty factors. The findings point out that market-based variables partially capture information on global risk, which is consistent with Hypothesis 1 and the findings in Asis et al. (2021). A separate PCA analysis is conducted with country frailty factors based on variables in 2 but not orthogonalized with global factors, providing largely similar results as Table 6.

[34]The global latent risk factor is estimated based on the first principal component of the PCA analysis of the country frailty factors.

[35]Following NUS Credit Research Initiative (2021) which finds three-month rate to be largely significant predictor of firm default risk across countries worldwide, I employ three-month as a measure of central banks monetary policy

I next identify common variations among the observable global factors by conducting PCA analysis among these factors. I then take the first five Principal Components, which sum to about 73% variations, and regress them against the global latent risk factors. Column (2) of Table A shows that the Principal Components can only explain about 25% of the variations in the global latent risk factor. These findings again confirm that observable global factors only contain little information about the global latent risk factor and correspondingly firm vulnerability to global systemic risk. In other words, sole reliance on observable global factors will underestimate firms' vulnerability to global systemic risk.

6.1 Economic significance and marginal effects of global frailty factor

The previous subsection identifies strong evidence of a common latent risk factor that impacts corporate financial distress risk worldwide. Based on this finding, I aim to investigate the economic significance of the global latent risk factor by quantifying the estimated number of corporate default events due to adverse movements in the global systemic risk factor.

I aim to understand the economic significance of the global systemic risk factor in each region by measuring its marginal impact on corporate debt distress risk worldwide. This approach quantifies the impact of changes in the frailty factor on the firm's default risk, holding all other explanatory variables constant. The marginal effect is calculated by taking a derivative of binary logit model, (1) as written below:

$$\frac{d\pi_{it}}{dx_j} = \frac{\beta_j exp(-\beta_0 - \beta X_{i,t-1})}{(1 + exp(-\beta_0 - \beta X_{i,t-1}))^2} = \beta_j(1 - \pi_{it})\pi_{it} \tag{8}$$

The above result suggests that one unit change of x_i results in a change in probability of default equal to the coefficient β_j multiply by (1 - π_{it}) and π_{it}. To reiterate, $\pi_{it} = P(Y_{i,t} = 1|I_{t-1})$.

Two equations of interest may be derived based on 8, the marginal effect equation: marginal effects at the mean (MEM) and average marginal effects (AME). MEM refers to the impact of one standard deviation increase of a selected explanatory variable on a firm's default risk, holding the rest of the explanatory variables at the sample mean. AME refers to the averages of individual marginal effects for one standard deviation increase of a selected explanatory variable on each firm, keeping the other explanatory variables at their actual value.

At a country level, Panel B of Table 7 presents the marginal impact of the global systemic risk factor.[36] Column 1 presents the standard deviation of the global systemic risk factor. Columns 2 and 3 present the MEM and AME of the global systemic risk factor,

[36]Table A.8 in appendix A reports the corresponding parameter estimates of the logit regressions with the global systemic risk factor.

respectively. Column 4 presents the expected corporate default events in one year due to a standard deviation increase in the global systemic risk factor computed using AME.

Panel B of Table 7 shows some variation in firms' vulnerability to global systemic risk across countries. In the extreme case, in Germany, one standard deviation increase in the global systemic risk factor is associated with 0.0292 percentage point AME increase in firms' default risk. On the other hand, in Japan, a standard deviation increase in the global systemic risk factor is associated with 0.0028 percentage point AME increase in firms' default risk.

The AME and MEM of the global systemic risk factor may seem numerically small at the individual firm level. However, this impact is sizeable when aggregated among firms in the entire data sample. For instance, a one standard deviation increase in the global systemic risk factor is associated with 1.88 and 1.08 additional default events in Germany and Japan in a year, respectively. A standard deviation increase in the global systemic risk factor, on average, constitutes 19.4% of default events in the data sample across countries worldwide. This number is disproportionately large, considering the joint waves of financial distress among firms worldwide triggered by adverse movements in the global systemic risk factor.

In extreme cases, the global systemic risk factor registers an increase of above three standard deviations during the early 2000s global macroeconomic recession. This observation translates to an average of 5 additional corporate default events across different countries in a year during a severe crisis period.

To provide a more intuitive interpretation of the impact of global systemic risk factor on corporate debt distress risk, I plot the firms' predicted probability of default at different values of the global systemic risk factor, holding values of the other explanatory variables at the sample mean. Figure 7 shows the plot of the global systemic risk factor factor across different regions. In terms of magnitude, the plot in figure 7 largely complements the empirical results in table 7.

Nonetheless, the plot largely shows that the global systemic risk factor displays a convex nature, indicating that firms worldwide are more vulnerable to extreme movements in global systemic risk. This finding raises concerns that firms worldwide are increasingly vulnerable adverse movement of the global systemic risk factor during crisis periods.

7 International Spillover and Channels of the Global Latent Risk Factor

7.1 International Corporate Default Risk Spillover

In this section, I investigate evidence of dynamic cross-country corporate default risk spillover. The risk spillover is assessed based on the country frailty factor, which, to reiterate, captures latent risk spillover beyond information reflected in explanatory variables.[37] To do so, I employ the Granger causality test, which studies predictive relationships among time series variables. The test is executed in the following way:

$$y_t = c_1 + \sum_{i=1}^{n} \alpha_{1,i} y_{t-i} + \sum_{i=1}^{n} \beta_{1,i} x_{t-i} + \epsilon_t$$

The null hypothesis for the above equation is that $\beta_1 = 0$, suggesting no evidence of spillover effects. In other words, there is no evidence of corporate default risk spillover or causal relation among country frailty factors. My alternative hypothesis is that $\beta_1 \neq 0$. In this case, x Granger causes y, suggesting evidence of risk spillover across country frailty factors. The tests above can be easily modified and applied to study Granger causal relation among different country frailty factors.

Considering variations in the time taken for the impact of default events in a region to be reflected in other countries, I control for the length of lags included in the causality tests up to 24 months. Table 8 presents the empirical results of the Granger Causal pattern between each region's frailty factors. This table provides the p-value of Granger Causality tests across the different economic regions. For brevity, table 8 only reports the lowest p-value for the Granger Causality tests, applied up to 24 months of lags. The table provides a concise overview of the evidence of dynamic dependence across frailty factors of different economic regions.

Table 8 reports substantial evidence of spillover in corporate default risk across different countries worldwide. Notably, the severity of corporate default risk spillover is largely not affected by differences in firms' structural characteristics across countries or their proximity in geographical location. For instance, Table 8 shows substantial evidence of spillover effect from the U.S. economy to Europe, U.K., Australia, and Advanced Asia, with the p-value of the Granger-causality tests being less than 5%. Other parts of the world also display similar results. A detailed breakdown of Granger-causality tests, reported in Appendix Table A.13 shows that the destabilizing corporate default risk spillover mainly occurs during the first six months, aligning with Azizpour et al. (2018) result that default risk

[37] The frailty factors are estimated based on accounting and market-based variables in Table 2. The frailty factors are then orthogonalized based on global factors in Table 2. This approach delineates additional risk information not reflected in the standard set of global factors and financing variables.

contagion tends to be more severe in the earlier period but decay over later lags. Overall, the empirical analysis shows a strong degree of dynamic dependence among frailty factors worldwide, underscoring the international interconnectedness of corporate debt distress risk worldwide.

7.2 Quantile Dependence

Apart from correlation or mean dependence of time series variables over time, regulators and policymakers are often concerned about coordinated extreme movements in financial variables, triggering severe losses in the financial system. As a complement to the Granger causal test and to investigate the severity of extreme tail corporate default risk dependence across different economic regions, I employ the modified cross-quantilogram method by Han et al. (2016). This approach quantifies the severity of quantile dependence (or correlation) among frailty factors of different countries over multiple periods. In other words, the method measures the risk that an extreme wave of corporate default events in an economic region may trigger multiple extreme waves of default events in other economies worldwide. The modification and application of the cross-quantilogram in the context of measuring tail risk dependence among frailty factors is described below:

I begin by defining two stationary time series: $\{x_{i,t},\ t \in \mathbb{Z}\}$, where i = 1,2. $x_{i,t}$ relates to a frailty factor for a specific region. I next define the quantile for $x_{i,t}$ as $q_{i,t}(\tau_i) = inf\{v : F_{x_i}(v) \geq \tau_i\}$. The objective is to measure serial dependence between two tail events: $\{x_{1,t} \geq q_{1,t}(\tau_1)\}$ and $\{x_{2,t-k} \geq q_{2,t-k}(\tau_2)\}$, where k is an integer that measures the number of lags.[38] $\tau = (\tau_1, \tau_2)$ is arbitrarily selected to account for the tail aspect of the frailty factor. To do so, I define a tail event as $\{1[x_{i,t} \geq q_{i,t}(.)]\}$, which is dubbed by Han et al. (2016) as quantile hit or quantile exceedance process for i = 1,2. 1[.] is an indicator function that takes a value of 1, if the frailty factor exceeds a specified value determined based on an arbitrarily selected quantile, suggesting the occurrence of an extreme event. Following Han et al. (2016), the cross-quantilogram for the cross-correlation between the quantile-hit processes is written as:

$$p_\tau(k) = \frac{E[\psi_{\tau_1}(x_{1,t} - q_{1,t}(\tau_1))\psi_{\tau_2}(x_{2,t-k} - q_{2,t-k}(\tau_2))]}{E[\psi^2_{\tau_1}(x_{1,t} - q_{1,t}(\tau_1)]E[\psi^2_{\tau_1}(x_{2,t-k} - q_{1,t-k}(\tau_1)]} \tag{9}$$

for k $\in \mathbb{Z}_{\neq 0}$, and $\psi_a(u)$ = 1[u > 0] - (1-a). The cross-quantilogram in (9) measures the degree of co-dependence across frailty factors at a specified quantile level over time. Notably, my approach of measuring quantile dependence among frailty factors worldwide

[38] It may be useful to note that Han et al. (2016) definition of tail events and original construction of the cross-quantilogram differ from us. In their paper, they define a tail event as $\{x_{1,t} \leq q_{1,t}(\tau_1)\}$. In this approach, an adverse event occurs when the economic or financial variable falls below a specific quantile value. In contrast, my paper deals with an adverse event that refers to the frailty factor exceeding a specified quantile value. In a working paper version of their paper, Han et al. (2016) also studied a similar approach of constructing the cross-quantilogram that this paper focuses on.

aligns with Forbes and Rigobon (2002) definition of contagion, which defines financial contagion as common extreme comovements of financial variables across different economic regions during crises - The same financial variables may not display any correlation or dependence during benign periods. This definition of financial contagion is widely adopted in the financial economics literature, such as Candelon and Tokpavi (2016), Blasques et al. (2016), among many others.

Based on the cross-quantilogram in (9), I measure the cross-quantilogram $\hat{p_{tau}}(k)$ among different frailty factors up to the lag k = 12 months. To measure dependence of extreme events, I set $\tau_1 = 0.9$, and $\tau_2 = 0.9$.[39] To ensure that our cross-quantilogram is significant, I also calculate the 90% bootstrap confidence intervals[40] for no quantile dependence, using 1000 bootstrap replicates.

Figure 5 shows the cross-quantilogram $\hat{p_{tau}}(k)$ of frailty factors from North America and Europe to the rest of the regions. Figure 6 shows a similar result from the perspective of the rest of the world. In both Figure 5 and Figure 6, the cross-quantilogram $\hat{p_{tau}}(k)$ is computed up to 12 lags and includes the corresponding 90% confidence interval. Across most countries worldwide, both figures depict a general trend that $\hat{p_{tau}}(k)$ exceeds the 90% confidence interval over multiple periods. The findings demonstrate significant evidence of tail risk dependence across frailty factors. Both Figure 5 and Figure 6 also show the degree of cross-correlation among the extreme quantile of the frailty factors to largely be at the highest at an earlier period but decline as the lag increases. This finding is consistent with Azizpour et al. (2018), which shows that the degree of corporate default contagion in the U.S. economy is most destabilizing in the earlier period. Overall, the cross-quantilogram method shows substantial evidence of extreme quantile dependence among frailty factors worldwide. This finding further supports hypothesis 3 and highlights the extreme degree of corporate default risk spillover worldwide.

8 Conclusion

Global corporate debt is currently at one of the most vulnerable points of all time. Rising corporate leverage compounded with higher for longer interest rates raise concerns over firms increasing exposure to systemic risk worldwide. While substantial research on corporate default risk has extensively studied the pertinent observable factors that impact corporate debt distress risk in the U.S. and other parts of the world, minimal studies have explored the joint vulnerability of international corporate debt issuance to systemic risk and other correlated latent risk factors.

[39] Both separate cases of $\tau_1 = 0.85$, and $\tau_2 = 0.85$, as well as $\tau_1 = 0.95$, and $\tau_2 = 0.95$ are also considered. Similar results are largely obtained for these cases.

[40] To be conservative, bootstrap confidence intervals are capped within an absolute value of 0.05. I will replace the confidence interval to be at 0.05 or - 0.05 if the calculation of the confidence interval falls within the absolute value of 0.05

After controlling for a holistic selection of firm fundamentals, I show that firms worldwide are vulnerable to a dynamic latent risk factor. The frailty factors can better explain firms' default risk exposure in an in-sample setting and provide a more realistic assessment of default risk out-of-sample. Despite separately estimating the frailty factor at the individual country level, econometrics analyses show a strong degree of common variations and dynamic dependence among the frailty factors over time. The findings raise concern of a global latent risk factor that impacts corporate debt distress risk worldwide.

Additional principal component analysis shows that a global frailty factor explains up to 45% of the variations across separately estimated frailty factors across different economic regions worldwide. Key global factors and financing variables can only explain up to 25% of the risk in the global frailty factor, indicating that global corporate credit markets are vulnerable to a common systemic risk factor not reflected in measurable explanatory global variables. Calculating the marginal effects of the global systemic risk factor substantiates the economic significance of this factor, revealing common latent vulnerabilities in international credit markets.

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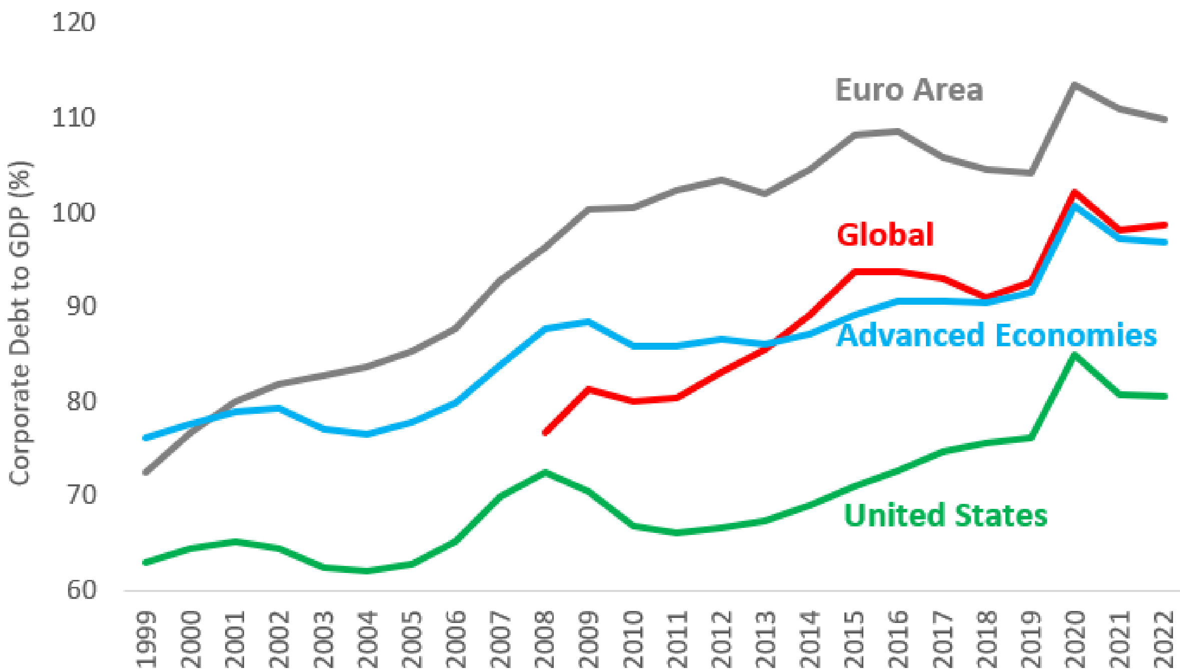
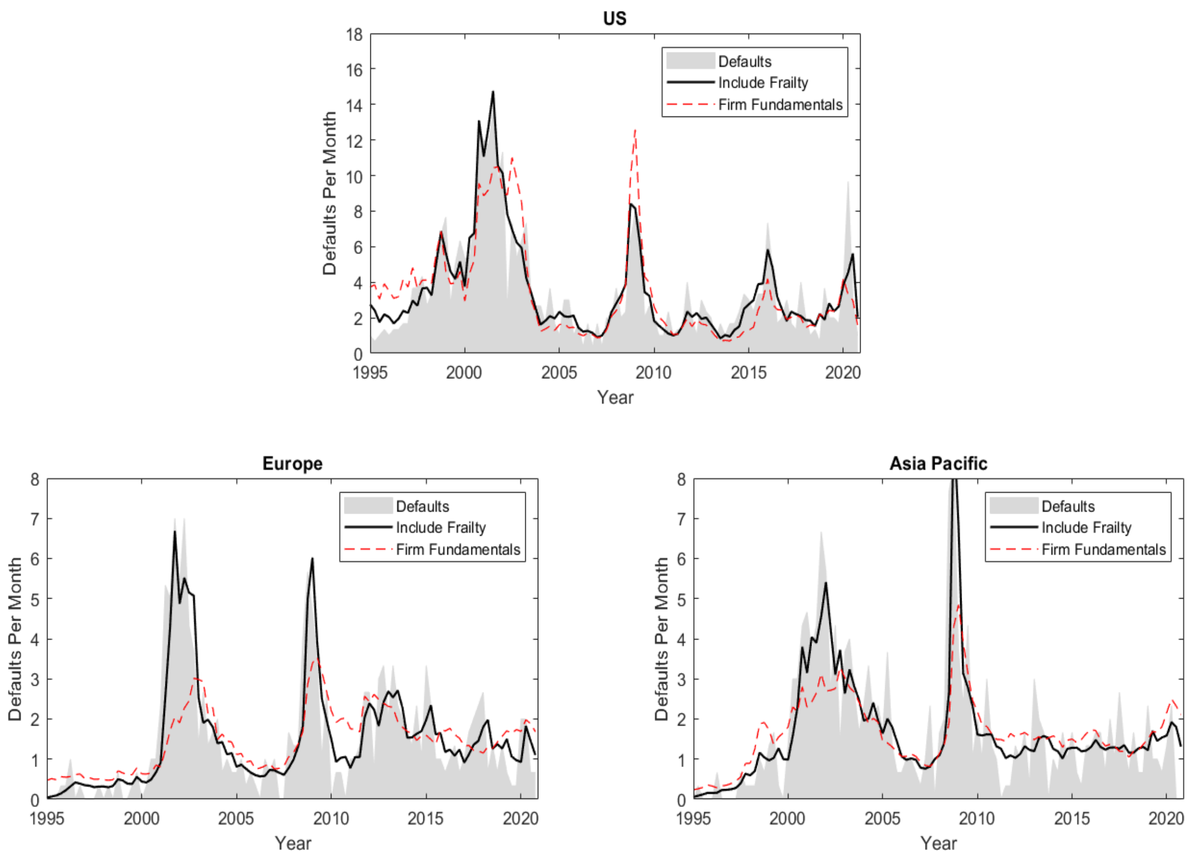
Figure 1: Global Non-Financial Corporate Leverage



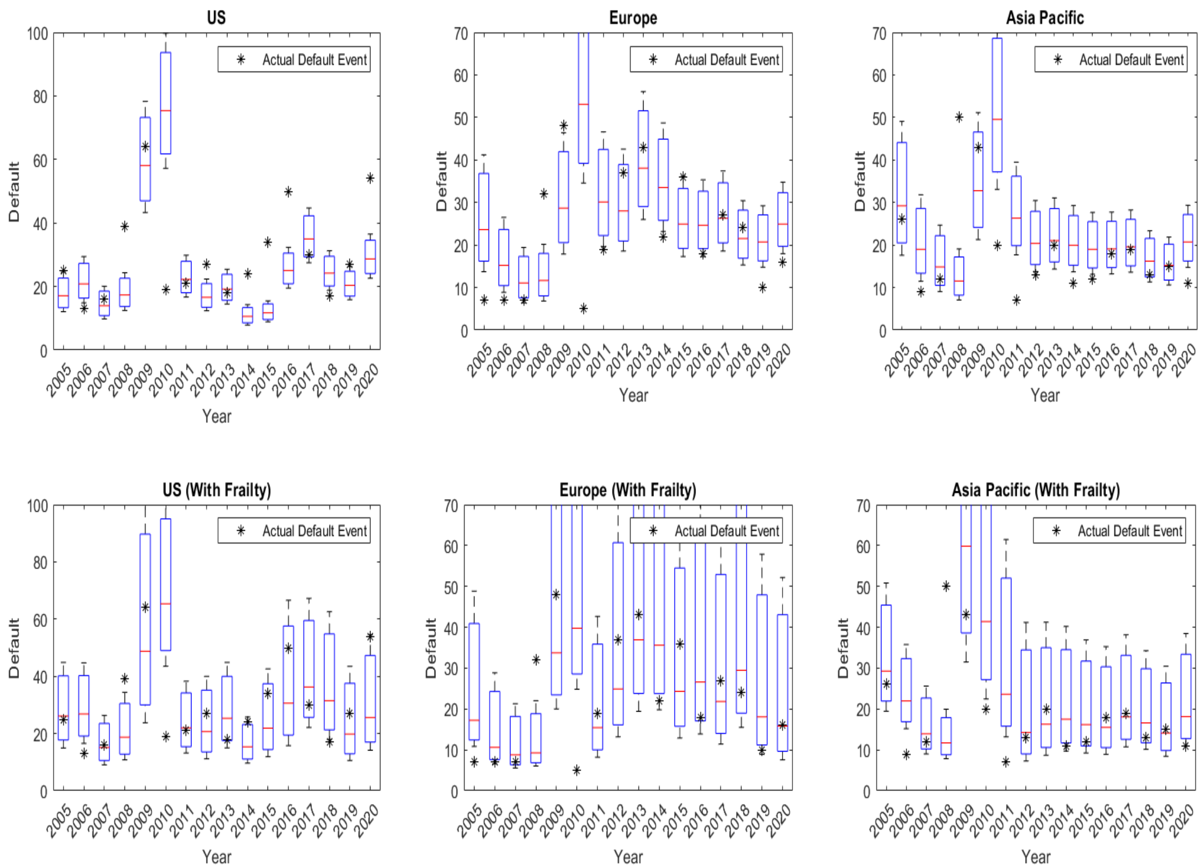
This figure shows the aggregated corporate leverage for the selected economies/regions: United States, Advanced Economies, Euro Area, and the Global Economy. Aggregated corporate leverage are represented in percentage term and is calculated by taking the aggregated corporate debt divided by the aggregated GDP for all economies in the region. Data source: BIS, Author's Calculation.

Figure 2: Corporate Default Risk Prediction with Frailty



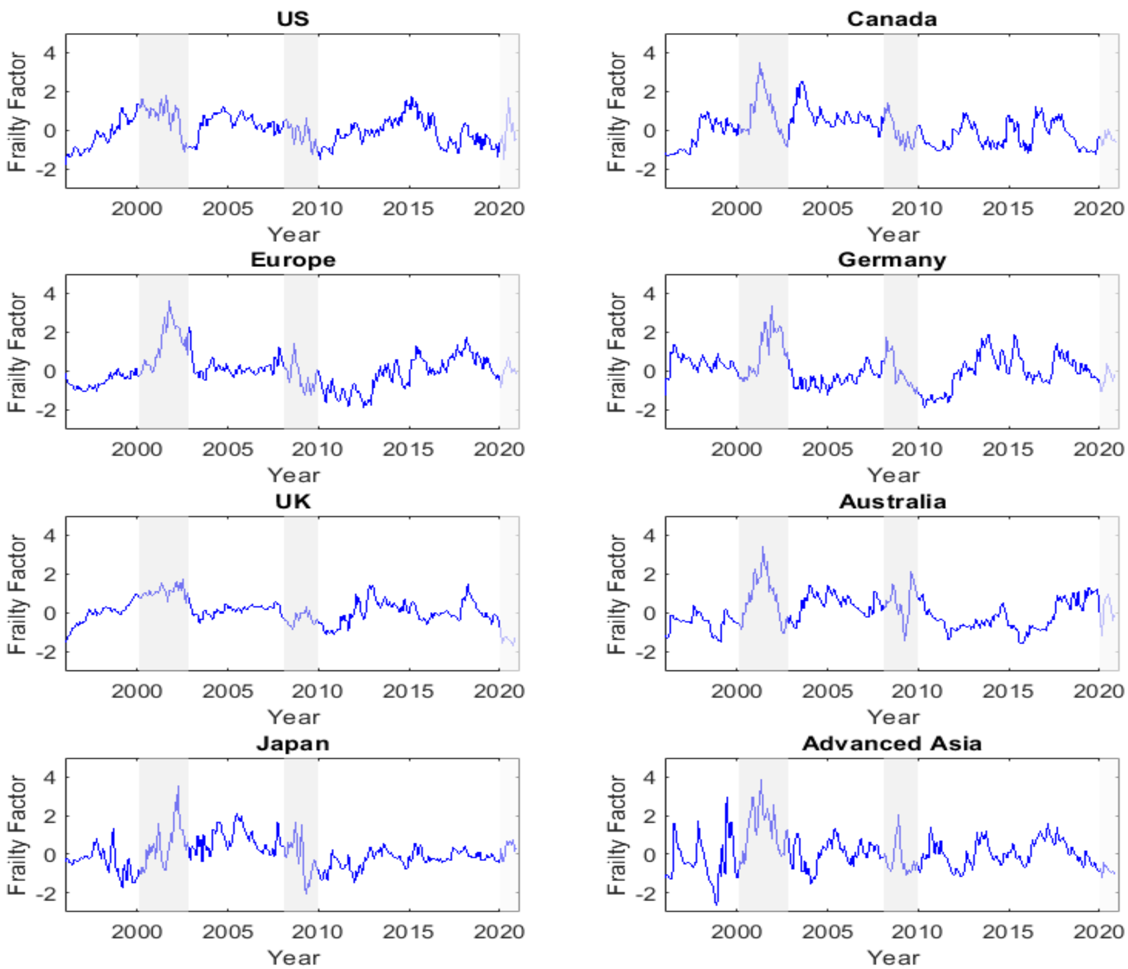
Time series comparison of actual and predicted defaults. The figure shows the number of actual defaults per month (average per quarter) and the corresponding predicted number of defaults using logit models based on Table 3, Panel A (with balance sheet and market-based variables) and Panel B (with Frailty). The predicted number of defaults in a month is the sum of the estimated probabilities of default for all firms, based on next month probability of default.

Figure 3: Out-of-Sample Default Risk Prediction



This figure depicts the Out-of-Sample forecast distribution of corporate default risk for U.S., Europe and Asia Pacific. The top three charts shows the default risk prediction without the frailty factor. The bottom three charts show the corresponding counterpart with the frailty factor. The red horizontal line depicts the mean estimate, while the extreme end of the box plot represents the tail distribution of the default risk forecast. The star represents the realized number of default events.

Figure 4: Global Frailty Factors



This figure shows the estimated frailty factors across different regions. The frailty factors are estimated based on the firm-specific explanatory variables in Table 2. The frailty factors are orthogonalized based on global factors in Table A.3 and standardized.

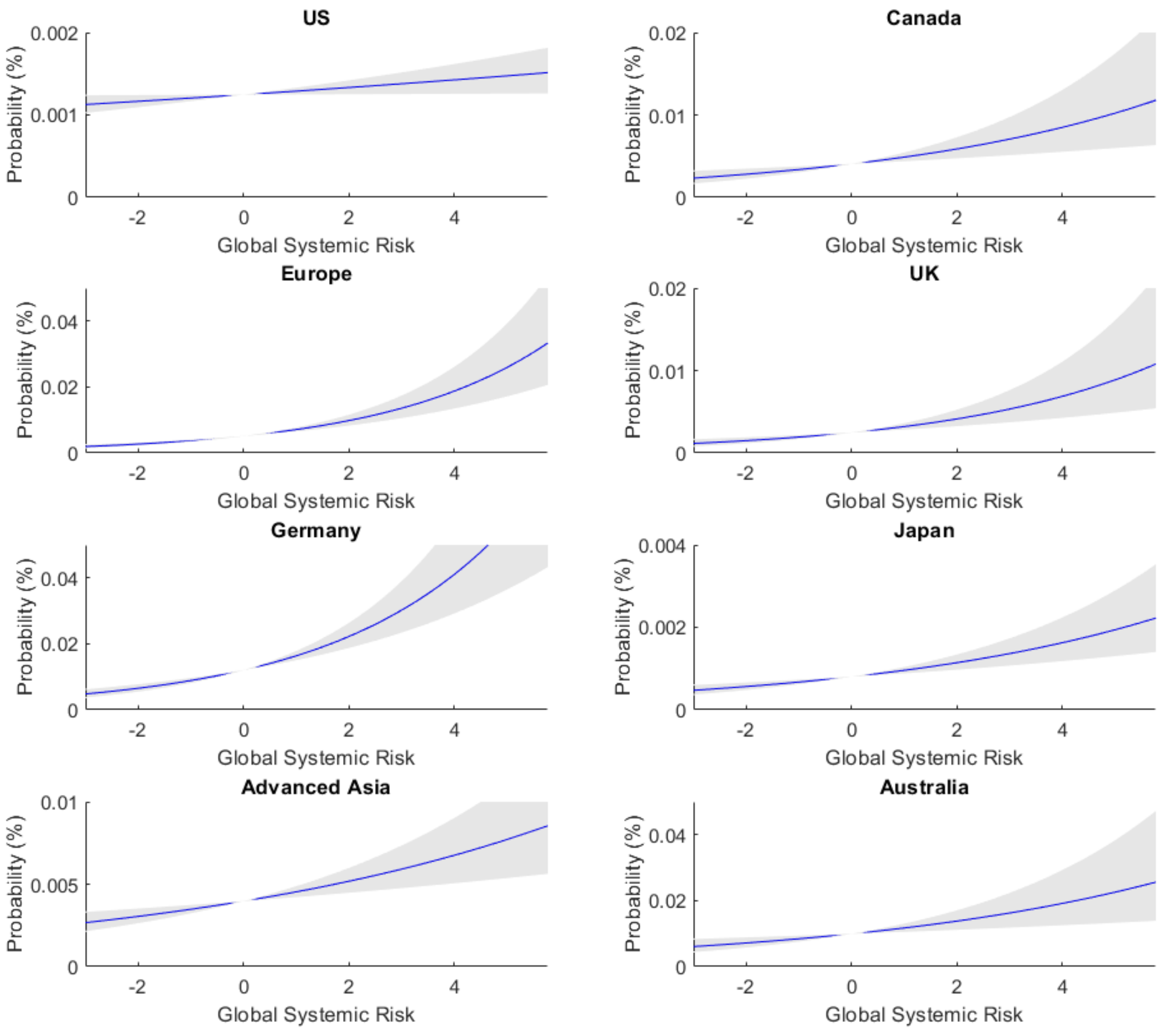
Figure 5: Cross-Quantilogram (North America and Europe)

The figure shows the sample cross-quantilogram $\hat{p}(k)$ from Asia to the rest of the world, at up to 12 lags. Bar graphs describe the sample cross-quantilograms and lines are the 95% bootstrap confidence intervals centered at zero. $\tau_1 = 0.90$, $\tau_2 = 0.90$

Figure 6: Cross Quantilogram (Asia Pacific and Germany)

The figure shows the sample cross-quantilogram $\hat{p}(k)$ from U.S. and Europe to the rest of the world, at up to 12 lags. Bar graphs describe the sample cross-quantilograms and lines are the 95% bootstrap confidence intervals centered at zero. $\tau_1 = 0.90$, $\tau_2 = 0.90$

Figure 7: Global Systemic Risk Factor plot



This figure shows the impact of the Global Systemic Risk Factor factor on firms' estimated default risk across different economic regions. The x-axis shows the variation of Global Systemic Risk factor. The shaded grey areas are the 95% confidence intervals, computed using the 95% confidence intervals of each variable's coefficient in the logit model based on Table 3.

Table 1: Classification of Countries and Corporate Default Action

(a) Panel A: Exclude market-based variables

Regions	Economies/Countries
North America	United States Canada
Europe	United Kingdom Germany **Other Europe** (Austria, Belgium, Denmark, Finland, France, Greece, Italy, Netherlands, Portugal, Spain, Sweden)
Asia Pacific	Japan Australia **Advanced Asia** (Hong Kong, Singapore, South Korea, Taiwan)

(b) Panel B: Types of Corporate Default Actions

Action Type	Subcategory
Bankruptcy	Administration, Arrangement, Canadian Companies' Creditors Arrangement Act (CCAA), Chapter 7,11,15 (United States bankruptcy code), Conservatorship, Insolvency, Japanese Corporate Reogranization Law (CRL), Judicial management, Liquidation, Pre-negotiation Chapter 11, Protection, Receivership, Rehabilitation, Rehabilitation (Thailand 1997), Reorganization, Restructuring, Section 304, Supreme Court declaration, Winding up, Workout, Sued by creditor, Petition withdrawn, Delisting
Default Corporate Action	Debt restructuring Bankruptcy, Coupon & principal payment, Coupon payment only, Interest payment, Loan payment, Principal payment, Alternative Dispute Resolution (ADR, Japan only), Regulatory action (Taiwan only), Financial difficulty and shutdown (Taiwan only), Buyback option
Delisting	Followed by Bankruptcy

Panel A presents the classification of countries/economies into different regions based on geographical proximity and similarities in structural characteristics of the economies. Panel B table presents the key corporate default actions that are covered in the CRI database. Within each of the key corporate default actions, it can be further classified into subcategories. Refer to NUS Credit Research Initiative (2021) for more information on the classification.

Table 2: Summary Statistics (Firm Specific Variables)

United States	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	-0.216	2.539	0.075	0.323	0.176	-0.013	2.366	-8.416
Default	-1.917	2.884	0.064	0.712	0.342	-0.150	0.199	-10.686
T-Test	***	***	***	***	***	***	***	***
Canada	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	-0.403	2.235	0.069	0.314	0.229	-0.014	0.887	-11.427
Default	-1.934	2.424	0.048	0.717	0.370	-0.148	-1.300	-12.802
T-Test	***		***	***	***	***	***	***
Europe	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	-0.013	2.104	0.061	0.449	0.142	-0.008	1.813	-9.626
Default	-0.901	2.678	0.055	0.748	0.251	-0.086	-0.392	-10.748
T-Test	***	***	*	***	***	***	***	***
UK	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	-0.222	2.539	0.084	0.351	0.150	-0.011	4.249	-11.603
Default	-1.435	2.287	0.068	0.686	0.258	-0.124	1.636	-13.080
T-Test	***		**	***	***	***	***	***
Germany	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	-0.059	2.174	0.083	0.448	0.165	-0.011	2.568	-8.831
Default	-1.010	1.828	0.085	0.684	0.287	-0.116	0.347	-10.307
T-Test	***	**		***	***	***	***	***
Advanced Asia	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	0.097	1.399	0.102	0.403	0.156	-0.010	-0.055	-6.374
Default	-0.757	1.354	0.055	0.695	0.233	-0.106	-1.630	-6.767
T-Test	***		***	***	***	***	***	**
Japan	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	0.134	1.297	0.150	0.499	0.120	-0.006	2.046	-4.384
Default	-0.431	1.758	0.074	0.791	0.213	-0.028	0.866	-5.654
T-Test	***	***	***	***	***	**	***	***
Australia	Profitability	MarketBook	Cash	Leverage	Sigma	Excess Returns	Stock Price	Relative Size
FullSample	-1.044	2.275	0.140	0.228	0.273	-0.015	-1.793	-11.780
Default	-2.182	2.045	0.094	0.545	0.338	-0.092	-2.978	-12.280
T-Test	***	†	***	***	***	***	***	***

The summary statistics for firm-specific explanatory variables (at firm months level) across different countries or regions. The column shows the firm fundamentals explanatory variables. Under each country or region, the first two rows show the simple means for the full sample and the mean for firms that default in the next month, respectively. The last row shows the results of a two-sample t-test for equal means of each group of defaulted firms against the full sample. ***, **, *, and † indicate $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$. The mean, median, and standard deviation are reported.

Table 3: Baseline logit regressions of firm's next month probability of default

(a) Panel A: Excluding Frailty Factor

Parameters	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Intercept	-7.975***	-5.854***	-10.991***	-5.169***	-4.231***	-9.718***	-15.939***	-6.681***
Profitability	-0.431***	-0.340***	-0.722***	-0.227***	-0.455***	-0.483***	-2.060***	-0.111***
Market to Book	0.093***	-0.003	0.114***	-0.039	-0.060†	0.093*	0.314***	-0.005
Cash	-2.065***	-1.416	1.112	-1.720†	-1.848*	-2.591***	-7.520***	-0.475
Leverage	6.268***	7.272***	5.259***	6.404***	2.200***	5.118***	6.352***	5.541***
Vol of Returns	3.198***	0.317	4.038***	3.537**	1.775*	2.860***	17.502***	0.641
Excess Return	-2.552***	-3.312***	-3.948***	-4.072***	-5.044***	-4.047***	-1.100†	-1.964***
Stock Price	-1.720***	-0.799***	-0.257***	-0.734***	-1.016***	-0.892***	-0.029	-0.518***
Relative Size	0.245***	0.522***	0.159***	0.416***	0.343***	0.441***	-0.006	0.419***
Loglikelihood	-5369	-788	-1365	-743	-989	-1769	-1133	-914
RS	0.367	0.276	0.191	0.241	0.204	0.209	0.255	0.142
AUC	0.974	0.958	0.923	0.927	0.920	0.909	0.940	0.878
Observations	1,146,921	218,992	572,720	344,744	164,840	860,473	980,245	340,642
Default	1,063	129	187	108	156	244	156	119

(b) Panel B: Including Frailty Factor

Parameters	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Profitability	-0.413***	-0.373***	-0.679***	-0.241***	-0.448***	-0.500***	-1.975***	-0.123***
Market to Book	0.080***	-0.004	0.119***	-0.017	-0.049	0.081†	0.322***	-0.007
Cash	-2.352***	-1.514	0.075	-2.040*	-1.899**	-2.405**	-7.881***	-0.645
Leverage	5.905***	7.089***	5.162***	6.172***	2.503***	4.987***	6.132***	5.446***
Vol of Returns	4.215***	-0.617	2.908***	2.876**	1.538†	2.577***	17.625***	0.456
Excess Return	-2.278***	-3.022***	-3.814***	-3.912***	-4.604***	-4.039***	-0.980	-1.812***
Stock Price	-1.879***	-0.949***	-0.328***	-0.726***	-1.027***	-0.899***	-0.052	-0.558***
Relative Size	0.356***	0.576***	0.150***	0.408***	0.276***	0.436***	0.013	0.428***
Theta (θ)	0.960***	0.930***	0.938***	0.953***	0.934***	0.870***	0.927***	0.944***
Alpha (α)	1.972***	1.713***	2.822***	2.996***	1.078***	2.329**	6.146***	2.908***
Delta (δ)	-0.262**	-0.338*	-0.661***	-0.235*	-0.324†	-1.254***	-1.141***	-0.371†
Loglikehood	-5325	-777	-1350	-724	-972	-1764	-1117	-900
RS	0.372	0.286	0.200	0.261	0.218	0.212	0.266	0.156
AUC	0.973	0.958	0.923	0.926	0.922	0.910	0.941	0.879
Observations	1,146,921	218,992	572,720	344,744	164,840	860,473	980,245	340,642
Default	1,063	129	187	108	156	244	156	119

This table presents the result of the logit regression for each country or region worldwide. The logit model includes firms' accounting and market-based variables to predict a firm's default risk in the next month. Panel A excludes the frailty factor. Panel B includes the frailty factor in model estimation. Pseudo-R2 refers to Mc-Fadden's Pseudo-R2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

Table 4: Out-of-Sample forecast assessment

(a) Panel A: Exclude Frailty Factor

Econometrics Test	US	Europe	Asia Pacific
Violation Rate	8/16	3/16	1/16
Unconditional Coverage	0.00***	0.00***	0.143
Independence	0.782	0.538	0.705
Mean Bias	51.2%	116.8%	62.2%
Root Mean Square Relative Bias	15.2	35.8	10.4

(b) Panel B: Include Frailty Factor

Econometrics Test	US	Europe	Asia Pacific
Violation Rate	1/16	1/16	1/16
Unconditional Coverage	0.143	0.143	0.143
Independence	0.705	0.705	0.705
Mean Bias	50.0%	79.1%	54.5%
Root Mean Square Relative Bias	12.0	16.6	8.1

This table presents the econometrics tests for the prediction of the number of defaults in the year ahead (out of sample). Panel A excludes frailty factor, while panel B includes frailty factor. This table presents the empirical results for several econometrics tests for the forecast accuracy of the number of defaults in the year ahead (out of sample). The violation rate shows the number of times that the realized default next year exceeds the forecast 99% value-at-risk. The unconditional coverage test is based on Kupiec (1995), which measures the null hypothesis that the violation rate does not exceed 1%. The independence test is based on Christoffersen (1998). The null hypothesis of Christoffersen (1998) test is that a binary first-order Markov chain for the hit indicators has a transition matrix based on the identity matrix – the asymptotic distribution follows a chi-squared with one degree of freedom. The mean relative bias is the average relative difference of the mean predicted default compared to the actual number of defaults. The root mean squared relative bias is the standard deviation of the latter.

Table 5: Drivers of Global Latent Risk Factor

	Regression 1 (Benchmark)	Regression 2 (With PC)
(Intercept)	-1.5868*** (0.3672)	0.4571*** (0.0785)
CRED Spread	1.319*** (0.2989)	
Global Growth Rate	-0.0138 (0.0651)	
Oil	-0.9001 (0.978)	
Slope	0.370*** (0.1006)	
TED	-0.2377 (0.2839)	
VIX	-0.0168 (0.0138)	
Yield	0.1738*** (0.0635)	
ΔUS Broad Dollar	0.1162 (0.0362)	
PC1		0.02784 (0.0362)
PC2		0.1878*** (0.0457)
PC3		-0.3328*** (0.0575)
PC4		0.3505*** (0.06)
PC5		-0.0889 (0.0707)
Number	300	259
Adjusted R^2	0.106	0.242

This table presents the results of the multivariate least squares regressions of the global frailty factor (Dependent variable) on a set of global factors and financing conditions (or Principal Components). Regression 1 is estimated based on a comprehensive selction of global factors covering multiple dimensions. Regression 2 is estimated with principal components as explanatory variables. The principal components are estimated based on a large selection of global factors and financing conditions selected in global financial cycle literature. Standard Errors are based on Newey-West Estimator. ***, **, and * indicates three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$ respectively.

Table 6: PCA of Frailty Factors

Vars	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
US	0.264	-0.023	0.56	-0.206	0.268	-0.54	0.365	-0.278
Canada	0.406	-0.39	0.443	-0.131	-0.134	0.638	-0.147	-0.153
Europe	0.377	0.178	-0.375	-0.286	-0.12	0.245	0.713	0.145
UK	0.361	0.188	0.283	0.083	-0.061	-0.15	-0.183	0.829
Germany	0.38	0.705	-0.042	-0.047	-0.233	-0.022	-0.366	-0.408
Advanced Asia	0.416	-0.096	-0.168	0.816	0.303	0.019	0.115	-0.133
Japan	0.244	-0.092	-0.34	-0.415	0.72	0.024	-0.349	0.052
Australia	0.341	-0.516	-0.351	-0.103	-0.476	-0.467	-0.185	-0.062
% Var	45.466	12.615	10.168	9.723	7.184	5.881	5.561	3.403

The table reports the Principal Component Analysis (PCA) of multiple frailty factors. The frailty factors are estimated based on Table 3, and orthogonalized with global factors based on Table A.3. The column presents the loadings of the frailty factor on the Principal Component factor, and the last line shows the corresponding variation accounted for by each PC factor.

Table 7: Marginal Analysis of the Frailty Factor

(a) Panel A: Marginal Analysis of the **Country** Frailty Factor

Economies	Stand Dev	MEM	AME	Δ Defaults
US	1.0823	0.0004	0.0275	12
Canada	0.9412	0.0027	0.0424	3.6
Europe	0.9435	0.0025	0.0145	3.24
UK	0.9834	0.0019	0.0257	3.44
Germany	1.0366	0.0053	0.0342	2.2
Advanced Asia	0.5452	0.0013	0.0086	2.96
Japan	0.9326	0.0004	0.0082	3.12
Australia	0.9221	0.0042	0.0157	2.08

(b) Panel B: Marginal Analysis of the **Global** Frailty Factor

Economies	Stand Dev	MEM	AME	Δ Defaults
US	1.555	0.00005	0.0031	1.36
Canada	1.448	0.00077	0.011	0.92
Europe	1.487	0.0018	0.0106	2.40
UK	1.49	0.00067	0.0081	1.08
Germany	1.536	0.004	0.0292	1.88
Advanced Asia	1.353	0.00054	0.0037	1.28
Japan	1.458	0.00015	0.0028	1.08
Australia	1.398	0.00166	0.0058	0.76

This table presents the marginal analysis of the frailty factor across different countries and regions. Panel A presents the marginal analysis of the country frailty factor, while Panel B presents the orthogonalized global frailty factor. Δ Defaults The parameters of the frailty factors are estimated by conducting separate regressions with the frailty factors as one of the control variables. Control variables are included based on Panel A of Table 3. Column 1 presents the standard deviation of the factors. Column 2 and 3 presents the MEM and AME respectively. Marginal effects at the mean (MEM) is the effect of a one standard deviation increase in the frailty factor on the probability of default for a firm where explanatory variables are kept at sample mean. Average marginal effects (AME) is the averages of the individual marginal effects for a standard deviation increase in the frailty factor for each firm where explanatory variables are kept their true value. Column 4 (Δ Defaults) presents the increase in corporate default events **in a year** with a one standard deviation increase in the frailty factor.

Table 8: International Corporate Default Risk Spillover

Economic Regions	US	Canada	Europe	UK	Germany	Japan	Australia	Advanced Asia
US	-	0.001***	0.191	0.006***	0.097*	0.020**	0.000***	0.410
Canada	0.115†	-	0.002***	0.027**	0.018**	0.038**	0.186	0.076*
Europe	0.004***	0.000***	-	0.007***	0.011**	0.061*	0.000***	0.001***
UK	0.006***	0.054*	0.007***	-	0.020**	0.253	0.061*	0.025**
Germany	0.168	0.009***	0.003***	0.024**	-	0.097*	0.005***	0.031**
Japan	0.077*	0.008***	0.001***	0.341	0.128†	-	0.000***	0.025**
Australia	0.000***	0.035**	0.064*	0.064*	0.366	0.041**	-	0.034**
AdvancedAsia	0.004***	0.077*	0.094*	0.043**	0.084*	0.466	0.103†	-

The table reports the p-values of the Granger Causality tests among the frailty factors of different economic regions worldwide. The length of lags included in the Granger Causality tests is up to 24 months. For brevity, among the 24 months lag, I report the lowest p-value of each Granger Causality tests across different economic regions worldwide. The column relates to the dependent variables in the Granger Causality tests, while the row relates to the independent variable. ***, **, *, † indicates three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, $p < 0.15$ respectively.

Appendix

Global Corporate Default Risk Factors: Frailty and Spillover Effects

A Appendix A

Table A.1: Number and Default Rate per Economic Entities and Year

Year	United States			Canada			Europe			United Kingdom			Germany			Adv Asia			Japan			Australia		
	#Def	#Full	%	#Def	#Full	%	#Def	#Full	%	#Def	#Full	%	#Def	#Full	%	#Def	#Full	%	#Def	#Full	%	#Def	#Full	%
1995	12	57563	0.02	0	6297	0	1	14033	0.01	0	10334	0	0	3759	0	0	4892	0	1	24978	0	0	6986	0
1996	16	61315	0.03	0	7706	0	0	15757	0	0	12616	0	5	4271	0.12	1	5347	0.02	0	29975	0	1	7467	0.01
1997	40	65723	0.06	4	9082	0.04	0	16961	0	0	14366	0	1	4419	0.02	1	5815	0.02	1	32073	0	1	7731	0.01
1998	56	65557	0.09	6	9739	0.06	2	18462	0.01	0	15375	0	1	4720	0.02	1	6623	0.02	6	33781	0.02	0	7894	0
1999	65	60969	0.11	7	9578	0.07	1	20089	0	1	14876	0.01	1	5344	0.02	5	7122	0.07	4	34812	0.01	2	8650	0.02
2000	92	59361	0.15	7	8199	0.09	3	21903	0.01	2	13791	0.01	2	6666	0.03	19	20767	0.09	9	35595	0.03	7	9305	0.08
2001	144	55687	0.26	15	7897	0.19	24	23444	0.1	8	14515	0.06	27	7986	0.34	29	24088	0.12	17	37130	0.05	13	10326	0.13
2002	82	50595	0.16	5	7319	0.07	21	23493	0.09	12	15100	0.08	28	8140	0.34	10	28543	0.04	28	38083	0.07	4	10745	0.04
2003	60	46317	0.13	9	7054	0.13	9	22809	0.04	3	14599	0.02	9	7548	0.12	15	32348	0.05	15	38353	0.04	6	10618	0.06
2004	29	44334	0.07	2	6958	0.03	6	22285	0.03	2	13923	0.01	5	7145	0.07	17	34556	0.05	10	38756	0.03	3	11216	0.03
2005	24	43878	0.05	2	7338	0.03	3	22044	0.01	0	14853	0	5	6977	0.07	11	36527	0.03	9	39726	0.02	3	12614	0.02
2006	13	43211	0.03	1	8238	0.01	1	22149	0	0	16703	0	5	6955	0.07	7	38707	0.02	2	40667	0	1	13781	0.01
2007	18	42342	0.04	4	8806	0.05	3	23250	0.01	0	17600	0	5	7608	0.07	4	40445	0.01	4	41656	0.01	3	14836	0.02
2008	44	41408	0.11	7	8896	0.08	9	24312	0.04	17	17528	0.1	11	8123	0.14	25	42587	0.06	20	41682	0.05	16	16285	0.1
2009	63	38611	0.16	10	8789	0.11	14	23886	0.06	15	16171	0.09	6	8105	0.07	17	43198	0.04	9	40778	0.02	13	16324	0.08
2010	19	36391	0.05	0	8739	0	4	23369	0.02	0	14877	0	0	7867	0	14	43849	0.03	5	39776	0.01	3	16368	0.02
2011	23	35240	0.07	3	9186	0.03	6	22875	0.03	8	13994	0.06	4	7592	0.05	3	45308	0.01	1	38945	0	1	16662	0.01
2012	25	34479	0.07	4	9207	0.04	6	22247	0.03	16	13314	0.12	7	7449	0.09	6	46918	0.01	5	38371	0.01	2	16929	0.01
2013	17	33958	0.05	3	8883	0.03	11	21766	0.05	6	12793	0.05	12	7155	0.17	15	47618	0.03	3	38188	0.01	3	16572	0.02
2014	27	34448	0.08	7	8473	0.08	7	21695	0.03	7	12600	0.06	5	6946	0.07	9	48945	0.02	1	38339	0	5	16466	0.03
2015	36	35150	0.1	6	8262	0.07	14	22276	0.06	3	12755	0.02	6	6431	0.09	8	50935	0.02	3	38677	0.01	3	15997	0.02
2016	49	34780	0.14	9	8153	0.11	6	23546	0.03	3	12612	0.02	2	6298	0.03	18	53213	0.03	0	39071	0	1	15979	0.01
2017	30	34237	0.09	5	8248	0.06	11	24539	0.04	4	12487	0.03	6	6178	0.1	18	55343	0.03	1	39466	0	7	16351	0.04
2018	16	34280	0.05	0	8574	0	9	25814	0.03	3	12421	0.02	4	6111	0.07	5	57301	0.01	0	39984	0	6	16533	0.04
2019	28	34232	0.08	2	9456	0.02	5	26339	0.02	2	12206	0.02	1	6055	0.02	6	59411	0.01	0	40488	0	10	16468	0.06
2020	55	34038	0.16	11	9786	0.11	11	26434	0.04	0	11475	0	5	5983	0.08	4	61185	0.01	2	40986	0	6	16067	0.04

This table presents the total count of default events, the total number of firms, and the respective default rate in each economic region per year. Total count and default events are organized based on firms with complete information on firm fundamentals as outlined in benchmark specification. Default events are counted based on realization of corporate default event in the next period.

Table A.2: Variables Construction

Variable Name	Variables Construction
Excess Return	Log (1 + firm returns) - log (1 + country (market) index returns)
Stock Price	Log price per share.
Relative Size	Log (Firm Market Cap) - log (Economy Stock Index Market Cap). The respective economy stock index that is used for each economy is based on NUS CRI. Refer to NUS Credit Research Initiative (2021) for more details.
Profitability	Ratio of net income to the market value of total assets, where the market value of assets is equal to the sum of the firm's market capitalization and total liabilities
Cash	Ratio of cash and cash equivalents to the market value of total assets
Market to Book Ratio	Ratio of market capitalization to book value of equity - book value of equity is total assets minus total liabilities. Calculation of the value follows Campbell et al. (2008) and Asis et al. (2021).
Leverage	Ratio of total liabilities to the market value of total assets.
Sigma (Vol of Returns)	By regressing the daily returns of the firm's market capitalization against the corresponding daily returns of the economy's stock index over the last 250 days, the Sigma is computed based on the standard deviation of the residuals of the regression. The computation of Sigma follows Shumway (2001) and is downloaded from NUS CRI. Refer to NUS Credit Research Initiative (2021) for more details.
U.S. Three-month Treasury bill yield (Yield)	Source: Federal Reserve Bank of New York
U.S. Yield Slope	The slope of the US yield curve calculated as the difference between the US 10-year Treasury rate and the Fed funds rate. Source: Federal Reserve Bank of New York
Oil Price	West Texas Intermediate Oil Price. Source: World Bank.
Global Growth Rate	GDP growth rate of G7 economy as a proxy for global growth rate. Source: OECD.
VIX	The slope of the US yield curve calculated as the difference between the US 5-year Treasury rate and the Fed funds rate. Source: FRED
TED Spread	The slope of the US yield curve calculated as the difference between the US 5-year Treasury rate and the Fed funds rate. Source: FRED
Moody's BAA and AAA corporate yields Spread	Credit spread between the Moody's BAA and AAA corporate yields. Source: FRED
Δ US Real Broad Effective Exchange Rate	Monthly percentage change of US real effective exchange rates, calculated as weighted averages of bilateral exchange rates adjusted by relative consumer prices. Source: BIS

Sources: Data and corporate default events for firm-specific related variables are retrieved from the CRI database, the Credit Research Initiative of the National University of Singapore (NUS CRI), accessed on July 1, 2021.

Table A.3: Summary Statistics (Global Factors)

Summary Statistics	Mean	Median	Std Dev
CRED Spread	0.993	0.9	0.407
Global Growth Rate	0.42	0.515	1.513
Oil Return	0.009	0.017	0.101
Slope	1.58	1.577	1.123
TED	0.463	0.36	0.38
VIX	20.445	18.775	8.004
Yield	2.149	1.567	2.07
Δ Broad \$US	0.00039	0.00021	0.0121

This table presents the summary statistics of the key global factors. The mean, median, and standard deviation are reported.

Table A.4: Baseline logit regressions of firm's next month probability of default (Excluding market-based variables)

(a) Panel A: Excluding Frailty Factor

Parameter	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Intercept	-12.545***	-12.410***	-12.140***	-12.406***	-9.266***	-11.470***	-14.652***	-10.441***
Profitability	-0.896***	-0.510***	-1.173***	-0.570***	-1.037***	-0.993***	-2.844***	-0.188***
MB	0.129***	0.027	0.154***	0.002	-0.054	0.167***	0.511***	0.035
Liquidity	-1.501***	-1.208	1.044	-1.451	-0.657	-4.136***	-7.970***	-0.559
Leverage	8.158***	8.077***	5.306***	7.424***	3.440***	5.527***	8.193***	5.634***
Loglike	-6112	-856	-1430	-820	-1095	-1922	-1192	-945
RS	0.280	0.214	0.153	0.163	0.118	0.141	0.216	0.114
AUC	0.951	0.927	0.899	0.899	0.855	0.871	0.912	0.848
Observations	1,159,187	218,992	575,964	363,996	171,994	941,859	980,492	345,290
Default	1083	129	187	112	163	268	156	120

(b) Panel B: Including Frailty Factor

Parameter	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Profitability	-0.893***	-0.521***	-1.129***	-0.567***	-1.007***	-0.997***	-2.695***	-0.194***
Market to Book	0.134***	0.030	0.154***	0.015	-0.045	0.153***	0.544***	0.032
Cash	-1.719***	-1.266	0.390	-2.184*	-0.980	-3.657***	-7.983***	-0.823
Leverage	7.787***	7.868***	5.292***	6.732***	3.520***	5.320***	7.322***	5.462***
Theta	0.957***	0.916***	0.949***	0.943***	0.913***	0.831***	0.964***	0.936***
Alpha	1.373**	1.213**	3.012***	3.162***	1.148***	3.510***	6.621***	3.235***
Delta	-0.521**	-1.026***	-0.616***	-0.692***	-0.811***	-1.935***	-0.514**	-0.661**
Loglike	-6068	-849	-1411	-794	-1077	-1912	-1170	-929
RS	0.285	0.220	0.164	0.189	0.133	0.145	0.230	0.128
AUC	0.951	0.928	0.898	0.899	0.854	0.871	0.913	0.849
Observations	1,146,921	218,992	572,720	344,744	164,840	860,473	980,245	340,642
Default	1,063	129	187	108	156	244	156	119

This table presents the result of the logit regression for each country or region worldwide. The logit model includes firms' accounting and market-based variables to predict a firm's default risk in the next month. Panel A excludes the frailty factor. Panel B includes the frailty factor in model estimation. Pseudo-R2 refers to Mc-Fadden's Pseudo-R2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

Table A.5: Likelihood Ratio Tests

Economies	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Test Statistics	88.45	22.63	29.70	37.98	33.83	10.19	33.10	29.11
P-Value	0.00***	0.00***	0.00***	0.00***	0.00***	0.01***	0.00***	0.00***

This table reports likelihood ratio test statistics and p-values. A likelihood ratio test evaluates the fit of an alternative model relative to a benchmark model. The test statistic is given by twice the difference between the maximum log-likelihood of the econometric model with frailty factor and the benchmark model. The test statistic has, asymptotically, a chi-squared distribution with degrees of freedom equal to the number of additional parameters included in the alternative. The degree of freedom in the test statistic is 2. *** indicates significance at the 99.9% level.

Table A.6: Out-Of-Sample Default Risk Assessment: Area Under the Curve (AUC)

Economies	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
With Frailty	0.973	0.948	0.915	0.908	0.923	0.911	0.917	0.882
Without Frailty	0.973	0.948	0.914	0.905	0.920	0.911	0.914	0.881

This table presents the Out-of-Sample Area Under the Curve (AUC) measure for different regions.

Table A.7: Logit regressions of firm's next month probability of default

Parameters	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Intercept	-1.652**	-0.468	-0.285	-0.656	1.048	-0.376	-1.821	-0.285
Profitability	-0.409***	-0.357***	-0.666***	-0.227***	-0.429***	-0.493***	-1.938***	-0.118***
Market Book	0.087***	-0.004	0.120***	-0.018	-0.038	0.089*	0.326***	-0.001
Cash	-2.013***	-1.459	0.398	-2.113*	-2.022**	-2.504**	-7.957***	-0.676
Lev	6.229***	7.269***	5.230***	6.240***	2.309***	5.026***	6.126***	5.439***
Vol of Returns	4.388***	-0.420	3.261***	2.767*	1.249	2.721***	17.349***	0.353
Excess Return	-2.444***	-3.172***	-3.900***	-4.038***	-4.639***	-4.048***	-1.079†	-1.866***
Stock Price	-1.729***	-0.868***	-0.293***	-0.688***	-1.050***	-0.878***	-0.055	-0.526***
Relative Size	0.272***	0.535***	0.136***	0.375***	0.302***	0.426***	0.006	0.400***
Frailty	0.925***	0.978***	1.008***	0.953***	0.936***	0.966***	0.908***	0.941***
Loglike	-5230	-776	-1341	-723	-969	-1763	-1106	-899
RS	0.374	0.284	0.200	0.259	0.217	0.211	0.266	0.155
AUC	0.974	0.958	0.923	0.926	0.921	0.909	0.940	0.879
Observations	1,089,912	212,695	558,698	334,488	161,089	855,731	955,266	333,737
Default	1,051	129	186	108	156	244	155	119

This table presents the result of the logit regression for each country or region worldwide. The logit model includes firms' accounting and market-based variables to predict a firm's default risk in the next month. An additional variable, the frailty factor, is incorporated into the logit model to study the impact of these variable on corporate debt distress risk, after controlling for firm fundamentals. The frailty factor is synthetically constructed based on the empirical result in Table 3. Pseudo-R2 refers to Mc-Fadden's Pseudo-R2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

Table A.8: Logit regressions of firm's next month probability of default

Parameters	US	Canada	Europe	UK	Germany	Advanced Asia	Japan	Australia
Intercept	-8.040***	-5.759***	-11.050***	-4.790***	-4.866***	-9.693***	-15.909***	-6.772***
Profitability	-0.417***	-0.341***	-0.680***	-0.194**	-0.403***	-0.502***	-2.093***	-0.106***
Market Book	0.094***	-0.010	0.120***	-0.035	-0.043	0.084†	0.305***	-0.001
Cash	-2.181***	-1.336	0.472	-1.820*	-2.010**	-2.417**	-7.425***	-0.534
Leverage	6.180***	7.251***	5.350***	6.523***	2.370***	4.973***	6.189***	5.509***
Vol of Returns	3.377***	0.081	3.034***	3.408**	1.165	2.744***	16.816***	0.614
Excess Return	-2.526***	-3.249***	-3.831***	-3.888***	-4.678***	-4.046***	-1.238*	-1.960***
Stock Price	-1.708***	-0.815***	-0.328***	-0.790***	-1.058***	-0.898***	0.008	-0.513***
Relative Size	0.236***	0.526***	0.144***	0.440***	0.289***	0.438***	-0.012	0.412***
Global Frailty	0.034**	0.181***	0.321***	0.260***	0.304***	0.133***	0.179***	0.161***
Loglike	-5266	-782	-1330	-733	-966	-1762	-1115	-909
RS	0.369	0.279	0.206	0.249	0.220	0.212	0.261	0.145
AUC	0.974	0.957	0.923	0.925	0.920	0.909	0.940	0.878
Observations	1,089,912	212,695	558,698	334,488	161,089	855,731	955,266	333,737
Default	1,051	129	186	108	156	244	155	119

This table presents the result of the logit regression for each country or region worldwide. The logit model includes firms' accounting and market-based variables to predict a firm's default risk in the next month. An additional variable, global frailty, is incorporated into the logit model to study the impact of these variable on corporate debt distress risk, after controlling for firm fundamentals. The global frailty is estimated based on the first Principal Component of Table 6. Pseudo-R2 refers to Mc-Fadden's Pseudo-R2, and AUC is the area under the ROC curve. ***, **, *, and † indicate four levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$ respectively.

Table A.9: PCA (Exclude Equities-Related Information)

Vars	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
US	0.357	-0.319	-0.459	-0.15	-0.087	-0.562	0.25	-0.389
Canada	0.316	-0.293	0.328	0.798	0.179	-0.036	0.191	-0.027
Europe	0.411	0.283	0.107	-0.257	0.112	-0.036	0.609	0.537
UK	0.292	0.539	-0.22	0.363	-0.604	-0.117	-0.237	0.098
Germany	0.334	0.492	-0.068	-0.018	0.673	-0.008	-0.282	-0.331
Advanced Asia	0.41	-0.11	-0.02	-0.153	-0.249	0.751	0.145	-0.386
Japan	0.319	-0.091	0.719	-0.341	-0.219	-0.293	-0.338	-0.093
Australia	0.37	-0.423	-0.318	-0.058	0.142	0.134	-0.508	0.532
% Var	50.293	14.718	10.12	7.535	5.949	5.001	3.558	2.826

The table reports the Principal Component Analysis (PCA) conducted across multiple frailty factors. The frailty factors are estimated without market-based variables. In each panel, we present the loadings on the Principal Component factor, and the corresponding variation that is accounted by each PC factor.

Table A.10: PCA (Include Emerging Markets and Equities)

Vars	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9
US	0.26	-0.025	0.559	0.008	0.291	-0.353	0.569	-0.244	-0.165
CAD	0.412	-0.254	0.34	0.112	-0.085	0.702	-0.186	-0.318	0.023
Europe	0.355	0.217	-0.243	-0.406	-0.112	0.359	0.555	0.386	0.064
UK	0.348	0.148	0.293	0.124	-0.082	-0.26	-0.214	0.315	0.733
Germany	0.333	0.611	0.131	-0.184	-0.265	-0.158	-0.379	-0.07	-0.47
Advanced Asia	0.393	0.145	-0.413	0.731	0.287	0	0.065	0.085	-0.16
Japan	0.241	-0.041	-0.234	-0.468	0.728	-0.04	-0.31	-0.162	0.112
Australia	0.354	-0.316	-0.422	-0.11	-0.452	-0.353	0.087	-0.479	0.139
Emerging Markets	0.258	-0.608	0.088	-0.084	-0.049	-0.186	-0.19	0.568	-0.392
% Var	42.66	15.786	9.15	8.793	6.408	5.3	5.033	4.327	2.543

The table reports the Principal Component Analysis (PCA) conducted across multiple frailty factors. The frailty factors are estimated with market-based variables. In each panel, I present the loadings on the Principal Component factor, and the corresponding variation that is accounted by each PC factor.

Table A.11: Global frailty factor: Marginal Analysis (With Emerging Markets)

Economies	Stand Dev	MEM	AME	Δ Defaults
US	1.59	0.00005	0.0035	1.52
Canada	1.472	0.00081	0.0117	1
Europe	1.501	0.00174	0.0105	2.36
UK	1.519	0.00063	0.0076	1
Germany	1.554	0.00389	0.0283	1.84
Advanced Asia	1.358	0.00055	0.0038	1.32
Japan	1.482	0.00015	0.0029	1.12
Australia	1.409	0.00174	0.0061	0.8
Emerging Markets	1.345	0.0066	0.0129	4.76

This table presents the marginal effects of the frailty factor in each economic regions. The parameters of the frailty factors are estimated by conducting separate regressions with the frailty factors as one of the control variables. Additional control variables are included based on Panel A of Table 3. Column 1 presents the standard deviation of the factors. Column two and three presents the MEM and AME respectively. Column 4 presents the increase in corporate default events in a year, after a standard deviation increase in the frailty factor.

Table A.12: Global Factors and Index

(a) Global Macroeconomic Condition
Global GDP Growth Rate
Oil Price
(b) Global Monetary Policy and Exchange Rate
US Three Month Treasury Bill (Level)
US Yield Curve Slope (Level)
Other Major Central Bank Three Month Rate (UK, China, Japan)
Δ Broad $US Exchange Rate
(c) Global Financial Condition and Capital Flows
VIX
Ted Spread
Moody's BAA and AAA corporate yield
Global Domestic Credit
Global Cross Border Flows
(d) Global Index
Global Supply Chain Pressure Index
Geopolitical Index
Global Uncertainty Index
Global Asset Prices Factor

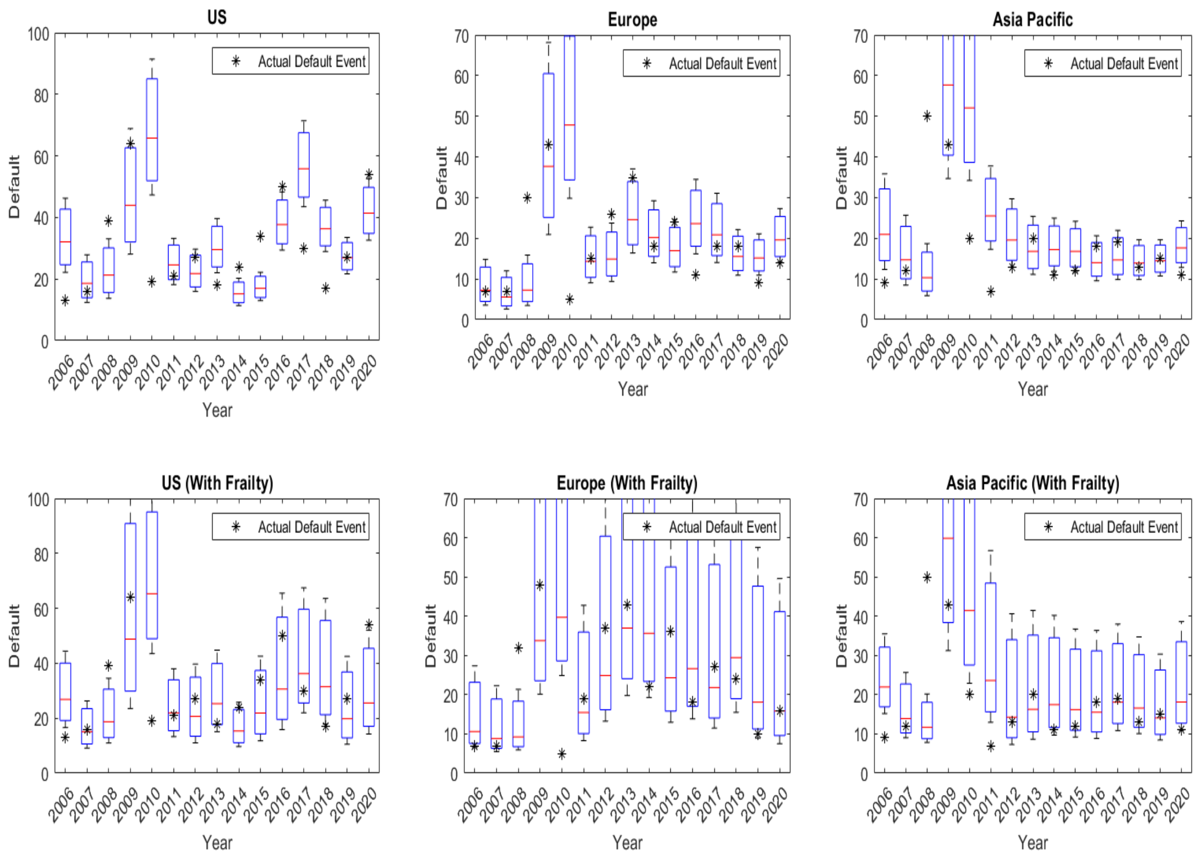
This table presents a broad list of global factors and financing conditions that are considered in global financial cycle and international finance literature.

Table A.13: Granger-Causality test of Frailty Factors

United States to ROW	Canada	Europe	UK	Germany	Japan	Australia	AdvancedAsia
Less than 6 months	0.165	0.004***	0.006***	0.168	0.077*	0.000***	0.004***
6 - 12 months	0.115†	0.012**	0.252	0.239	0.603	0.001***	0.014**
12 - 24 months	0.212	0.004***	0.047**	0.211	0.911	0.001***	0.009***
Canada to ROW	US	Europe	UK	Germany	Japan	Australia	AdvancedAsia
Less than 6 months	0.001***	0.000***	0.054*	0.009***	0.008***	0.037**	0.100*
6 - 12 months	0.122†	0.000***	0.097*	0.024**	0.010**	0.175	0.221
12 - 24 months	0.082*	0.000***	0.077*	0.010**	0.056*	0.035**	0.077*
Europe to ROW	US	Canada	UK	Germany	Japan	Australia	AdvancedAsia
Less than 6 months	0.494	0.028**	0.471	0.004***	0.001***	0.480	0.134†
6 - 12 months	0.456	0.016**	0.597	0.004***	0.044**	0.064*	0.094*
12 - 24 months	0.191	0.002***	0.007***	0.003***	0.084*	0.145†	0.117†
UK to ROW	US	Canada	Europe	Germany	Japan	Australia	AdvancedAsia
Less than 6 months	0.006***	0.127†	0.007***	0.024**	0.341	0.465	0.043**
6 - 12 months	0.263	0.027**	0.015**	0.189	0.465	0.064*	0.296
12 - 24 months	0.599	0.317	0.040**	0.140†	0.699	0.078*	0.557
Germany to ROW	US	Canada	Europe	UK	Japan	Australia	AdvancedAsia
Less than 6 months	0.167	0.048**	0.018**	0.105†	0.128†	0.366	0.235
6 - 12 months	0.097*	0.018**	0.318	0.020**	0.141†	0.554	0.084*
12 - 24 months	0.423	0.050*	0.011**	0.031**	0.233	0.637	0.131†
Advanced Asia to ROW	US	Canada	Europe	UK	Germany	Japan	Australia
Less than 6 months	0.410	0.201	0.001***	0.025**	0.031**	0.057*	0.036**
6 - 12 months	0.501	0.076*	0.001***	0.256	0.205	0.132†	0.034**
12 - 24 months	0.562	0.102†	0.003***	0.541	0.369	0.025**	0.064*
Japan to ROW	US	Canada	Europe	UK	Germany	Australia	AdvancedAsia
Less than 6 months	0.020**	0.470	0.061*	0.253	0.402	0.050*	0.583
6 - 12 months	0.023**	0.038**	0.236	0.262	0.414	0.041**	0.901
12 - 24 months	0.154	0.127†	0.172	0.528	0.097*	0.262	0.466
Australia to ROW	US	Canada	Europe	UK	Germany	Japan	AdvancedAsia
Less than 6 months	0.023**	0.253	0.036**	0.735	0.418	0.000***	0.103†
6 - 12 months	0.001***	0.286	0.006***	0.077*	0.143†	0.000***	0.734
12 - 24 months	0.000***	0.186	0.000***	0.061*	0.005***	0.003***	0.839

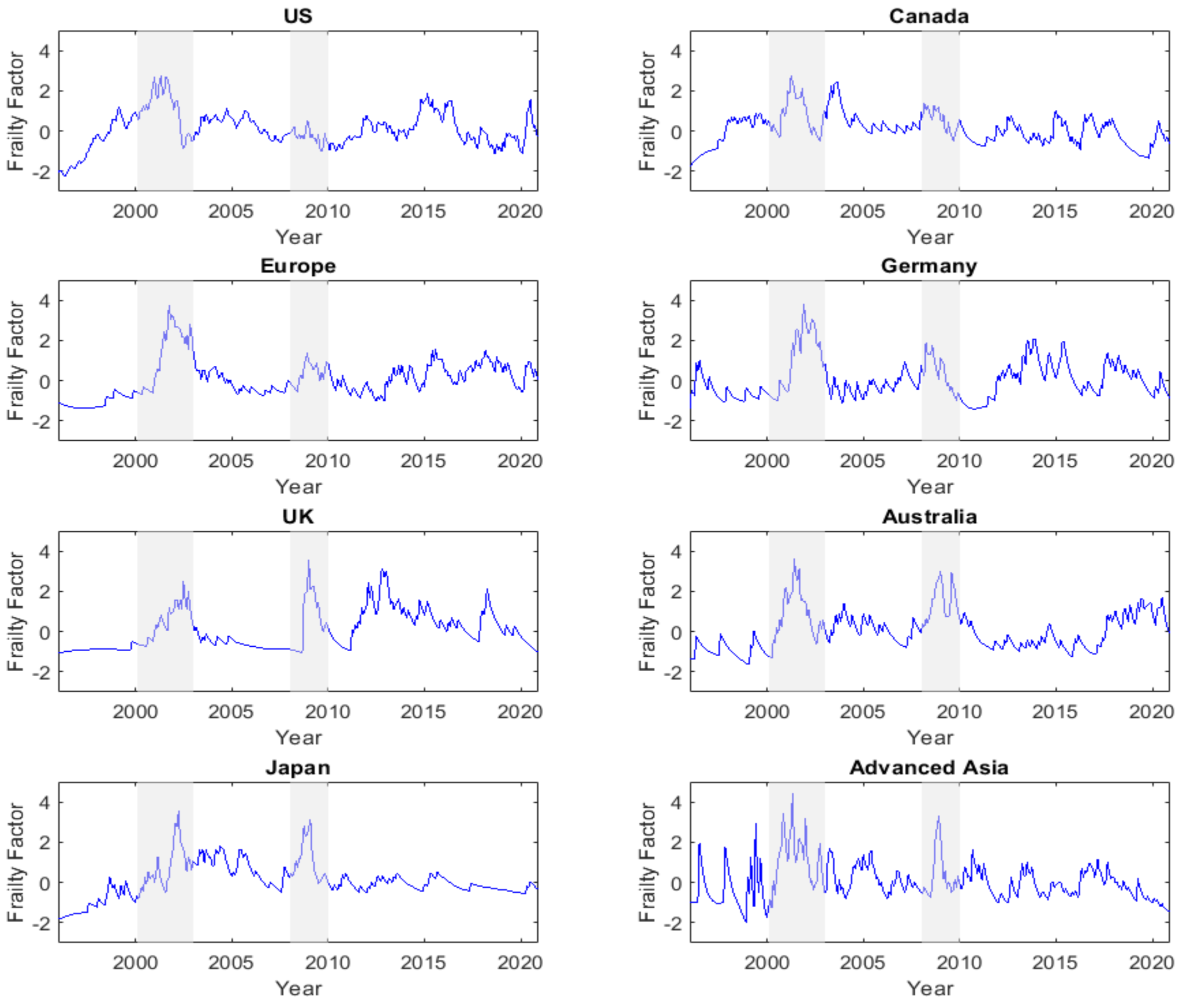
Granger Causality tests for frailty factors across economic regions worldwide. The tests is conducted up to 24 months of lag. For brevity, the 24 months of lag is classified into three categories: Less than 6 months, 6 - 12 months, 12 -24 months. The lowest p-value of the test is reported in each category. ROW: Rest of the world. ***, **, *, and † indicate $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$

Figure A.1: Out-of-Sample Default Risk Prediction



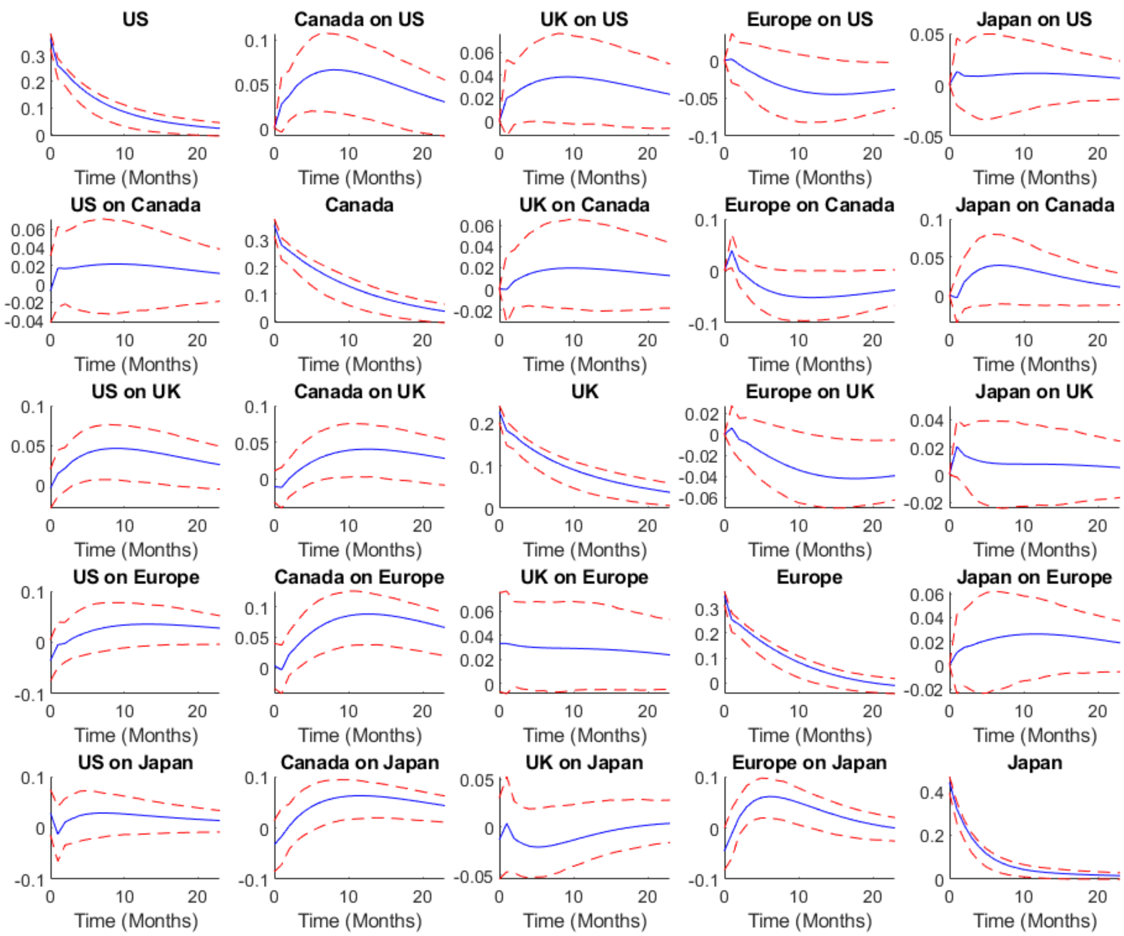
This figure depicts the Out-of-Sample forecast distribution of corporate default risk for U.S., Europe and Asia Pacific. The top three charts shows the default risk prediction without the frailty factor. The bottom three charts show the corresponding counterpart with the frailty factor. The red horizontal line depicts the mean estimate, while the extreme end of the box plot represents the tail distribution of the default risk forecast. The star represents the realized number of default events. The corporate default risk models are estimated with firm fundamentals based on 3 and systematic factors outlined in Section 5.4.

Figure A.2: Global Frailty Factors



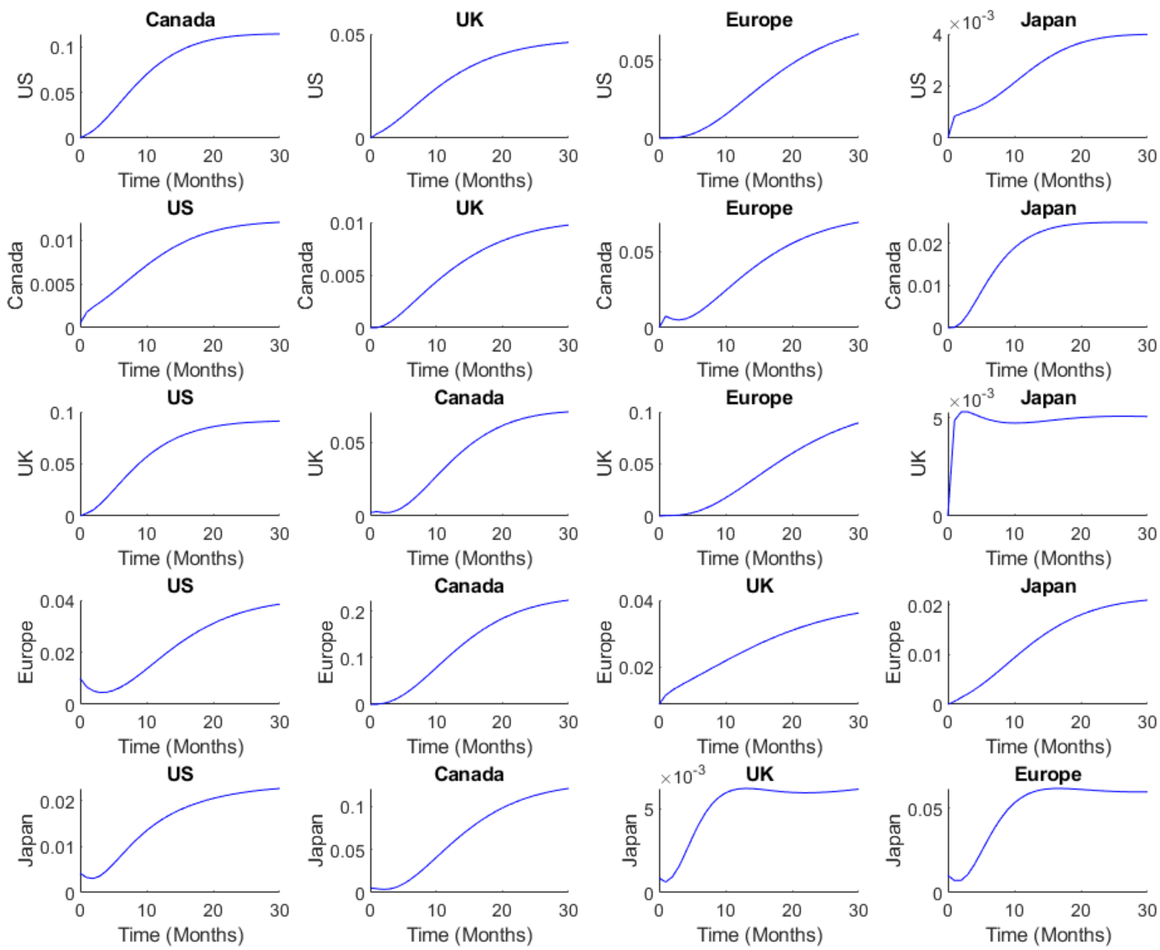
This figure shows the estimated frailty factors across different regions. The frailty factors are estimated based on the explanatory variables in Table A.4, which exclude market-based variables. The frailty factors are standardized.

Figure A.3: Impulse Response Functions based on reduced-form VAR



This figure presents the impulse response functions based on the frailty factors of the five economic regions (U.S., U.K., Germany, Europe, Japan). The dashed red lines are the 90% confidence intervals, constructed using bootstrap sampling with 1,000 repetitions.

Figure A.4: Forecast Error Variance Decomposition



This figure presents the forecast error variance decomposition at different time horizons. The economy in the row represents the explained variance due to the shocks of the frailty factor of the economy in the column.