Global Corporate Default Risk Factors: Frailty and Spillover Effects*

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Abstract

By employing a dataset that contains an international coverage of corporate default events, this paper shows strong evidence of a common global dynamic latent risk factor that impacts corporate debt distress risk worldwide. The global latent risk factor is constructed by identifying common variations among separately estimated dynamic latent risk factors (frailty) of different economic regions worldwide. The frailty factor of each economic region is estimated after controlling for a holistic selection of firm fundamentals, capturing systemic risk and omitted macroeconomic factors. Standard global factors and financing variables can only explain up to 30% of the global frailty factor, indicating substantial evidence of a global systemic risk factor that drives international corporate debt distress.

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 leverage has risen from 76.8% in 2008 to a peak of 98.7% in 2022, standing at one of the highest points of all time. This trend is driven by most key economic regions worldwide, facilitated by low-interest rates and other favorable lending conditions over the past few decades. Figure 1 depicts the rising trend of non-financial corporate leverage for major economic regions around the world. Notably, the increase in corporate leverage is especially prevalent during the worst period of the Covid-19 pandemic in 2020 due to the unprecedented economic shock and government support worldwide to prevent corporations from falling into financial distress.

The global trend of rising corporate leverage poses an increasing threat to international financial stability. Firms with high corporate leverage face a greater risk of defaulting on their financial obligations due to more expensive borrowing costs and increasing vulnerability to shocks in their cash flows. In compounding this issue, major central banks worldwide have aggressively increased interest rates over the last year and have committed to hiking interest rates in the near future to combat persistently high inflation. The rising interest rates trend adversely aggravates the burden on firms' debt obligations, thus exposing them to greater risks of financial distress.

Firms defaulting on larger amounts of financial obligations generate more severe systemic risk to the overall corporate credit market at the economy level and even on a global scale. Default action by a critical firm (or firms) imposes financial burdens on surviving 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 create a more destabilizing financial contagion effect. The recent and ongoing debt distress of Evergrande, one of the most indebted property developers in the world, raised concerns over the increasing systemic risk exposure across financial markets worldwide. Following the revelation of negative reports of Evergrande's financial distress, firms in China and beyond have increasingly faced financial distress due to restrictions in obtaining funds, raising concerns over firms' worldwide joint vulnerability to systemic risk.[1]

The paper makes two main contributions. First, across different economies/economic regions worldwide, I quantify firms' vulnerability to a dynamic latent risk (frailty) factor. The frailty factor is estimated based on controlling for a holistic selection of explanatory variables, covering multiple dimensions of firm fundamentals. The estimated frailty factor

[1] Global financial institutions and investors were increasingly cautious in providing funds to real estate firms in China and related firms worldwide upon release of news relating to Evergrande debt distress. Consequently, surviving related firms faced borrowing restrictions, increasing their risk of financial distress. Numerous related firms have since defaulted on their financial obligations, despite a healthy balance sheet, and previously showed minimal signs of financial distress, raising concerns over firms increasing exposure to systemic risk.

captures systemic risk, and other omitted systematic macroeconomic factors that impact corporate debt distress risk. Across different economies worldwide, I show that incorporating the frailty factor provides a better explanation of corporate default risk exposure, confirming that corporate debt issuance is vulnerable to a dynamic latent risk factor. Out-of-sample, I show that incorporating the frailty factor provides a consistently more accurate and realistic estimation of corporate default risk. Specifically, the econometric model with the frailty factor estimates corporate default events with a smaller mean bias and can potentially account for the extreme clustering of corporate default events under crises. The counterpart econometric model without the frailty factor cannot adequately account for the severe clustering of default events during crises, even with default risk prediction at extreme quantile intervals.

Second, I identify a common global latent risk factor that impacts corporate debt distress risk worldwide. The global factor is constructed based on identifying a common and substantial share of the variations among separately estimated frailty factors of different economic regions worldwide. Subsequently, based on a multivariate regression, I show that a standard set of global factors and financing conditions can only provide a minimal explanation of the risk inherent in the global frailty factor. The employed global factors are identified based on corporate default risk and global financial cycle literature, including variables such as US monetary policy, global risk aversion (VIX), or other measures of global liquidity. With this finding, I orthogonalize the global frailty factors based on a comprehensive set of measurable global factors and financing conditions to construct a global latent risk factor. The latent risk factor captures firms' worldwide common exposure to systemic risk beyond the information contained in firm fundamentals and global factors.

The economic case for incorporating frailty factors in corporate default risk assessment can be easily justified. Debt obligations issued by corporations are vulnerable to systemic risk. Measurable firm fundamentals and external systematic conditions may not adequately account for the corporate debt issuance exposure to systemic risk, leading to the underestimation of overall corporate default risk exposure in an economy. Giesecke and Kim (2011), in the context of corporate default risk, define systemic risk as the consecutive failure of a sufficiently large proportion of firms. Systemic risk triggers almost simultaneous waves of corporate distress due to corporate default contagion and other forms of firms' interlinkages. Financial contagion in the credit markets may arise from several channels. Two of these are: firms' direct interlinkages[2] and the information channel.[3] Defaults by key firms in the global economy may elevate the financial distress risk of surviving firms due to firms' business linkages and other forms of financial network effects. Even without

[2]For example, production network literature (See Acemoglu et al. (2012)) points out that firms are interconnected. Global value chain literature (See Antràs and Chor (2013)) also provides a similar intuition

[3]For example, Oh (2013) uses a global game model to illustrate the effect of contagion based on the information channel.

direct economic linkages among firms, the revelation of harmful news about a critical firm can trigger destabilizing capital flow movements worldwide due to concerns that surviving firms in an economy or even related firms in the rest of the world are impacted by a similar risk factor. Consequently, these firms face greater challenges in raising funds, increasing their financial distress risk exposure. In short, firm-specific and systematic variables may not sufficiently account for the corporate sector vulnerabilities to systemic risk, suggesting that sole reliance on the former explanatory variables underestimates corporate default risk exposure.

The endogenous nature of corporate default actions renders firm fundamentals and other systematic variables inadequate in holistically accounting for corporate debt distress risk exposure, thus justifying the incorporation of the frailty factor in corporate default risk assessment. Bhamra et al. (2010a) highlight that firms' default option is less valuable under an adverse macroeconomic outlook due to a decline in collateral value and a reduction in the present value of the future payoff. Consequently, aggregate corporate default risk exposure at the economy level is underestimated due to firms' greater incentives to default on their financial obligations during crises. In this case, corporate default risk models estimated based on data largely from benign periods may not have accounted for the time-varying incentives of firms to default, thus underestimating default risk exposure under crises.

A distinct feature of this paper lies in employing a dataset that contains a global coverage of corporate default events. The dataset allows the exploration of the significance of the frailty factor across multiple economic regions worldwide, covering several adverse episodes of clustering in corporate default events. These include Asian Financial Crisis, the Global Macroeconomic Recession in the early 2000s, the Global Financial Crisis in 2008, the Eurozone Sovereign Debt Crisis, and to a lesser extent, the Covid-19 pandemic.

Separately across multiple economic regions, I begin by estimating a binary logit model that measures firms' probability of default. The explanatory variables are selected based on Campbell et al. (2008), comprising a comprehensive set of firms' balance sheets and market-based variables. This approach provides a holistic assessment of a firm's distress risk exposure across multiple dimensions, such as profitability, liquidity, and leverage. The selected variables are standard and widely used in macroeconomic and finance literature to study firms' financial distress risk exposure across multiple economies worldwide. Overall, the corporate default risk models generally provide a relatively accurate assessment of aggregate corporate default risk exposure under benign periods for all economic regions. However, the default risk models largely underestimate overall aggregate corporate default risk exposure during severe macroeconomic recessions or financial crises.

The prior corporate default risk models raise concerns over omitted factors that impact distress risk in corporate debt portfolios but are excluded from the econometrics model, thus underestimating the risk exposure in the corporate debt portfolios. In order to capture the omitted factor, I incorporate a frailty factor – dynamic latent variable – into the corporate default risk model. The frailty factor is estimated based on a non-standard Generalized Autoregressive Score (GAS) paradigm. A distinct aspect of my approach in estimating the frailty factor lies in computing the innovation term based on the generalized residuals, which is the empirical difference between estimated and actual default risk exposure. The frailty factor is dynamically updated based on the computed generalized residual, which intuitively captures systemic risk and other omitted systematic factors that impact corporate debt distress risk. The econometrics specification for estimating the frailty factor is modified based on Babii et al. (2019), which focuses on a different financial risk issue from this paper.[4]

My approach for estimating the frailty factor is distinct from the existing 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. Instead, as compared to prior corporate default clustering literature, I estimate the frailty factor in a big data setting – A dataset containing millions of observations at the firm-level and relatively extensive selections of explanatory variables. This approach is feasible by dynamically updating the frailty factor based on generalized residuals, allowing the frailty factors to be flexibly estimated in a big data setting.[5] Considering this paper's focus on identifying vulnerabilities in corporate debt on an international scale, employing big datasets that account for firm heterogeneity based on multiple components of firm fundamentals while estimating the frailty factors is critical. Specifically, firms across different economies are more vulnerable to different risk factors due to distinct structural characteristics. Consequently, econometrics models specification using U.S. data or developed based on industry aggregated data,[6] generally leads to poorer predictive performance when applied in other economies.[7]

Based on the non-standard GAS paradigm of estimating the frailty factors, I find strong evidence of a frailty factor that impacts corporate debt distress risk. The finding holds across different economic regions worldwide, even after controlling for a holistic selection of firm fundamentals based on Campbell et al. (2008) explanatory variables. Specifically, the frailty factors are highly significant across different economies and exhibit a better explanation of the clustering of corporate default events during crises. The finding

[4]Besides Babii et al. (2019), Hansen and Schmidtblaicher (2021) also uses a similar GAS econometrics approach in allowing parameters of the model to vary over time. However, Hansen and Schmidtblaicher (2021) focus on vaccine compliance and an alternate setting, where the dependent variable follows a binomial distribution.

[5]Prior approaches of estimating the frailty factor in corporate default clustering literature employs simulation or other computationally intensive methods, largely restricting datasets to a modest size - the dataset is restricted to either industry aggregated data or a limited selection of explanatory variables.

[6]Industry aggregated data omits firm-level balance sheet information, and are not able to account for firm-level heterogeneity. Most research in corporate default clustering estimates the frailty factor based on industry or economy-aggregated data due to the computationally intensive nature of estimating the frailty factor with firm-level data

[7]Asis et al. (2021) and CRI (2021) provide empiricial results that support these findings based on an international firm-level data.

confirms that sole reliance on firm fundamentals is inadequate in comprehensively assessing firms' default risk exposure. Applying the likelihood ratio test and AUC out-of-sample analysis further supports the relevance of the frailty factor in explaining corporate default risk exposure without compromising the econometrics model's capability to distinguish individual firms based on distress risk exposure.

I next measure the economic significance of the frailty factor in each economic region by conducting marginal assessments. This approach quantifies firms' vulnerability to adverse movements of the dynamic latent risk factor based on estimated corporate default events. I conduct the marginal assessments by separately estimating the corporate default risk logit model with the previously estimated synthetic frailty factor and control for firm fundamentals. Based on the coefficient of the frailty factor for all economic regions, a standard deviation increase in the frailty factors estimates an approximate increase of 6 corporate default events in a year. This value comprises about 6% of default events in the overall data sample, excluding the U.S. economy.

Subsequently, I show that incorporating the frailty factor can provide a more realistic prediction of corporate default events in an out-of-sample setting. Consistent with prior corporate default clustering literature (See Duffie et al. (2009), Azizpour et al. (2018), etc), I first show that excluding the frailty factor provides a severe underestimation of corporate default risk exposure during crises, even with the prediction at extreme quantile intervals. This finding holds for all economic regions worldwide. Incorporating the frailty factor provides a more realistic forecast of corporate default risk exposure by 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 frailty factor that explains a substantial share of the variation among these economies' frailty factors. Standard observable global factors and financing variables can only explain up to 30% of the risk inherent in the global frailty factor, indicating strong evidence that a substantial proportion of the risk in the global factor is latent. Based on this finding, I orthogonalize the global frailty factors with this set of measurable global factors and financing variables to construct a latent global systemic risk factor[8] that impacts corporate debt distress risk worldwide but is not explained by observable factors. Subsequently, after controlling for firm fundamentals, I compute the marginal analysis of the global systemic risk factor across different economic regions to quantify the economic significance of this factor in different economic regions worldwide.

Finally, I study the mechanism behind the latent global risk factor that impacts cor-

[8]The global latent risk factor captures common factor that impacts corporate debt distress risk worldwide. Firm fundamentals and the standard set of global factors cannot explain the risk contained in the global latent risk factor. Thus, this global factor captures common systemic risk that impacts corporate debt distress risk worldwide. Subsequently, I will use the term global latent risk factor and global systemic risk factor interchangeably to illustrate the latent nature of global systemic risk.

porate debt distress risk worldwide. I show that adverse movements of the frailty factor of an economy transmit financial distress risk to firms worldwide. The corporate distress risk spillover is measured based on the estimated frailty factor of each economy, which captures risk information not reflected in firm fundamentals and measurable global factors. In measuring the severity of financial distress risk spillover, I employ the Granger-Causal analysis. The tests are complemented with a reduced-form Vector Autoregression (VAR) analysis, quantifying the severity of corporate default risk spillover over multiple periods for different economies worldwide. The VAR model shows that, on average, 22% of the risk variations of the frailty factor in an economy is triggered due to adverse movements of frailty factors of external economies. This finding raises concerns that international corporate default risk spillover plays a substantial role in constructing the latent global risk factor that impacts corporate debt distress risk worldwide. I also employ Han et al. (2016) cross-quantilogram method to study the severity of quantile dependence among the frailty factors. These tests also support a strong degree of dynamic dependence among frailty factors at the extreme quantiles, further supporting evidence of international distress risk spillover as a channel that constructs 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 balance sheet variables that are significant predictor of firms' bankruptcy risk. Subsequent later 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 have identified a wide range of domestic macro-financial variables that impact corporate debt distress risk. Asis et al. (2021) points out that global financing variables impact corporate default risk. Across different economies worldwide, this paper quantifies firms' vulnerability to a dynamic latent risk factor and how incorporating this factor provides a more realistic assessment of corporate default risk, even after controlling for a holistic selection of key explanatory variables identified in prior corporate default risk literature. This finding confirms that sole reliance on firm fundamentals and macro-financial variables is universally inadequate to provide a comprehensive assessment of firms' financial vulnerability.

Second, this paper contributes to the strand that studies the clustering of corporate default events. 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. This finding has inspired the corporate default clustering literature, which has since proposed two key approaches to account for this phenomenon. A dynamic latent variable (frailty) is the first approach. By using simulation methods to estimate the frailty factors, Duffie et al. (2009) and Koopman et al. (2011) 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 of default risk exposure even at the extreme quantile interval. Creal et al. (2014) also identify a similar finding based on 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. Instead of focusing solely on the U.S. economy, I contribute to the corporate default clustering literature by studying this phenomenon internationally. The separate estimation of frailty factors across economies enables further analysis of the dynamic relations of these factors worldwide. My econometric analysis uncovers a substantial degree of common variations among separately estimated frailty factors worldwide and dynamic spillovers of these factors over time. This finding raises concerns over global corporate debt portfolios' joint vulnerability to a common latent risk factor.

Finally, this paper contributes to a recent and growing body of research on the global financial cycle in international finance. This field of research identifies a global risk factor that describes common international comovement of financial assets across different financial markets, such as commodities, equities, and bonds (Rey (2015)). Miranda-Agrippino and Rey (2020) identify evidence for a common global factor that accounts for a considerable degree of correlation among risky assets worldwide. In the area of currency markets, Lustig et al. (2011) identify evidence of a common global risk factor that drives variation in currency risk exposure. In the capital flow literature, Forbes and Warnock (2012), Habib and Venditti (2019), Chari et al. (2020), Chari et al. (2022), among others, highlight that a proxy for global risk measures accounts for international cross-border capital flows. I contribute to this field of research by highlighting significant evidence for a global systemic risk factor that impacts corporate debt distress risk and accounts for common waves of default events worldwide. Apart from measurable global factors and financing conditions, this finding raises concerns that global corporate credit markets are vulnerable to a common latent risk factor beyond information reflected in firm fundamentals.

The paper proceeds as follows. Section 2 outlines the econometrics specification for estimating the frailty factor in an economy and the economic justification for incorporating a common global frailty factor that impacts corporate debt distress risk worldwide. Section 3 describes the data and the explanatory variables selection approach. Section 4 presents multiple empirical results that study the relevance of the frailty factor in forecasting corporate default risk. Section 5 outlines the approach to estimating the global systemic risk factor and the economic significance of this factor. Section 6 presents evidence on international corporate default risk spillover and contagion based on the estimated frailty factors. Section 7 concludes.

2 Econometrics Model Specification

This section outlines the econometrics specification for incorporating a frailty factor into a corporate default risk econometrics model. Subsequently, I delineate the economic intuition for firms' vulnerability to the frailty factor and the global systemic risk factor in corporate default risk assessment. Numerous studies in corporate default risk literature have documented that firm fundamentals and systematic variables are inadequate in holistically assessing the vulnerabilities in corporate debt portfolios, especially under crises, triggering multiple waves of clustering of corporate default events. However, corporate default risk models in finance or related literature seldom incorporate a frailty factor or other contagion factor in assessing firms' default risk exposure due to the computationally intensive nature of incorporating an unobserved latent factor in an econometric model. To mitigate this issue, I rely on a non-standard GAS paradigm approach for estimating the time-varying latent factor (frailty). This approach is notably more computationally efficient than simulation methods and other prior methods employed by corporate default clustering literature in estimating the frailty factor.

2.1 Benchmark Model Specification: Binary Logit Model

Before introducing the approach of estimating the frailty factor, I first specify the corporate default risk measure. Following a large body of research in default risk prediction, I rely on the dynamic logit model as the benchmark model in default risk estimation (See Shumway (2001), Campbell et al. (2008), Asis et al. (2021), etc). Compared to most other econometrics models in existing corporate default risk literature, this approach is superior for its computational efficiency in utilizing past and present information to predict 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 that relates to the 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 also 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 experience a default event. Besides a default event, firms may also exit the data sample under 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 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.

2.2 Binary Logit Model with Frailty

In this subsection, I outline the econometrics specification of estimating the frailty factor and follow up with the economic justification for considering the frailty component in the next subsection. The specification of the frailty factor follows Babii et al. (2019), which addresses a different financial risk issue from this paper. Instead of estimating a constant intercept term in the binary logit model, I include a time-varying factor based on the GAS paradigm. I can modify the model written in (1) as:

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

The term f_t relates to the frailty factor, a time-varying unobserved latent variable estimated based on information from the explanatory variables and realized corporate default events. This approach of constructing the frailty factor suggests that a common latent risk factor broadly impacts firms within the same time period. 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 additional extensions. Based on the GAS model paradigm, the frailty factor is assumed to follow an autoregressive form. Specifically, the frailty factor satisfies the following recursion:

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

Innovation term:

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

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 (4), the frailty factor is dynamically updated based on the generalized residuals. In the case of a binary logit model, generalized residuals is computed as the difference between empirical default rate and model predicted default rate, as defined in (5) and (6), respectively.[9] This approach indicates that higher (lower) realization of default events will dynamically increase (decrease) the next period frailty factor based on higher (lower) innovations. Given the stylized observation of worldwide clustering in corporate default events during crises, incorporating the frailty factor into the reduced-form econometrics model may more adequately explain the clustering of default events exhibited in the data as compared to sole reliance on observable explanatory variables.[10]

Notably, my construction of the innovation term deviates from the standard application of GAS models in economics and finance literature. Most GAS models are applied in settings with continuous dependent variables, such as the modeling of equities volatility clustering by Bollerslev (1986) and modeling dependence between different financial assets by Patton (2006). In these cases, the innovation term is computed by scaling the score function with the standard deviation. However, in my case, the dependent variable is binary, suggesting that the frailty factor impacts corporate default risk in a discontinuous manner. As such, scaling of score function by the standard deviation may not be an appropriate approach for updating the dynamics of the frailty factor. Following Babii et al. (2019), which also focuses on applications of GAS models with binary dependent variable, I also allow the GAS dynamics to be driven by the generalized residuals. This approach is appropriate as the generalized residuals are computed between -1 and 1. Detailed theoretical results that justify using the generalized residuals approach for calculating innovation term, where the dependent variable is binary (discontinuous), are presented in Babii et al. (2019).

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 and resulting QMLE

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

[10] Table 3 shows that corporate default events tend to cluster during the early 2000s (Global Macroeconomic Recession) and 2008 (Global Financial Crisis). Refer to section 3.3 for more details.

estimator ($\hat{\psi}$) 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 standard estimation of a binary logit model without the frailty factor.

To reiterate, my approach to estimating the frailty factor relies on a non-standard GAS paradigm, which dynamically updates the frailty factor using generalized residuals (1) - (7). This approach is comparatively computationally efficient as it avoids estimating the frailty factors using simulations or handling multiple complicated equations that require numerical derivatives to derive the parameters' solutions. This approach to estimating the frailty factors is especially crucial in estimating firms' vulnerability to latent risk factors beyond information contained in a holistic selection of observable explanatory variables.

2.3 The economic justification for incorporating the frailty factor

The international economics literature highlights that corporate debt is vulnerable 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 across financial markets 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 and VIX. Since the valuation of firms' financial assets impacts their corporate financing and borrowing costs, adverse movements in global factors and financing conditions hamper firms' access to financial funding, increasing firms' worldwide exposure to financial distress risk.

Asis et al. (2021) shows that global financing conditions impact firms' market value, in turn transmitting to their financial distress risk exposure. They also employ a set of observable global financing conditions to construct a composite measure of corporations' exposure to global financing conditions – the global factor Z score. 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.

Suppose observable global factors, such as U.S. monetary policy or measures of global liquidity, are excluded from the econometrics model. In this case, the global frailty risk factor is expected to capture these international risk factors and other omitted variables. If hypothesis 1 is true, this finding suggests a substantial degree of common variation can be identified among separately estimated frailty factors across different economies worldwide. 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 after a rigorous selection of the relevant explanatory variables. Consequently, the corporate default risk econometrics model estimated solely based on observable explanatory variables may underestimate vulnerabilities in corporate debt portfolios. This insight motivates the following hypothesis:

Hypothesis 2: A common global latent risk factor impacts corporate debt distress risk worldwide. Standard set of global factors and financing variables are inadequate in explaining the risk in the latent global risk factor.

Several strands of literature in corporate finance and international macroeconomics support evidence of a common global latent risk factor that impacts corporate debt distress risk worldwide. The first strand highlights the vulnerability of global corporate credit markets to systemic risk. As discussed previously, the key channel in which systemic risk arises is due to the transmission of financial distress risk from firms' direct business and financial interlinkages, as well as other forms of network relations, such as informational contagion. Acemoglu et al. (2015), Eisenberg and Noe (2001), Elliott et al. (2014), among other studies in production networks, indicate that the failure of firms to fulfill their financial obligations may increase default risks of related surviving firms due to business and financial linkages. Firm fundamentals and external domestic macroeconomic conditions overlook the transmission of financial distress risk from firm interlinkages. Thus, sole reliance on the former explanatory variables largely underestimates overall corporate default risk exposure in an economy.

Global value chain literature raises concerns that firms worldwide are vulnerable to a common systemic risk factor. Antras et al. (2017), Antràs and Chor (2013), and others illustrate that firms source for input materials internationally rather than operate in a domicile economy in isolation. Consequently, disruption of business activities among critical firms in the global value chain due to bankruptcy or other forms of financial distress may hamper economic activities worldwide, increasing the risk that firms worldwide will fall into financial distress. 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, justifying the incorporation of a global latent risk factor that impacts corporate default risk worldwide.

Besides firms' direct economic linkages, corporate financial distress may also be contagious due to the informational channel. Based on the global games method, Oh (2013) points out that default by a critical firm (or firms) in the economy may reveal harmful information that elevates default risk for other surviving firms. When a critical firm in the economy has defaulted, creditors may believe that other related firms could also be exposed to the same risk. In this case, creditors are inclined to practice discriminatory lending practices against other surviving firms, even if these firms may not be exposed to the same risk factor. Unfortunately, these discriminatory lending practices reduce credit supply for surviving healthy firms, increasing firms' exposure to financial distress risk and potentially triggering the clustering of corporate default events. Giesecke (2004) also point out a similar finding using a structural model of multi-firm default.

The endogenous nature of corporate default actions is also another channel that exposes the global corporate credit markets to systemic risk. Bhamra et al. (2010b), Hackbarth et al. (2006), Bhamra et al. (2010a), Bhamra et al. (2021), and others, point out that firms' default option is less valuable during a severe macroeconomic recession or financial crisis due to decline in the present value of future earnings and collateral value. Consequently, firms have fewer incentives to fulfill their financial obligations due to an increase in their default boundary, thus triggering the clustering of default events frequently exhibited during crises. Under adverse global macroeconomic recessions or financial crises, firms worldwide have greater incentives to default on their financial obligations. Unfortunately, the parameters of the standard corporate default risk econometrics model are calibrated using data mainly from benign periods. This approach cannot adequately account for the endogenous nature of corporate default actions, thus underestimating corporate default risk exposure under crises.

The financial fragility literature also support the presence of a global latent risk factor that impacts firms' distress risk worldwide. Gabaix (2011) points out that large firms are systemically important as they dominate most of the economic activity in the U.S. economy. Consequently, adverse shocks to the largest firms impact aggregate output in the economy, exposing firms in the rest of the economy to greater financial distress risk as the diversification of shocks in the aggregate data is minimal. For instance, Gabaix (2011) notes that idiosyncratic movements of the largest 100 firms in the U.S. economy explain about one-third of variations in output growth. 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 an adverse shock to a large key firm in the emerging markets transmits risk to other firms in this region. Their findings raise concerns that increasing large firms' (or several critical firms') exposure to financial distress risk may elevate the vulnerabilities of other firms in emerging markets and beyond. Based on the systemic risk and financial fragility literature, this motivates the third hypothesis:

Hypothesis 3: Adverse shocks (reflected in the frailty factor) to firms in an economic region trigger financial distress risk spillover to firms worldwide. The financial distress risk spillover gives rise to the global latent risk factor.

In accounting for the latent global risk factor that impacts corporate debt distress risk, my empirical approach can be succinctly summarized in three key steps. First, I separately estimate a latent risk factor that impacts corporate debt distress risk across different economic regions worldwide. Second, I delineate the latent aspect of the frailty risk factor that impacts corporate debt distress risk by orthogonalizing the regional frailty factor with a set of observable key global factors and financing variables. Third, I conduct a principal component analysis among the orthogonalized latent risk factor to capture a common global latent risk factor that jointly drives the distress risk of firms across different economic regions worldwide. The global latent risk factor – termed global systemic risk factor – allows us to study the time series dynamic of the latent factor and quantify its impact on corporate debt distress risk in each economic region.

3 Data and Methodology

3.1 Firm Fundamentals and Systematic Variables Selection

A critical aspect of measuring firms' distress risk exposure is the selection of pertinent explanatory variables. This section outlines my approach in selecting the relevant firm fundamentals and global factors that provide a comprehensive assessment of firms' financial distress risk exposure.

I select and construct the firm fundamentals explanatory variables based on Campbell et al. (2008). This approach provides a holistic measurement of firms' distress risk exposure across multiple dimensions, such as profitability, leverage, and market-based information. Campbell et al. (2008) selection of explanatory variables is inspired by 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 by a large range of macroeconomics and finance research, that includes both U.S., other developed economies, and emerging market economies.[11]

As discussed in the previous sections, one of the key focuses of this paper lies in constructing a global frailty factor that impacts corporate debt distress risk across different economic regions. In quantifying the proportion of risk that standard observable global

[11] For instance, in the area of assessing for distress risk premium puzzle, Aretz et al. (2018) use Campbell et al. (2008) explanatory variables to assess if distress risk premium is present in the non-developed economies outside of the U.S. economy. Asis et al. (2021) also address a similar question but focuses on emerging markets economy.

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. Broadly, the selected global factors can be classified into four main categories: (1) U.S. Monetary Policy, (2) Global Risk Aversion, (3) Global liquidity, and (4) Global Macroeconomic Conditions. These 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.

The economic intuition that outlines the global factors' impact on corporate distress risk can be easily justified. Global financial cycle literature, such as Miranda-Agrippino and Rey (2020) and Chari et al. (2021), points out that tightening U.S. monetary policy triggers an increase in bond yield and a decline in asset prices worldwide. With depressed valuation of financial assets, firms face higher corporate financing costs (Bruno and Shin (2015)), and become more exposed to financial distress. A rise in the U.S. interest rate also leads to the 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 stronger global economic growth rate favors the prospects of firms' financing capabilities and business outlook. In this case, strong global economic growth is expected to reduce overall corporate default risk exposure (see 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 indicates the global inflation rate. Depressed oil price reflects a low global inflation rate, reducing the incentives for firms to fulfill 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 large risk premium, which increases firms' borrowing costs worldwide. Other global financing variables, such as TED spread and credit spread between BAA-AAA corporate yield, reflect global liquidity. Adverse movements in these global financing variables signal increasing challenges for firms' worldwide access to financial funding, translating to higher distress risk exposure.

3.2 Model Performance

Corporate default risk literature has employed multiple statistical measures to assess and compare the predictive performance of default risk models. Considering that most of these measures provide an almost equivalent assessment of default risk models' based on similar dimensions, I only rely on two key measures for the subsequent empirical analysis.

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). This measure relies on the cumulative fraction of corporate defaults as a function of the model's estimated firms' distress risk ranked from the highest to the lowest. Based on the model's estimated default risk, this measure is used to assess the default risk model's ability to discriminate between defaulted and non-defaulted firms. 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 also rely on McFadden's pseudo-R^2 to measure the goodness of fit of the econometrics models. This measure compares the numerical value of our estimated default risk model's likelihood (L) to an alternative model that only contains the intercept parameter (L_0). Specifically, the measure is computed as 1 - $\frac{L}{L_0}$.

3.3 The Data

My dataset contains a worldwide coverage of firm-level data across different countries/economies. This data includes information on corporate default events and comprehensive coverage of firm-specific and systematic variables.

A bulk of the data is retrieved 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 relating to 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. As such, my analysis focuses on data from January 1995 to December 2020 and covers 21 economies across North America, Europe, and the Asia Pacific region.[12] Notably, corporate default is a rare event. The dataset shows that the average corporate default rate for most economies comprises less than 0.05% each year. Numerous countries/economies lack sufficient data on corporate default events, which hinders meaningful statistical analysis if my corporate default risk analysis focuses on a specific economy. To mitigate this issue, I group several countries/economies 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 economies/economic regions. They are the United States, Canada, Europe, United Kingdom, Germany, Japan, Australia, and Advanced Asia (Singapore, Hong Kong, Taiwan, and South Korea). Table 1 presents the economies that are included in each of the economic regions.

[12] While NUS CRI database may contain data for a large number of economies worldwide, data in most economies are sparse. To ensure sufficient data for data analysis, I only consider economies that contain an average of 100 firms each year and at least one default event throughout the entire data sample.

Besides worldwide coverage of corporate default events, my dataset also contains detailed background information relating to each corporate default event. Specifically, Table 2 shows that for each corporate default event, I can classify them into three main categories: (1) Bankruptcy, (2) Default, (3) Debt Restructuring. Within each category, I can further classify them into an additional subcategory containing background information for each corporate default event. This information is useful as different countries/economies have variations in bankruptcy laws and may differ in the definition of corporate default events. To be consistent in the classification of distress indicators across different economies, delayed payments made within a grace period are not classified as an indicator of financial distress.

As each observation requires data for all explanatory variables to estimate the binary logit model, some observations are excluded due to missing observations, mainly in the earlier period of the data sample. Table 3 presents the number of firm-months per year, the respective default events, and the default rate for each economic entity in the benchmark specification after removing 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. Importantly, corporate default events do not occur uniformly over time for all economic regions worldwide. In a cause for concern, corporate default events worldwide tend to cluster under crises, such as during the early 2000s global macroeconomic recession and the 2008 Global Financial Crisis.

Table 3 also shows a notable distinction in corporate default rates across different regions. Unlike corporate default rates in the U.S., most other economies exhibit lower default rates. This observation is unsurprising due to differences in structural characteristics across economies. 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 identified in section 3.1, the firm fundamentals explanatory variables can be classified into two main categories: firm-specific accounting ratio and market-based variables. The 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 economies in Europe are expressed in Euro, while the rest are expressed in U.S. dollars.

Following Campbell et al. (2008), I winsorized the firm-specific variables at 5th and

95th percentiles. This approach controls for potential errors and eliminate unusual outliers in the balance sheet and market data. 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 U.S. three-month Treasury bill yield (Yield), 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. 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, TED Spread and Moody's BAA and AAA corporate credit spread are collected from the FRED, Federal Reserve Bank of St. Louis, Federal Reserve Bank of New York. Global Growth Rate is based on the GDP growth rate of the G7 economies and is collected from OECD. Global growth rate is available at a quarterly frequency, while the rest of global variables are available in monthly frequency and are common to all firms in the data sample. Unlike firm-specific variables, I do not winsorize systematic variables. Appendix Table A.1 presents additional details on the construction and the data source of the explanatory variables.

3.4 Summary Statistics

Table 4 reports the descriptive statistics for the firms' explanatory variables of the eight key economic 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 assess if there is a statistically significant difference in means between the full sample and defaulted firms. The indicator for defaulted firms is measured in the month before the default event (t-1). Table 5 reports the summary statistics of the global factors and financing variables employed in the paper.

Table 4 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, which employ a similar set of explanatory variables.

4 Empirical Results

This section evaluates the significance and relevance of the frailty factor in explaining for corporate default risk exposure on an international scale, particularly focusing on the clustering of corporate default events. 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.

Across different economic regions, I first construct logit models based on firm balance sheet variables. Next, I augment the logit models with market-based variables. Subsequently, to assess the impact of systemic risk and omitted macroeconomic variables on corporate debt distress risk, I incorporate the frailty factor into the logit models. As discussed in section 2, the frailty factor is estimated based on an unconventional GAS framework, where the innovation term is constructed using generalized residuals.

4.1 Firm Fundamentals

Following Campbell et al. (2008), I first estimate a baseline logistic regression that studies firms' distress risk exposure based on the information in balance sheet variables. I separately estimate the binary logit models for the eight different economies. This step allows the subsequent estimation of the impact of the global latent risk factor on corporate debt distress risk while avoiding the confounding effects of simultaneously including market-based and global variables in subsequent analysis.

Table 6 reports the logit model estimates that only include the firms' balance-sheet variables. Across all eight economic 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 6 also shows that corporate default risk is mostly negatively correlated with liquidity (CASH) and positively correlated with market-to-book (MB). However, for some economic regions, the parameter estimates for these variables are insignificant or display counterintuitive signs. 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 not statistically significant. 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.

Table 7 reports the estimates of the logit model that incorporates both firms' balance sheet and market-based variables. In accordance with the findings in 6, table 7 shows that profitability and leverage are still highly significant at the 1% level and display the correct sign.

Additionally, across all eight economic regions, table 7 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. 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).[13]

For each economic region, the loglikelihood, pseudo-R^2, and AUC is considerably higher in table 7 as compared to 6. The finding indicates that incorporating market-based variables provide a universal better explanation of corporate default risk exposure across different economic regions worldwide.

4.2 GAS Frailty Specification

In this subsection, I present the empirical results of the binary logit model that incorporates the frailty factor while still controlling for the firm-specific explanatory variables presented in the previous section.

Table 9 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 for the firm-specific variables described in 7. 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 firm fundamentals. The significant Theta (θ) parameter indicates that the frailty factor in subsequent periods linearly correlates with the frailty factor in the past periods. 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

[13]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 defacult 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

risk model is appropriate.[14]

As compared to the results in table 7, the parameter estimates for all firm fundamentals largely remains statistically significance and display similar magnitude, even after incorporating the frailty factor. The results indicate that the frailty factor does not substitute the firm fundamentals explanatory variables.

A comparison of loglikelihood and pseudo-R^2 based on results in Table 7 and 9 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. Table 10 reports the results for the likelihood ratio tests across all economic regions. Relative to the corporate default risk model that only contains balance sheet and market-based variables, the likelihood ratio tests are all statistically significant at the 0.1% 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,[15] figure 2 plots the actual number of default events in comparison with the model predicted corporate default risk based on explanatory variables in Table 7, 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 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 that compares the default risk model with frailty and the alternative benchmark model without 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 distinguishing individual firms' distress risk exposure. These results hold for all regions. For instance, in the U.S., the OOS AUC for the default risk model with and

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

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

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 economic regions are reported in Table A.2 in the Internet Appendix A. Nonetheless, the key contribution of the frailty factors lies in providing a more realistic estimation of corporate default risk from an aggregate economy perspective 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.

In providing a more intuitive insight to the parameter estimate of the frailty factor, I also quantify the economic significance of the frailty factor. Specifically, I measure the marginal increment of corporate default events due to one standard deviation movement of the frailty factor in each economic region. [16] Table 13 reports the key empirical results of the marginal analysis of the frailty factor specific to each region.[17] 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** based on 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 in 6 corporate default events in a year, excluding the U.S. economy, which is almost 4% of the default events in the data sample.

Overall, Table 13 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.[18]

4.3 Out-of-Sample Analysis and Tail Risk Prediction

Apart from identifying weaknesses and the relevant risk factors that reveal vulnerabilities in corporate debt portfolios in-sample, financial economists are also concerned about the relevant factors that provide a reliable assessment of corporate default risk out-of-sample. A reliable forecast of corporate default risk is critical for portfolio management, capital

[16] Additional description of the computation and interpretation of the empirical results in the marginal analysis is presented in section 5.1

[17] It is challenging to compute to the marginal impact of the frailty factor based on the parameter estimates of the frailty component in Table 9. To mitigate this issue, I separately run a separate logit regression based on the frailty factor that is synthetically estimated in Table 9, 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.

[18] Given the relative computational efficient approach to estimating the frailty factor as compared to prior 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 4.4.

allocation, and identification of risk exposure in corporate debt portfolios.

This subsection studies if incorporating frailty factors can provide a more reliable assessment of corporate default risk out-of-sample across key economic regions worldwide. I focus on forecasting the mean and distribution of the potential number of corporate default events in year t + 1, based on the explanatory variables and parameters estimated up to year t.[19] In other words, the parameters of the corporate default risk models are estimated recursively up to the end of year t. Based on the estimated parameter, information on the explanatory variable in year t is used to forecast the distribution of default risk in period t +1.

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), which indicates that the frailty factor is dynamically updated 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.[20]

Across all three economic regions, Figure 3 shows that the benchmark corporate default risk model largely underestimates corporate default risk exposure during crises. For instance, coinciding with one of the more 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 prediction in these periods stands only at 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. [21]. 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 also broadly shows that incorporating the frailty factor provides a more reliable mean estimate of corporate default events across all three economic regions, especially under crises. Specifically, compared to the counterpart without the frailty factor, the econometrics models with the frailty factor consistently produce a mean estimate closer to the

[19]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

[20]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.

[21]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 frailty factor provides a more realistic assessment of default risk by forecasting the extreme distribution at 50 and 52, respectively.

realized default events across the entire period. Additional econometrics analysis supports the observation in Figure 3, holding for all three key economic regions.

Table 11 presents the results of the econometric analysis. The results strongly support 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. 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 aim to assess if the actual realization of corporate default events at the extreme interval is consistent with the econometric model prediction. The independence test aim to assess if the breach in corporate default events is independent. The tests confirm 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.

In order to show that including the frailty factor provides a more reliable mean estimate of default risk, I 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 11 shows that including the frailty factor provides a smaller absolute error and root mean square relative bias measure for all three economic regions. This finding supports that incorporating the frailty factor produces a more accurate forecast of default risk.

4.4 Incorporating systematic factors

Thus far, my econometrics analysis largely employs firms' balance sheets 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 three-month interest rate, GDP growth rate, and industrial production.[22] Jointly across research in corporate default risk literature, which includes Campbell et al.

[22] To avoid multicollinearity issue, three-month rate is excluded for the U.S. economy

(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.

Based on the additional systematic variables, I repeat the key econometrics analysis in the previous section. The main results are broadly similar. The frailty factors are still highly significant across different economic regions worldwide. Based on the likelihood ratio tests, incorporating frailty factors can better explain firms' corporate default risk exposure. I also conduct an out-of-sample analysis and obtain the same key results. Even with additional systematic variables, excluding frailty factors still underestimate clustered default risk exposure, especially under crises, confirming the importance of systemic risk as the key driver of corporate debt distress. Overall, the findings indicate that firms are still vulnerable to a dynamic latent risk factor, even after considering the key systematic factors employed in corporate default risk literature. The additional empirical analysis detailed in this subsection is available upon request.

5 Global Systemic Risk Factor

In this section, I show substantial evidence of a common global systemic risk factor that explains simultaneous waves of corporate default events worldwide. Firm fundamentals, including market-based variables, and global factors cannot adequately explain the risk inherent in the global systemic risk factor. This finding indicates substantial evidence of a global systemic risk factor that cannot be explained by observable global factors and financing conditions.[23]

Before investigating the static correlation among the frailty factor worldwide, I first present the time series plot of the frailty factors in each economic region. Figure 4 depicts the plot of the frailty factors for different economic regions based on corporate default risk model of table 8.[24] To reiterate, the frailty factor captures corporate distress risk information that is not contained in firm-balance sheet variables. 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 economic regions largely peak around the early 2000s and to a less extent during the 2008 period, indicating that adverse movement in frailty factors are the most severe during these periods. These observations provide

[23]In this and the subsequent section, I will define global frailty factor as a common factor derived from regional frailty factors that only control for firms' balance sheet variables. The global frailty factor captures risk information on measurable global factors, financing conditions, and other omitted variables. In contrast, the global systemic risk factor is a common latent global risk factor constructed after controlling for firms' balance sheets, market-based variables, and orthogonalizing for the impact of standard set global factors. This factor accounts for risk information unexplained by the standard global factors and financing conditions.

[24]The economies in each region are based on Table 1. The frailty factors are separately estimated among different regions and are standardized to allow for convenient comparison across regions.

preliminary evidence of a common global systemic risk factor that impact corporate debt distress risk worldwide.

I conduct the Principal Component Analysis (PCA) among the frailty factors to identify evidence of a common global frailty factor that impacts corporate debt distress risk worldwide. Table 15 presents the result for the PCA analysis based on estimated frailty factors, excluding market-based variables. The results include 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. The first Principal Component explains above 50% 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. The finding indicates evidence of a common global latent risk factor that impacts firms' default risk across different regions worldwide, thus confirming hypothesis 1.

I next conduct a Principal Component Analysis (PCA) among frailty factors that include market-based variables in the estimation. The frailty factors for each region are orthogonalized based on the set global factors and financing conditions identified in section 3. The objective is to assess for evidence of a common global latent risk factor that impacts corporate debt distress risk but cannot be explained by firm fundamentals and observable global financing variables. Table 16 presents the result. The top panel of Table 16 shows that the first PC explains above 45% of the common variations among all the frailty factors, a slight decline as compared to the previous estimation without the market-based variables.[25] Similarly, the frailty factors in all regions load almost equally on the first PC factor with an average of 0.35. The findings suggest that market-based information and global factors may have accounted for a portion of the risk exposure in the global frailty factor estimated in Table 15. This finding supports Asis et al. (2021), and also confirms hypothesis 1. However, these explanatory variables still cannot comprehensively capture the overall risk inherent in the latent global systemic risk factor that impacts corporate debt distress risk worldwide.

Based on the same global factors, I investigate the proportion of risk that standard global factors can explain in the latent global frailty factors. Table 12 presents the result of the multivariate regression with the latent global frailty factor as the dependent variable. Column (1) and (2) depicts the global frailty factor estimated based on regional frailty factors without and with market-based variables respectively. Standard global factors can only explain about 27% of the variations in the global latent risk factor, as represented by the adjusted R^2. After including market-based variables, the adjusted R^2 declines to about 10%. The finding is consistent with Asis et al. (2021), which points out that a portion of firms' vulnerabilities to global factors are reflected in equities information. Across both

[25] A similar application of the principal component analysis among frailty factors that are estimated with market-based variables but are not orthogonalized constructs first principal component that measures above 40% of the variations among different frailty factors.

regressions, I observe that U.S. monetary slope, monetary yield, corporate bond credit spread, and TED spread are highly significant for both or at least one of the regressions. However, key observable global factors and financing variables can only explain a minor proportion of risk in the global frailty factor, thus supporting hypothesis 2.

5.1 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.

Table 13 presents the MEM and AME of the frailty factor that is specific to each region.[26] Based on the variations in the numerical magnitude of the MEM and AME for each region, the result suggests a wide heterogeneity in the average impact of the global systemic risk factor on corporate debt distress risk across different regions. In the more extreme case, the MEM and AME of the global systemic risk factor on Europe firms is 0.00176 and 0.0106. The result suggests that one unit standard deviation increase in the

[26] MEM and AME are computed based on the parameter estimate of the global systemic risk factor, after controlling for the explanatory variables as presented in Table 7. The parameter estimates of the logit regressions are available upon request.

global systemic risk factor will lead to an average increase in Europe firms' risk of default by 0.0106 percentage points (based on AME). This translates to an average increase of 2.36 default events in one year, comprising about 50% of the default events in Europe in each year. In one of the more benign cases, the AME of the global systemic risk factor on Japan's firms is 0.0029. This result suggests that one standard deviation increase in the global systemic risk factor elevates the average firm's default risk in Japan by 0.0029 percentage points, translating to about 1.12 default events in a year. Overall, a one standard deviation increase in the global systemic risk factor leads to an average increase of 1.35 default events in each economic region in a year, comprising up to 20% of the realized default events in the global economy each year, excluding the U.S. economy.

The AME and MEM of the global systemic risk factor may seem numerically small at the individual firm level. However, this impact may be disproportionately large when aggregated among firms across the entire data sample. Table 13 presents the expected number of default event in a year due to one standard deviation increase in the global systemic risk factor. In extreme cases, the global systemic risk factor registers an increase of above three standard deviation during the early 2000s global macroeconomic recession. This translate to an average increase of 5 default events in each economic region in a year during 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 13.

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 the global systemic risk factor. This finding raises concerns that firms worldwide are increasingly vulnerable to falling into financial distress during crises due to unfavorable movement in the global systemic risk factor.

6 International Spillover and Channels of the Global Latent Risk Factor

The previous section identifies a strong degree of static variations among frailty factors worldwide. This section focuses on the mechanisms constructing the global latent risk factor. Based on hypothesis 3, indicating that an adverse shock to firms in an economy transmits financial distress risk to firms in the rest of the world, I focus on identifying corporate default risk spillover over time as the key channel driving the global latent risk factor.[27]

6.1 International Corporate Default Risk Spillover

In investigating evidence of transmission of corporate financial distress risk among economies worldwide, I first conduct the Granger causality tests among frailty factors of different economic regions. As discussed in previous sections, the frailty factors capture additional risk factors not reflected in firm fundamentals and global factors.[28] This approach enables us to assess for evidence of corporate default risk spillover across different economies worldwide, not reflected in firm fundamentals and global factors. The Granger causality test studies predictive relationships among time series variables, which can be employed to study spillover relations across frailty factors. The test can be set up in the following way:

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

Based on the above equation, the null hypothesis is that $\beta_1 = 0$. The null hypothesis suggests that there is no evidence of spillover effects. This suggests that there is no evidence of corporate default risk spillover or causal relation among frailty factors of different regions. Our alternative hypothesis is that $\beta_1 \neq 0$. In this case, x Granger causes y, and there is evidence of spillover effects across different regions' frailty factors. The tests above can be easily modified and applied to study Granger causal relation among frailty factors of different regions.

Considering the variation in the time taken for the impact of default events in a region to be reflected in other economic entities, I control for the length of lags included in the causality tests up to 24 months. Table 14 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 14 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 14 reports substantial evidence of spillover in corporate default risk across differ-

[27] Ideally, having granular data on international firm-level supply chains may provide a deeper insight into the link between corporate business linkages and transmission of financial distress risk. However, available dataset in this area, such as FactSet, only spans a short time series and are mostly sparse on international firm supply chain relations. Otherwise, detailed, granular data on other forms of firm interlinkages worldwide are often confidential. Based on this limitation, my econometric analysis focuses on financial distress risk spillover based on estimated frailty factors of different economies worldwide.

[28] In this section, the frailty factors are estimated based on explanatory variables in table 9, which controls for balance sheet and market-based variables. The frailty factors are then orthogonalized based on global factors in table **??**. This approach allows us to delineate additional risk information not reflected in the standard set of global factors and financing variables.

ent economic regions. Notably, both variations in firms' structural characteristics across economies and proximity of geographical location largely do not affect the severity of corporate default risk spillover. For instance, Table 14 shows substantial evidence of spillover effect from the U.S. economy to Europe, U.K., Australia, and Advanced Asia, as the p-value of the Granger-causality tests is less than 5%. Table 14 also reports similar results in other parts of the world. A detailed breakdown of Granger-causality tests, reported in Appendix Table A.5 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 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, further supporting evidence of a common global latent risk factor that impacts corporate debt distress risk worldwide.

Complementing the Granger-Causality tests, I employ the reduced-form Vector Autoregression model (VAR), examining the dynamic relationship among frailty factors over time. This approach quantifies the severity of cross-economies corporate default risk spillover beyond information reflected in firm fundamentals and global factors. For parsimonious estimation of the VAR model, the key incorporated frailty factors cover five key economies across different continents: U.S., U.K., Germany, Europe, and Japan.[29]The VAR model is written as:

$$Y_t = \mu + A_{t-1}Y_{t-1} + A_{t-2}Y_{t-2} + \varepsilon \tag{9}$$

μ and A are parameters to be estimated. Standard econometrics tests, such as AIC and BIC, suggest one lag. However, the Lagrange multiplier test for autocorrelation in the residuals of the VAR model shows that including two lags eliminates the serial correlation in the residuals. Therefore, the VAR is specified with two lags.

Based on the VAR model in 9, I conduct an impulse response analysis, studying how an adverse shock to an economy impacts the frailty factors in the rest of the world. The shocks are based on a one standard deviation generalized shock to the frailty factor. Figure 8 presents the impulse response functions with 90% confidence intervals, up to 24 months of lag. The confidence intervals are constructed based on bootstrap sample analysis.

Across different economies worldwide, figure 8 largely shows that a standard deviation shock to the frailty factor of a specific economy adversely impacts the frailty factors worldwide over multiple periods. For instance, a standard deviation shock to the frailty factor of the U.S. triggers adverse movements of the frailty factors in the U.K., peaking at month 10 with a response of 0.57. The impact mostly remains statistically significant

[29]In considering the tradeoff between estimating a parsimonious model and mitigating against omitted variable bias that may compromise the interpretation of the VAR model results. The VAR model only considers five economies. A separate estimation of frailty factors with other economies largely yielded the same findings. These results are available upon request.

for the entire 24 months of lag. Largely similar results are also observed for shocks on the frailty factors of other economies and their transmission to the rest of the world.[30]

6.1.1 Variance Decomposition

I next conduct a variance decomposition based on the estimated VAR model (9), focusing on the variations of frailty factor in an economy due to adverse movements of frailty factors from external economic regions. Figure 9 displays the variance decomposition of the variables contained in the VAR model (9) at different horizons.

The figure shows that innovations in the frailty factors of external economies explain up to 25% of the variations in the U.S. frailty factor. Specifically, Canada, U.K., and Europe explain up to 11%, 5%, and 8% of the variations in the U.K. frailty factor. Similarly, external economies explain 28% and 33% of the variations among the frailty factors in U.K. and Europe, respectively. On average, the frailty factors from external economies explain almost 25% of the variations of a specific frailty factor in an economic region. Overall, the variance decomposition analysis reveals a considerable degree of interactions among the frailty factors in the VAR model, pointing to the importance of the transmission of corporate default risk shocks worldwide as the driver of the global latent risk factor.

6.2 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, which trigger severe losses in the financial system. In investigating 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 economic regions 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

[30]Instead of negative shocks, there are few cases of "positive transmission" of shocks. However, these results should be interpreted with caution as they are insignificant.

number of lags.[31] $\tau = (\tau_1, \tau_2)$ 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:

$$p_\tau(k) = \frac{E[\psi_{\tau_1}(x_{1,t} - q_{1,t}(\tau_1))\psi_{\tau_2}(x_{2,t-k} - q_{2,t-k}(\tau_2))]}{E[\psi^2_{\tau_1}(x_{1,t} - q_{1,t}(\tau_1)]E[\psi^2_{\tau_1}(x_{2,t-k} - q_{1,t-k}(\tau_1)]} \tag{10}$$

for k $\in \mathbb{Z}_{\neq 0}$, and $\psi_a(u) = 1[\mathrm{u} > 0]$ - (1-a). The cross-quantilogram in (9) measures 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 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.

Following the cross-quantilogram stated above, 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 τ_1= 0.9, and τ_2 = 0.9.[32] To ensure that our cross-quantilogram is significant, I also calculate the 90% bootstrap confidence intervals[33] 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 cross-quantilogram 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 include the corresponding 90% confidence interval. Across most economic regions 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

[31] 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 our paper focuses on.

[32] Both separate cases of τ_1= 0.85, and τ_2 = 0.85, as well as τ_1= 0.95, and τ_2 = 0.95 are also considered. In both alternate cases, I also largely obtain similar results.

[33] 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

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 across frailty factors of different economies over time. This finding further supports hypothesis 3 and international corporate default risk spillover as the driver of a global latent risk factor that impacts corporate default risk worldwide.

7 Conclusion

Global corporate debt is currently at one of the most vulnerable points of all time. While substantial research on corporate default risk has extensively studied the pertinent 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.

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 economy level, econometrics analyses show a strong degree of common variations and dynamic dependence among the frailty factors over time. These findings support evidence 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 50% of the variations across separately estimated frailty factors across different economic regions worldwide. Key global factors and financing variables can only explain up to 30% of the risk in the global frailty factor, indicating that global corporate credit markets is vulnerable to a common international systemic risk factor not reflected in measurable explanatory variables. Marginal analysis shows that adverse movements in the global systemic risk factor trigger common waves of corporate debt distress risk worldwide, revealing vulnerabilities in international credit markets that are not accounted for by global factors and financing conditions.

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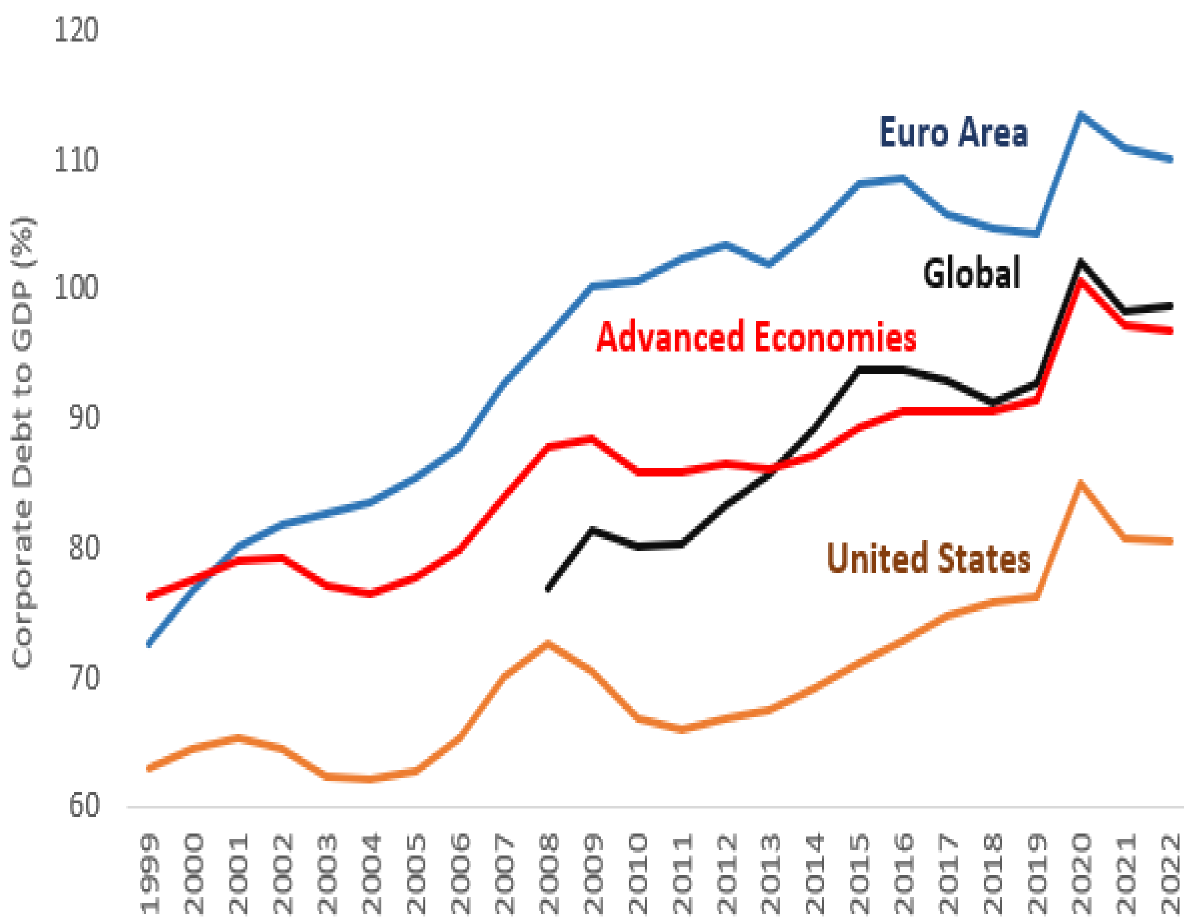
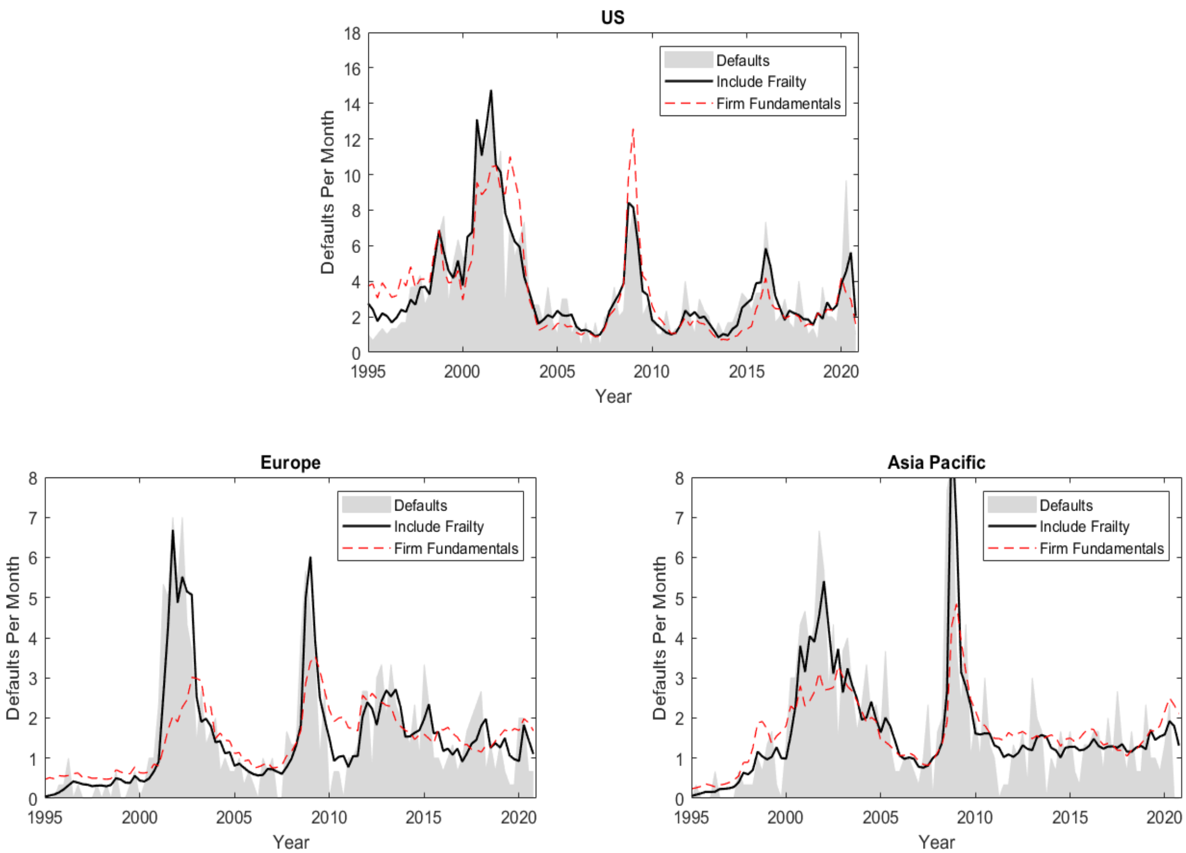
Figure 1: Global Non-Financial Corporate Leverage



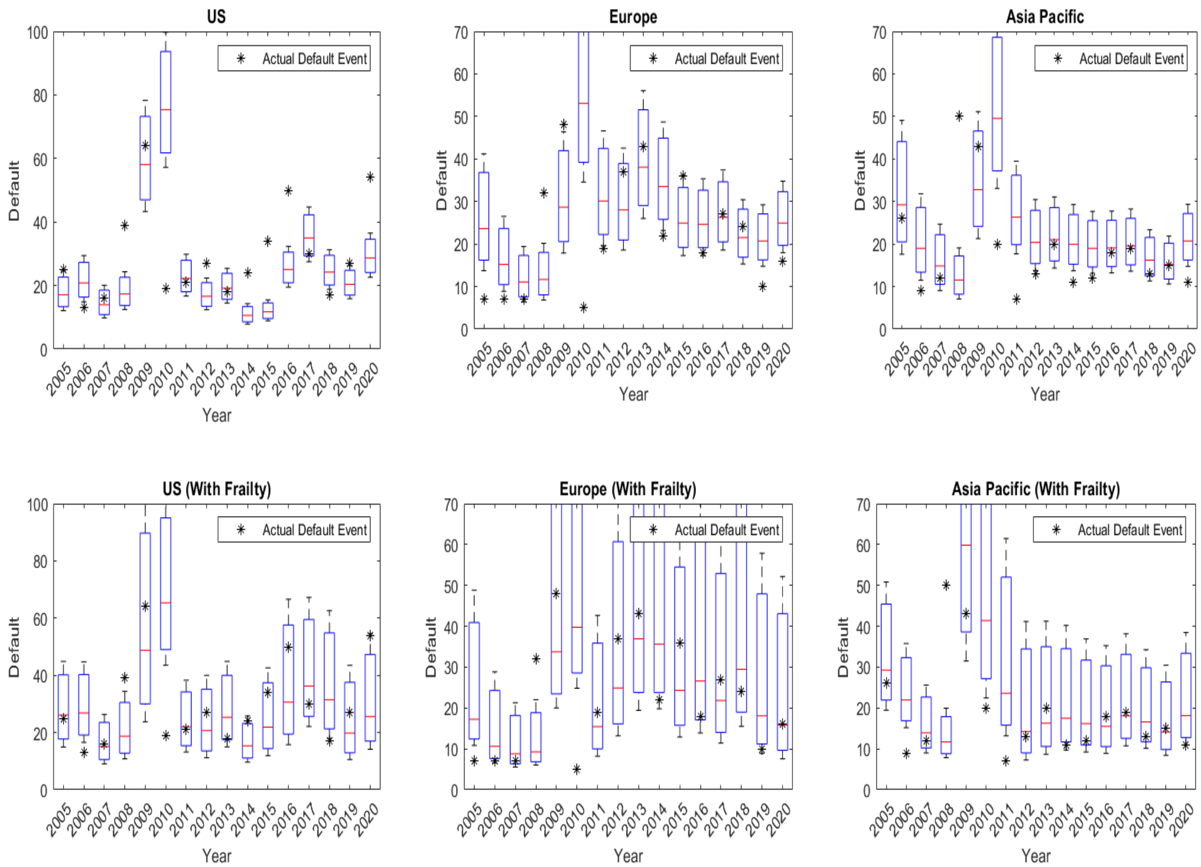
This figure shows the aggregated corporate leverage for the selected economies/regions: United States, Advanced Economies, Euro Area, and the global economy. Aggregated corporate leverage are represented in percentage term and is calculated by taking the aggregated corporate debt divided by the aggregated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

Figure 2: Corporate Default Risk Prediction with Frailty



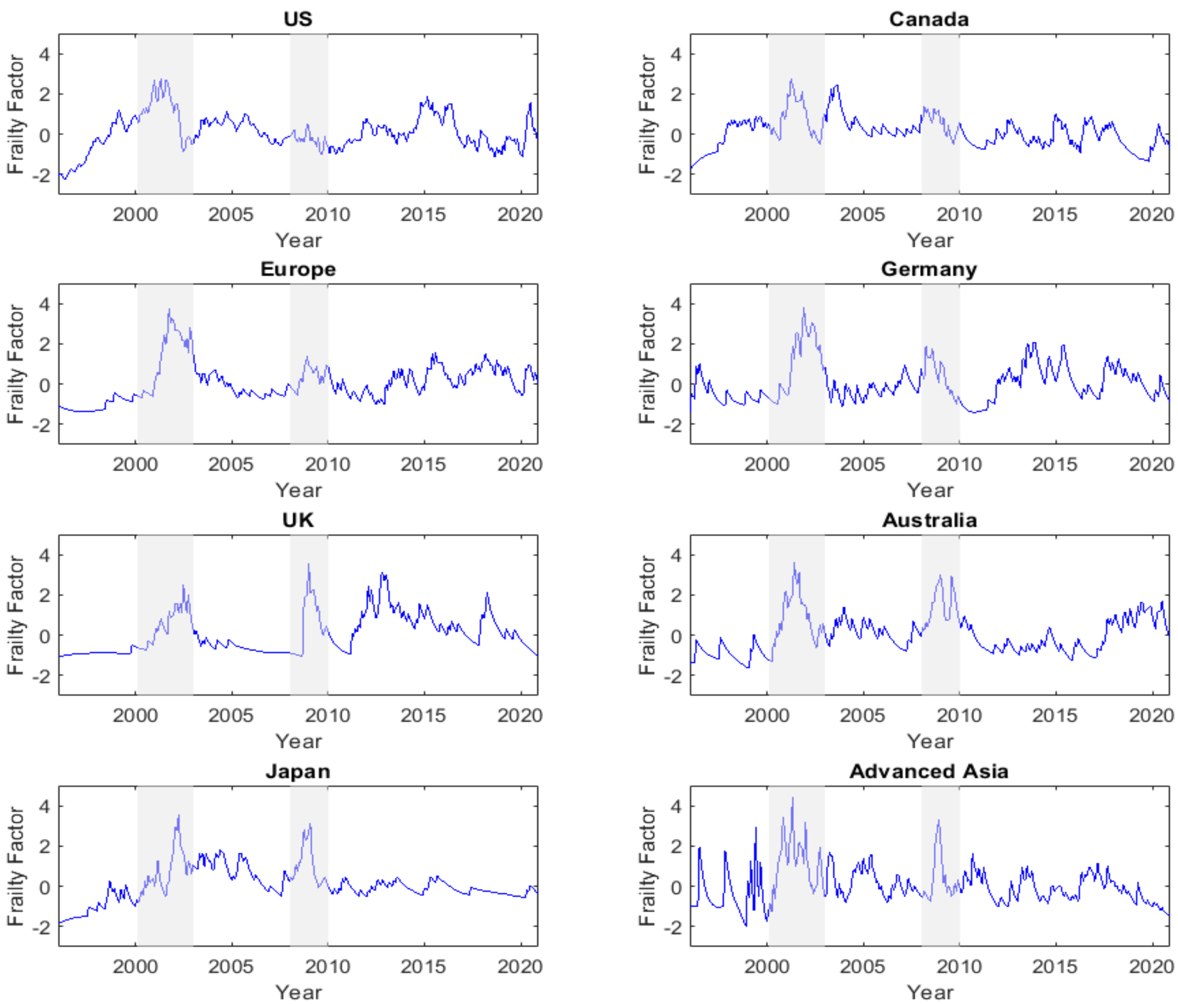
Time series comparison of actual and predicted defaults. The figure shows the number of actual defaults per month (average per quarter) and the corresponding predicted number of defaults using logit models based on Table 7 (with balance sheet and market-based variables) and Table 9 (with Frailty). The 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 explanatory variables in Table 8, which exclude market-based variables. The frailty factors are standardized.

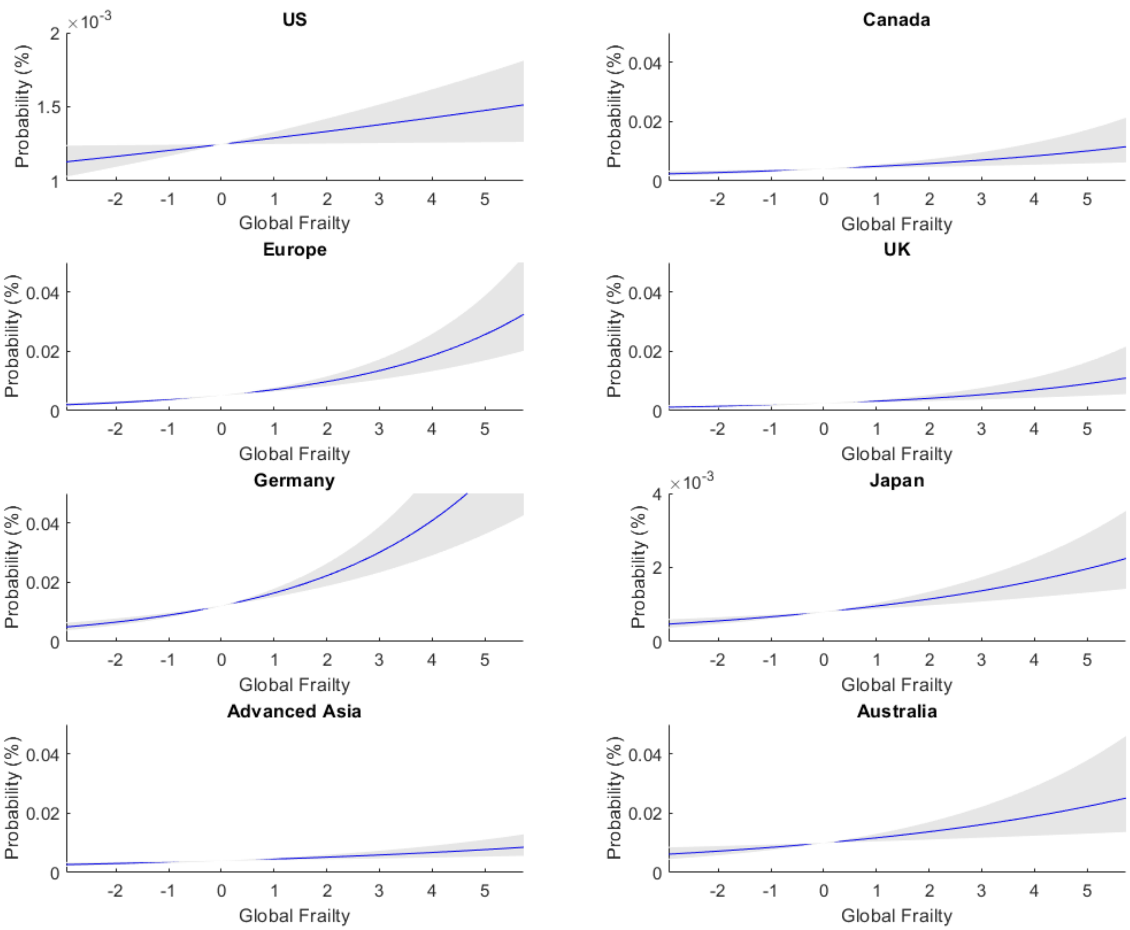
Figure 5: Cross-Quantilogram (North America and Europe)

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)

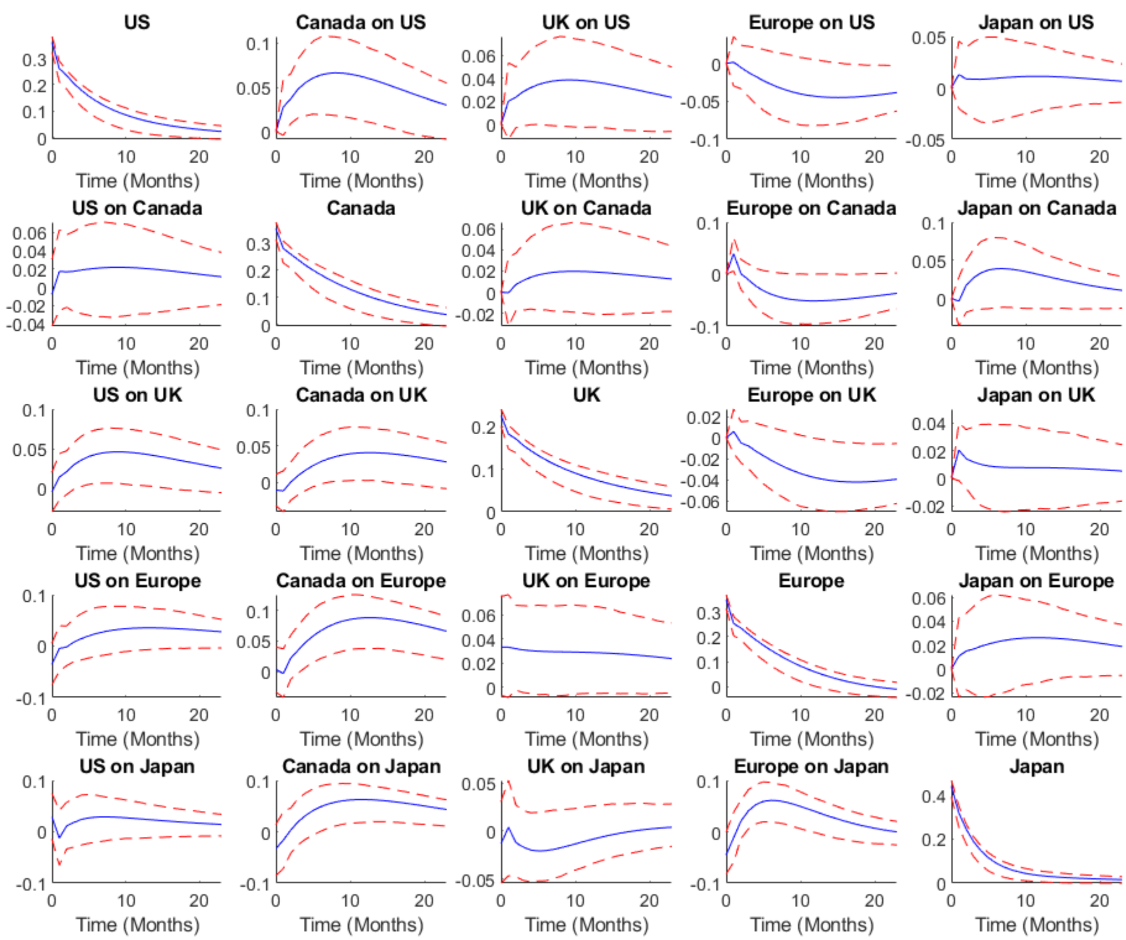
The figure shows the sample cross-quantilogram $\hat{p}(k)$ from U.S. and Europe to the rest of the world, at up to 12 lags. Bar graphs describe the sample cross-quantilograms and lines are the 95% bootstrap confidence intervals centered at zero. $\tau_1 = 0.90$, $\tau_2 = 0.90$

Figure 7: Global Systemic Risk Factor plot



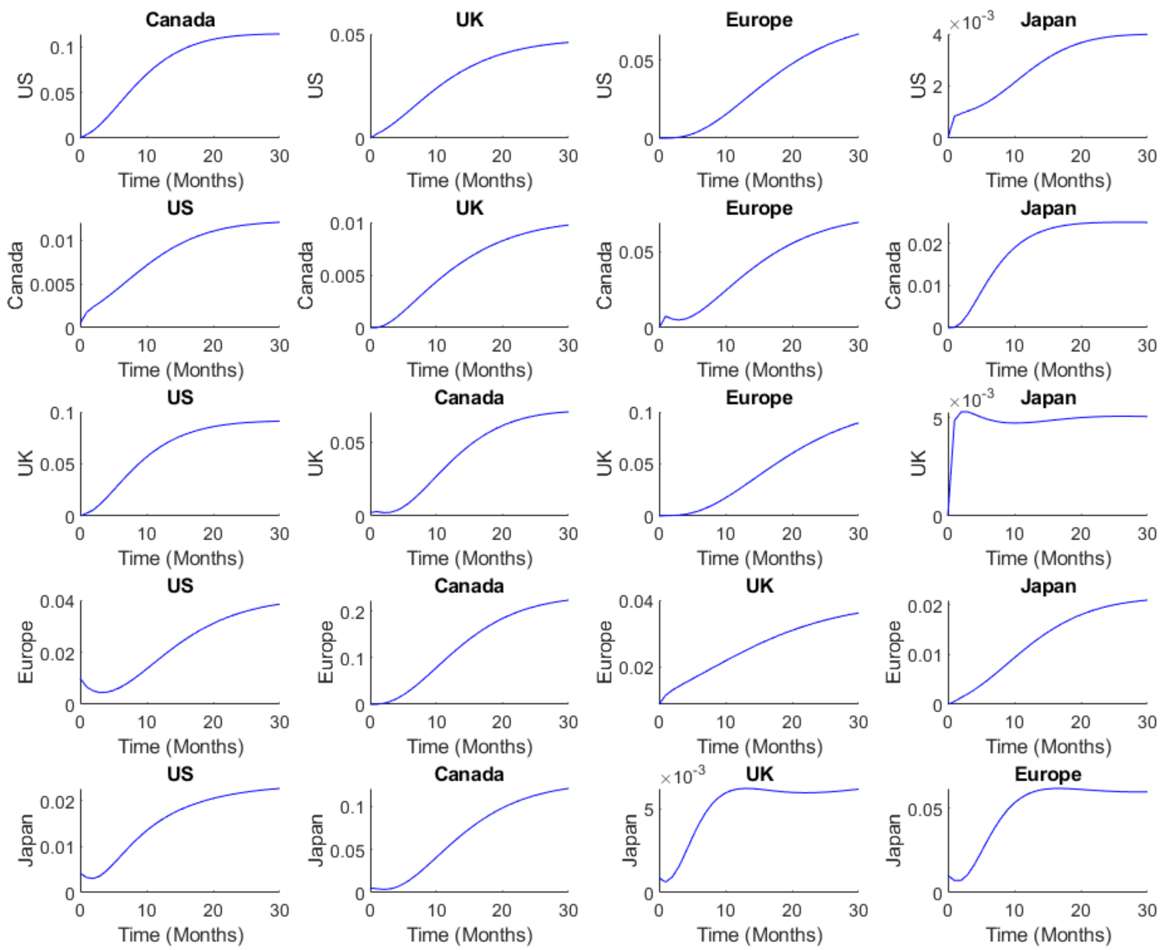
This figure shows the impact of the Global Systemic Risk Factor factor on firms' estimated default risk across different economic regions. The x-axis shows the variation of GCDLF factor, while keeping the other explanatory variables at the sample mean. The shaded grey areas are the 95% confidence intervals, computed using the 95% confidence intervals of each variable's coefficient in the logit model based on Table 9.

Figure 8: 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 9: 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.

Table 1: Economic Regions: Classification of Countries/Economies

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

This table presents the classification of countries/economies into different regions based on geographical proximity and similarities in structural characteristics of the economies

Table 2: Types of Corporate Default Events

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	Bankruptcy
Default Corporate Action	Bankruptcy, Coupon & principal payment, Coupon payment only, Debt restructuring, Interest payment, Loan payment, Principal payment, Alternative Dispute Resolution (ADR, Japan only), Regulatory action (Taiwan only), Financial difficulty and shutdown (Taiwan only), Buyback option

This table presents the three main types of corporate default events that are covered in the CRI database. Within each type of corporate default events, it can be further classified into numerous subcategories.

Table 3: 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 4: 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	***	**		***	***	***	***	***
AdvancedAsia	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	***	†	***	***	***	***	***	***

Summary statistics for firm-months with data for all firm-specific and systematic variables. The first two columns show simple means for full sample, and means for firms that default in the next month. The last column shows the results of a two-sample t-test for equal means of each group of defaulted firms against the whole sample. ***, **, *, and † indicate $p < 0.01$, $p < 0.05$, $p < 0.10$, and $p < 0.15$

Table 5: 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

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

Table 6: Logit regressions of firm's next month probability of default
(Without Market-Based Variables)

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

This table presents the result of the logit regression for the key economic regions worldwide. The logit model includes firms' balance sheets variables to predict a firm's default risk in the next month. 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 7: Logit regressions of firm's next month probability of default

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

This table presents the result of the logit regression for the key economic regions worldwide. The logit model includes firms' balance sheets and market-based variables to predict a firm's default risk in the next month. 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 8: Logit regressions of firm's next month probability of default (With GAS frailty) (Without Market-Based Variables)

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 the key economic regions worldwide. The logit model includes firms' balance sheets and market-based variables to predict a firm's default risk in the next month. 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 9: Logit regressions of firm's next month probability of default (Include GAS frailty)

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 the key economic regions worldwide. The logit model includes firms' balance sheets and market-based variables to predict a firm's default risk in the next month. 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 10: 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 11: 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	0.000***	0.000***	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

Table 12: Drivers of Global Latent Risk Factor

	Regression 1 (Without MB)	Regression 2 (With MB)
(Intercept)	-1.7924***	-1.6033***
	(0.3814)	(0.3679)
CRED Spread	1.8978***	1.2677***
	(0.3086)	(0.2977)
Global Growth Rate	-0.0165	-0.0169
	(0.0676)	(0.0652)
Oil	-1.0209	-1.0379
	(1.0119)	(0.976)
Slope	0.3384***	0.3647***
	(0.1045)	(0.1008)
TED	-0.6992**	-0.2371
	(0.2939)	(0.2835)
Vix	-0.006	-0.0133
	(0.0141)	(0.0136)
Yield	0.0226	0.1701***
	(0.0659)	(0.0636)
Number	300	300
Adjusted R^2	0.262	0.102

This table presents the results of the multivariate least squares regressions of the global frailty factor on a set of global factors and financing conditions. In Regression 1, frailty factors are estimated without market-based variables. In contrast, market-based variables are included in the estimation of frailty factors in Regression 2. ***, **, and * indicates three levels of statistical significance of the coefficients: $p < 0.01$, $p < 0.05$, and $p < 0.10$ respectively.

Table 13: Marginal Analysis of the frailty factor

Economies	Stand Dev	MEM	AME	Δ Defaults
US	0.283	0.0011	0.0855	37.28
Canada	0.408	0.0038	0.0582	4.96
Europe	0.346	0.0059	0.0333	7.44
UK	0.773	0.0023	0.0304	4.08
Germany	0.473	0.0135	0.0893	5.76
Advanced Asia	0.169	0.004	0.0273	9.36
Japan	0.403	0.0007	0.0146	5.6
Australia	0.434	0.0089	0.0334	4.48

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 based on Table 9. 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 14: 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.

Table 15: 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 16: PCA (Include Equities-Related Information)

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) 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 17: Global frailty factor: Marginal Analysis

Economies	Stand Dev	MEM	AME	Δ Defaults
US	1.555	0.00005	0.0031	1.36
Canada	1.455	0.00075	0.0108	0.92
Europe	1.487	0.00176	0.0106	2.36
UK	1.496	0.00068	0.0083	1.12
Germany	1.543	0.00397	0.029	1.88
Advanced Asia	1.36	0.00054	0.0038	1.28
Japan	1.464	0.00015	0.0029	1.12
Australia	1.404	0.00163	0.0057	0.76

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 Table 9. 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.

Appendix

Global Corporate Default Risk Factors: Frailty and Spillover Effects

A Appendix A

Table A.1: 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 CRI (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, where book value of equity is total assets minus total liabilities. Following Campbell et al. (2008) and Asis et al. (2021) in the calculation of this value. If a firm has negative book value of equity, the book value of equity is set to $1 so as to place that firm's market-to-book ratio in the right-hand side of the distribution.
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 CRI (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

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.2: 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.3: 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 the key economic regions worldwide. The logit model includes firms' balance sheets 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 9. 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.4: 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 the key economic regions worldwide. The logit model includes firms' balance sheets 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. 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: 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	$0.115^{\dagger}$	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	$0.122^{\dagger}$	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	$0.134^{\dagger}$
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^{*}	$0.145^{\dagger}$	$0.117^{\dagger}$
UK to ROW	US	Canada	Europe	Germany	Japan	Australia	AdvancedAsia
Less than 6 months	0.006^{***}	$0.127^{\dagger}$	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^{**}	$0.140^{\dagger}$	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^{**}	$0.105^{\dagger}$	$0.128^{\dagger}$	0.366	0.235
6 - 12 months	0.097^{*}	0.018^{**}	0.318	0.020^{**}	$0.141^{\dagger}$	0.554	0.084^{*}
12 - 24 months	0.423	0.050^{*}	0.011^{**}	0.031^{**}	0.233	0.637	$0.131^{\dagger}$
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	$0.132^{\dagger}$	0.034^{**}
12 - 24 months	0.562	$0.102^{\dagger}$	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	$0.127^{\dagger}$	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^{***}	$0.103^{\dagger}$
6 - 12 months	0.001^{***}	0.286	0.006^{***}	0.077^{*}	$0.143^{\dagger}$	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 $p < 0.15$