# Option-Implied Local Currency Credit Spreads

ABSTRACT

We develop an option-based framework to measure corporate credit spreads in both local (LC) and foreign (FC) currencies. These measures isolate the underlying default risk while allowing cross-currency differences to reflect the pricing of default risk across currencies. Using FX and stock index options from 29 developed and emerging markets, we construct comparable LC and FC spreads not widely available in bond markets. LC spreads predict economic activity at both country and global levels, while the FC-LC spread differential reflects a risk premium that forecasts exchange rate movements. Our framework clarifies the link between currency denomination in credit pricing and exchange rate dynamics.

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# 1 Introduction

We develop an option-based measure of corporate credit spreads across currencies. Using equity index and foreign exchange options, we construct matched local- and foreign-currency credit spreads that correspond to the same underlying default probability. Any difference between the two spreads therefore reflects a currency component in the pricing of credit risk.

Credit spreads are widely used indicators of financial conditions and economic activity (e.g., Gilchrist and Zakrajšek, 2012; Krishnamurthy and Muir, 2025; Krishnamurthy and Li, 2025). At the same time, corporate borrowing increasingly occurs in multiple currencies, and non-dollar corporate debt now represents a substantial share of global credit markets (Maggiori, Neiman, and Schreger, 2020). As firms issue debt in different currencies, credit spreads denominated in different currencies may reflect distinct exposures to currency risk and global financial conditions. Studying credit spreads across currencies has therefore become increasingly important. Yet, comparable multi-currency credit spreads are rarely available from corporate bond data.[1] We address this challenge by inferring them from option markets.

To construct such measures, we build on the option-implied credit spread framework of Culp, Nozawa, and Veronesi (2018) and extend it to a multi-currency setting. We consider pseudo-firms that invest in a country's stock market index (e.g., the FTSE 100) and finance this position with zero-coupon debt denominated in local currency. Following Merton (1974), the firm's debt can be viewed as a short put option on the underlying asset. This structure allows us to value pseudo debt directly from traded index options, so that the firm's balance sheet is fully observable and inferred from market prices. Pseudo credit spreads are computed as the difference between pseudo bond yields and option-implied risk-free rates (Brenner and Galai, 1986; Van Binsbergen, Diamond, and Grotteria, 2022).

We then construct matched credit spreads for pseudo-firms with identical default probabilities but debt denominated in different currencies. To obtain the foreign-currency (FC)

[1] Appendix Table A.1 underscores that bond data are not directly comparable across currencies: local-currency indices cover domestic issuers, while USD indices reflect global issuance, and they differ markedly in composition, maturity, ratings, and data availability across countries.

counterpart, we use USD-denominated ETFs that track the local stock market index and the put options written on these ETFs. When options on the USD ETFs lack sufficient liquidity, we synthesize USD credit spreads by combining option-implied volatility on the local index and the exchange rate.

Prior studies examine credit risk across currencies using either sovereign local-currency spreads (Du and Schreger, 2016) or the corporate currency basis, i.e., the price discrepancy between bonds issued in different currencies by the same firm (Galai and Wiener, 2012; Caramichael, Gopinath, and Liao, 2021; Hu, Shi, Viswanath-Natraj, and Wang, 2022; Galvez, Gambacorta, Mayordomo, and Serena, 2021). We introduce a novel measure of cross-currency corporate credit risk by inferring credit spreads directly from option markets and benchmark equity indices.

Compared to existing approaches, pseudo spreads offer several advantages. Because the framework embeds identical default probabilities across currencies, it enables consistent cross-currency comparisons within a unified pricing model. In contrast, corporate currency basis measures rely on matched bonds issued in different currencies by the same firm and may be affected by differences in liquidity, taxation, regulation, or investor clientele across markets. In addition, the option-based construction yields systematic measures of short-term credit spreads – for example at three-month horizons – whereas short-maturity corporate bonds are often scarce or illiquid. Finally, because pseudo spreads are derived from benchmark equity indices, they capture aggregate corporate credit conditions rather than the characteristics of individual bond issues, which is particularly relevant in bank-based financial systems (Ayala, Nedeljkovic, and Saborowski, 2017).

We construct a monthly panel of local- and foreign-currency pseudo credit spreads for 29 countries and the Eurozone from 1996 to 2023. The data combine options on local stock market indices with options on USD-denominated ETFs tracking the same indices, covering both developed and emerging markets. The resulting panel provides systematic measures of corporate credit spreads across currencies at maturities of 3, 6, 12, and 24 months.

We first document several empirical properties of pseudo credit spreads. Pseudo spreads

closely resemble credit spreads inferred from corporate bonds in both magnitude and cyclical behavior. For example, the average six-month local-currency (LC) pseudo spread for developed economies is approximately 3.44%, about 120 basis points lower than the 4.64% observed for the foreign-currency (FC) counterpart. FC spreads are generally higher and more sensitive to economic downturns.

Although LC and FC spreads exhibit substantial co-movement, they differ markedly in both levels and dynamics despite embedding identical default probabilities. These differences therefore reflect currency-related risk premia in the pricing of corporate credit risk. Consistent with a risk premium interpretation, the ratio of risk-neutral to physical default probabilities is systematically higher for FC-denominated spreads. These ratios typically range between 1 and 3 but occasionally exceed 10, a pattern consistent with the magnitude of risk premia documented in corporate bond markets (Berndt, Douglas, Duffie, and Ferguson, 2018).

To interpret these patterns, we develop a stylized model of multi-currency credit spreads calibrated to U.K. data. The model reproduces two central empirical features: USD-denominated credit spreads are higher on average and more sensitive to economic downturns than their GBP counterparts. The framework shows that these differences arise from the interaction between exchange rate dynamics, equity market fluctuations, and the corresponding risk premia. The framework also clarifies how credit spreads aggregate from individual firms to market indices, showing that index spreads can be either higher or lower than the average spreads of their constituent firms depending on whether loss given default is treated as constant or endogenous.

We next examine the determinants of LC credit spreads, addressing the literature's predominant focus on USD-denominated spreads. LC spreads respond strongly to both default risk and risk premia: a 1 percentage point increase in the physical default probability $P$ raises spreads by about 35 basis points, while a 1 percentage point increase in the risk premium $(Q - P)$, where $Q$ denotes the risk-neutral default probability, raises spreads by roughly 55 basis points. LC spreads also increase with higher stock market volatility, currency depreciation, and elevated economic uncertainty, consistent with heightened perceived risk.

Conversely, spreads tend to be lower in countries with larger foreign exchange reserves and lower domestic inflation, suggesting that stronger monetary policy credibility helps anchor local-currency credit conditions.

Pseudo quanto spreads – the difference between USD and local-currency credit spreads – primarily reflect cross-currency variation in risk premia. Consistent with our model, they arise from the covariance between default risk and the pricing kernel rather than from differences in physical default probabilities. Their dynamics are driven mainly by exchange rate volatility, relative equity market performance, and interest rate differentials, while global factors play a more limited role. These results establish the pseudo quanto spread as a measure of the currency-specific pricing of corporate credit risk.

In the final step of our analysis, we assess the informational content of our pseudo credit spreads for forecasting real economic activity and exchange rates. We find that pseudo credit spreads are strong predictors of future GDP growth. A 100 basis point increase in a country's LC spreads forecasts a 0.025 percentage point decline in aggregate GDP growth over the next quarter (approximately 0.1 pp on an annualized basis). Decomposing the spread reveals that both the physical default probability ($P$) and the credit risk premium ($Q - P$) significantly predict GDP growth at both one-quarter and one-year horizons. At the country level, a 100 bp increase in LC pseudo spreads is associated with a 0.31 percentage point decline in GDP growth over the subsequent year. These predictive relationships remain robust after controlling for a broad set of macro-financial variables and standard credit indicators, including the GZ spread (Gilchrist and Zakrajšek, 2012) and the U.S. pseudo spread (Culp, Nozawa, and Veronesi, 2018). This result underscores the unique, country-specific information embedded in our measure.

In addition, pseudo credit spreads, and especially pseudo quanto spreads, contain predictive information about exchange rate movements. Higher LC pseudo spreads forecast local currency appreciation at the one-year horizon, consistent with a risk premium channel. The predictive power of the quanto spread is particularly strong in countries where exchange rates co-move with local equity markets or global financial conditions, providing further support for a risk-based explanation of the observed currency predictability.

Our empirical findings are consistent with evidence of exchange rate predictability with measures of risk premia, as in Kremens and Martin (2019) and Della Corte, Jeanneret, and Patelli (2023) or Kremens, Martin, and Varela (2025), but extend this literature in several important ways. While prior studies primarily rely on equity-based quanto measures or sovereign credit spreads, we introduce a credit-based quanto spread derived from corporate pseudo credit spreads, an approach that is both theoretically grounded and practically implementable using option market data. This framework helps isolate the risk premium embedded in credit markets, distinct from default expectations, and offers a broader, cross-country perspective on exchange rate predictability. Overall, our results contribute a novel dimension to the literature, showing that pseudo credit spreads not only serve as predictors of economic growth but also encode valuable information on the pricing of credit risk across currencies.

Our analysis of LC credit risk relates to Du and Schreger (2016), who compute sovereign LC credit spreads using bond and swap data. In contrast, we derive corporate LC credit risk from traded equity index options, following the methodology of Culp et al. (2018) and building on the foundational insights of Merton (1974). While Culp et al. (2018) focus on the cross-section of U.S. equities, we extend their framework internationally to construct a measure of corporate credit spreads in both local and foreign currencies. We show that LC debt exhibits lower systematic risk than its FC counterpart, suggesting that the credit spread differential between FC and LC debt largely reflects differences in risk premia. Our option-implied measure of multi-currency credit spreads contributes to the emerging literature on the corporate basis, which is linked to firms' currency preferences in debt financing (Caramichael, Gopinath, and Liao, 2021; Galvez, Gambacorta, Mayordomo, and Serena, 2021) or investors' demand for the US dollar (Hu, Shi, Viswanath-Natraj, and Wang, 2022).

More broadly, our work connects to the literature on firms' currency choices in debt issuance. Maggiori, Neiman, and Schreger (2020) document that larger firms are more likely to issue debt in foreign currency, while smaller firms predominantly borrow in local currency. Similarly, Eren, Malamud, and Zhou (2023) show that firms in emerging markets often favor foreign currency debt, even when local currency borrowing would provide a bet-

ter hedge during economic downturns. Using firm-level bond data, Bruno and Shin (2017, 2020) find that emerging market firms frequently pursue a carry trade strategy by issuing dollar-denominated debt to finance investments in domestic currency assets.

Overall, this paper makes several key contributions to the literature on credit risk and international finance. Theoretically, we develop a framework that explains how the joint dynamics of exchange rates and stock market returns generate differential pricing of default risk – and hence credit spreads – across currencies. Methodologically, we extend the pseudo-firm approach to facilitate systematic cross-currency comparisons of credit spreads while holding default risk constant. Empirically, we document new stylized facts about the behavior of credit spreads across currencies and show that the currency dimension of credit spreads contains valuable information about future economic conditions.

Section 2 outlines our methodology and describes the construction of pseudo credit spreads across currencies, using the U.K. as an illustrative case. Section 3 develops a stylized framework to explain the observed differences between LC and FC credit spreads. Section 4 presents the international option sample and examines the economic drivers of pseudo credit spreads. Section 5 investigates the predictive content of these spreads for future economic activity and exchange rates. We conclude in Section 6.

# 2 Option-Implied Credit Spreads Across Currencies

We first define pseudo firms and their debt claims and map option prices into credit spreads across currencies. We then validate the empirical properties of these spreads and show that they capture economically meaningful variation in credit risk.

## 2.1 Pseudo Bonds

Pseudo firms are synthetic entities with fully observable balance sheets. Consider a firm that holds the stock market index (e.g., S&P500), so that its assets satisfy $A_t = SPX_t$. The firm

finances this position with equity and zero-coupon debt of face value $K$ and maturity $T$.

Debt is risky because the firm defaults when $A_t < K$, in which case bondholders receive $A_T$; otherwise they receive $K$. The payoff can therefore be written as $\min(K, A_T)$. Following Merton (1974), the value of the pseudo bond at time $t < T$ is given by:

$$\widehat{B}_t(K,T) = K\widehat{Z}_t(T) - \widehat{P}_t^{SPX}(K,T), \tag{1}$$

where $\widehat{Z}_t(T)$ denotes the price of a risk-free discount bond, $\widehat{P}_t^{SPX}(K,T)$ the price of a European put option on the index, and where we use the notation $\widehat{(\cdot)}$ to indicate traded or observable market instruments. The implied leverage is determined by $K/A_t$, which pins down the firm's default threshold.

## 2.2 Default Probabilities and Credit Spreads

We recover default probabilities and credit spreads from option-implied pseudo bond prices. For a pseudo firm defined by strike $K$ and horizon $\tau$, the ex-ante default probability is:

$$p_t(\tau) = \mathbb{P}\left[A_{t+\tau} < K \mid \mathcal{F}_t\right], \tag{2}$$

where $\mathcal{F}_t$ denotes the time-$t$ information set. We model asset growth over horizon $\tau$ as:

$$\ln(A_{t+\tau}/A_t) = \mu_{t,\tau} + \sigma_{t,\tau}\varepsilon_{t+\tau}, \tag{3}$$

where $\mu_{t,\tau}$ and $\sigma_{t,\tau}$ denote conditional mean and volatility, and $\varepsilon_{t+\tau}$ are standardized shocks.

We estimate $\mu_{t,\tau}$ using predictive regressions with the dividend-price ratio and $\sigma_{t,\tau}$ via a GARCH(1,1) model. Using these estimates, we construct the empirical shock distribution:

$$\widehat{\varepsilon}_{t+\tau} = \left(\ln(A_{t+\tau}/A_t) - \widehat{\mu}_{t,\tau}\right)/\widehat{\sigma}_{t,\tau}, \tag{4}$$

and compute default probabilities nonparametrically as:

$$\widehat{p}_t(\tau) = \mathbb{P}\left[\widehat{\varepsilon}_{t+\tau} < X_t\right], \quad X_t = \left(\ln(K/A_t) - \widehat{\mu}_{t,\tau}\right)/\widehat{\sigma}_{t,\tau}. \tag{5}$$

We assign pseudo bonds to rating categories by matching $\widehat{p}_t(\tau)$ to Moody's historical default frequencies (Moody's, 2022).

Credit spreads follow directly from pseudo bond prices. For each $(K, T)$, we compute the pseudo yield:

$$\widehat{y}_t(K,T) = -\left(T-t\right)^{-1} \ln\left(\widehat{B}_t(K,T)/K\right), \tag{6}$$

using 1996 to 2023 SPX option data from OptionMetrics and define credit spreads as:

$$\widehat{cs}_t(K,T) = \widehat{y}_t(K,T) - \widehat{r}_t(T), \tag{7}$$

constructed using zero-coupon yields from the Federal Reserve Economic Data (FRED) constant maturity Treasury rates. We construct aggregate spreads by averaging across options within rating categories and maturities. Appendix A provides implementation details.

Panel (a) in Figure 1 shows that our reconstructed spreads closely match those in Culp et al. (2018), confirming the validity of the approach. A regression of their spreads on ours over the overlapping period yields an adjusted $R^2$ of 0.85 (0.82) and a slope coefficient of 0.93 (0.78) for investment-grade (high-yield) spreads.

## 2.3 Option-Implied Risk Free Rates

We depart from Culp et al. (2018) and infer risk-free rates directly from option prices to ensure consistency with our construction of pseudo credit spreads. Specifically, we extract discount rates from box spreads using put-call parity applied to European-style index options, following Brenner and Galai (1986) and Van Binsbergen et al. (2022).

These option-implied rates are free of credit risk and convenience yields. Panel (b) of Figure 1 shows that credit spreads constructed using box rates closely match those obtained using Treasury yields of (Gürkaynak et al., 2007), with correlations exceeding 0.98 across both investment-grade and high-yield segments.

## 2.4 Local and Foreign Currency Credit Spreads

We extend the framework to construct credit spreads in both local and foreign currencies. This requires option data on the domestic equity index and on instruments tracking the same index in foreign currency.

We illustrate the approach using the U.K., where we observe options on the FTSE100 index in GBP (ESX) and on USD-denominated exchange-traded funds (ETFs) tracking the same index. USD denotes the foreign currency throughout and is denoted by \$. We focus on six-month maturities, where option liquidity is highest.

Conceptually, we compare the credit spread of a pseudo firm issuing debt in local currency with that of an otherwise identical firm issuing debt in foreign currency. The two firms share identical default risk, so differences in their credit spreads reflect the pricing of risk across currencies and not differences in covenants or legal structures.

Panel (a) of Figure 2 plots the resulting local-currency credit spread.[2] The series exhibits substantial time variation, with pronounced increases during major macroeconomic episodes such as the Global Financial Crisis, Brexit, and the COVID-19 pandemic.

To construct foreign-currency (FC) credit spreads, we use USD-denominated ETF options tracking the same underlying index. In the U.K. case, we rely on options on USD-denominated ETFs referencing the FTSE100.

The key step is to construct matched pseudo bonds with identical default probabilities across currencies. Since corporations cannot selectively default by currency, the physical default

[2]We restrict ex-ante default probabilities to remain below the CCC Global Corporate Average Cumulative Default Rate reported by S&P for the period 1981-2023, i.e., 25.98% (35.95%) for maturities equal or lower than 12 (24) months for the two-year horizon. We use only options with maturities between 91 and 365 days.

probability must be the same for local- and foreign-currency debt.[3] We therefore choose the FC strike $K^{\$}$ such that:

$$\widehat{p}_t(\tau) = \mathbb{P}\left[A_{t+\tau} < K \mid \mathcal{F}_t\right] \equiv \widehat{p}_t^{\$}(\tau) = \mathbb{P}\left[A_{t+\tau}^{\$} < K^{\$} \mid \mathcal{F}_t\right], \tag{8}$$

where $A_{t+\tau}^{\$}$ denotes the index value in foreign currency.

In practice, an exact match is rarely available, so we average across options with strikes and maturities that closely align with the target default probability and horizon (see Appendix A for details). We then compute FC credit spreads using option-implied risk-free rates from box spreads.

Panel (a) of Figure 2 shows that FC spreads co-move closely with their LC counterparts but are typically higher and more volatile. By construction, default probabilities are nearly identical across currencies, confirming that cross-currency differences in spreads reflect differences in risk premia. Panel (b) of Figure 2 shows that default probabilities are nearly identical across currencies, consistent with the construction. Panel (c) reports the number of options used to construct the indices, reflecting the tighter selection required for foreign-currency spreads.

## 2.5 Synthetic Local and Foreign Currency Credit Spreads

When USD-denominated ETF options are unavailable, we construct synthetic foreign-currency (FC) pseudo bonds. The key idea is to replicate FC-denominated claims using the local-currency index and the exchange rate.

We define the FC asset value as $A_t^{\$} = A_t S_t$, where $S_t$ denotes the exchange rate in units of foreign currency per unit of local currency. The corresponding pseudo bond price is:

$$\widehat{B}_t^{\$}(K^{\$}, T) = K^{\$}\widehat{Z}_t^{\$}(T) - \widehat{P}_t^{\$}(K^{\$}, T), \tag{9}$$

[3] Physical default probabilities are identical across currencies, but risk-neutral probabilities may differ due to variation in risk premia.

where $\widehat{P}_t^{\$}(K^{\$}, T)$ denotes the price of a put option on $A_t^{\$}$. As before, we choose the strike $K^{\$}$ to match the physical default probability of the local-currency pseudo bond (see Appendix A.4). The option horizon $\tau$ is set to match that of the LC-denominated pseudo bond.

In the absence of traded FC options, we price $\widehat{P}_t^{\$}(K^{\$}, T)$ using the Black-Scholes-Merton formula (Black and Scholes, 1973) with inputs $(A_t^{\$}, K^{\$}, \widehat{r}_t^{\$}, \widehat{\sigma}_t^{\$})$. The FC volatility satisfies

$$\sigma^{\$} = \sqrt{\sigma^2 + \sigma_S^2 + 2\rho\sigma\sigma_S}, \tag{10}$$

where $\sigma$ and $\sigma_S$ denote equity and exchange rate volatilities, and $\rho$ their correlation. We implement a conditional version using option-implied volatilities and rolling estimates of $\rho$ (see Appendix B.2).[4]

Risk-free rates in foreign currency are inferred from covered interest parity by combining local box rates with the forward premium (Du and Schreger, 2016), which provides a market-consistent funding benchmark even in the presence of CIP deviations (Appendix A.5).

Figure 3 compares empirical and synthetic spreads across currencies. Panel (a) shows local-currency spreads, Panel (b) foreign-currency spreads, and Panel (c) the combined series. Synthetic spreads closely track their empirical counterparts, supporting the validity of the construction. The resulting series reflect the credit risk of twin pseudo firms issuing debt in different currencies but sharing identical default probabilities.

## 2.6 Stylized Facts on Local and Foreign Currency Credit Spreads

We document several stylized facts on the joint behavior of local- and foreign-currency (LC and FC) pseudo credit spreads.

Figure 4 summarizes the joint behavior of local- and foreign-currency credit spreads. Panel (a) shows that FC spreads are generally higher and more volatile than their LC counterparts,

[4] In implementation, we use option-implied equity volatility and at-the-money FX implied volatility, and estimate the correlation $\rho$ using a rolling window of monthly returns. Following Della Corte et al. (2023), we use realized correlations as a proxy for their risk-neutral counterparts.

averaging 3.90% and 2.90%, respectively. Panel (b) reports the ratio of FC to LC spreads, which exceeds one for most of the sample. Panel (c) shows the spread differential, indicating an average gap of about 100 basis points.

Figure 5 examines the relation between physical and risk-neutral default probabilities and the associated leverage dynamics. The ratio of risk-neutral to physical default probabilities, shown in Panel (a), is generally above one and varies substantially over time, especially during periods of market stress (9/11, Global Financial Crisis, COVID pandemic). It typically ranges between 1 and 3 but can exceed 10 in extreme episodes.[5]

A comparison across currencies in Panel (b) shows that this wedge is often larger for FC pseudo bonds, even though implied volatility is frequently lower in foreign currency. Finally, Panel (c) reports implied leverage ratios, defined as $L_t = A_t/K$ and $L_t^{\$} = A_t^{\$}/K^{\$}$, indicating that FC-denominated pseudo firms experience more pronounced deleveraging during downturns.

Finally, Figure 6 shows that cross-currency differences in credit spreads, also known as quanto spreads, are tightly linked to differences in risk-neutral default probabilities. The positive relation between the quanto spread and the differential in risk-adjusted default probabilities indicates that cross-currency variation in spreads primarily reflects differences in risk premia rather than in physical default risk.

## 2.7 Connection to a Structural Credit Risk Model

We validate our measure by embedding it in a standard structural model of credit risk. Specifically, we simulate a firm in the Merton (1974) framework and construct a corresponding pseudo firm whose physical default probability matches that of the underlying firm. We then compare the credit spreads of the two.

[5]Risk-neutral default probabilities are computed using the Black-Scholes-Merton framework, while physical default probabilities are estimated from the historical distribution of normalized index return shocks, as described in Section 2.2.

This exercise shows that pseudo credit spreads provide an economically meaningful proxy for corporate credit risk rather than a mechanical transformation of option prices. Because pseudo firms share the same underlying default risk, their spreads co-move closely with those of the underlying firm, exhibiting a tight, near-linear relationship, while differences in levels reflect variation in risk premia embedded in option prices. Appendix C provides the full implementation.

### 2.8 Reconciling Firm- and Index-level Credit Spreads.

A related concern is that pseudo spreads are constructed from aggregate equity indices, which differ from individual firms due to diversification. In standard structural models with constant loss given default, diversification lowers asset volatility and raises the asset Sharpe ratio at the index level. For a given physical default probability, this implies higher risk-neutral default probabilities and therefore higher credit spreads for the index. This prediction runs counter to the empirical evidence in Table 2 of Culp et al. (2018), which shows that firm-level spreads exceed index spreads. We show that this apparent tension is resolved once loss given default is allowed to vary endogenously. In this case, higher idiosyncratic volatility at the firm level increases the severity of default states and thus expected losses, which can outweigh the Sharpe-ratio effect and generate higher firm-level spreads. Appendix D provides a formal analysis and supporting simulation evidence.

## 3 A Framework for Cross-Currency Credit Risk Premia

We develop a stylized framework to interpret differences between LC and FC pseudo credit spreads. The key insight is that, even when default risk is identical across currencies, credit spreads can differ due to differences in risk premia.

## 3.1 Economic Mechanism

**The framework.** Consider two pseudo firms that invest in the same underlying equity index but issue debt in different currencies. Let the LC-denominated asset $A_t$ and the exchange rate $S_t$ (USD per unit of LC) follow geometric Brownian motions:

$$dA_t/A_t = \mu\, dt + \sigma\, dW_t, \qquad dS_t/S_t = \mu_S\, dt + \sigma_S\, dW_t^S, \tag{11}$$

where $\mu$ and $\sigma$ denote the expected return and volatility of the equity index, and $\mu_S$ and $\sigma_S$ denote the expected exchange rate return and volatility. The shocks $dW_t$ and $dW_t^S$ are standard Brownian motions with correlation $\rho$, capturing the co-movement between equity and exchange rate returns.

The asset value in foreign currency is given by $A_t^{\$} = A_t S_t$. Applying Itô's lemma yields:

$$dA_t^{\$}/A_t^{\$} = (\mu + \mu_S + \rho\sigma\sigma_S)\, dt + \sigma^{\$} dW_t^{\$}, \tag{12}$$

where $\sigma^{\$} = \sqrt{\sigma^2 + \sigma_S^2 + 2\rho\sigma\sigma_S}$.

**Risk premia and the pricing kernel.** To link expected returns to risk premia, we rely on the fundamental theorem of asset pricing. Let $M_t$ denote the stochastic discount factor (SDF) that prices assets in local currency. For any asset with return $dX_t/X_t$, the no-arbitrage condition implies:[6]

$$\mathbb{E}_t\left[\frac{dM_t}{M_t}\frac{dX_t}{X_t}\right] = 0, \tag{13}$$

which can be rewritten as:

$$\mathbb{E}_t\left[\frac{dX_t}{X_t}\right] = r\, dt - \mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dX_t}{X_t}\right), \tag{14}$$

[6]This expression is the continuous-time equivalent to $\mathbb{E}\left[M_{t+1}R_{t+1}\right] = 1$, where $R_{t+1} = \frac{S_t}{S_{t+1}}(1 + r^{\$})$ is the gross return of the currency trade in the two-period case.

where $r$ is the local currency risk-free rate. Thus, expected excess returns are determined by the covariance of asset returns with the SDF.

Applying this relation to the equity index yields:

$$\mu = r + \lambda_A, \qquad \lambda_A = -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dA_t}{A_t}\right), \tag{15}$$

where $\lambda_A$ is the equity risk premium. Similarly, for the exchange rate we obtain:

$$\mu_S = r^{\$} - r + \sigma_S^2 + \lambda_S, \qquad \lambda_S = -\mathrm{Cov}_t\left(\frac{dM_t}{M_t}, \frac{dS_t}{S_t}\right), \tag{16}$$

where $\lambda_S$ is the currency risk premium.

These expressions highlight that both equity and currency risk premia are driven by their exposure to the SDF, that is, by how they co-move with marginal utility. Assets that perform poorly in bad states of the world (when $M_t$ is high) command positive risk premia.

Under the risk-neutral measure, expected returns equal the corresponding risk-free rates, so that credit spreads are determined by risk-neutral default probabilities. Under the physical measure, however, expected returns reflect compensation for risk, and therefore differ across currencies.

Using the SDF-based decomposition above together with the dynamics of $A_t$ and $S_t$, the expected return on the USD-denominated asset can be written as

$$\mu^{\$} = r^{\$} + \underbrace{\lambda_A + \lambda_S + \rho\sigma\sigma_S + \sigma_S^2}_{\lambda_A^{\$}}. \tag{17}$$

with $\lambda_A^{\$}$ capturing the foreign currency stock market risk premium. The first two terms, $\lambda_A$ and $\lambda_S$, capture the equity and currency risk premia, respectively. The covariance term $\rho\sigma\sigma_S$ reflects the co-movement between equity and exchange rate returns, while $\sigma_S^2$ arises from the convexity of the exchange rate in levels.

**Implications.** Two implications follow. First, assets denominated in foreign currency carry additional risk through exchange rate exposure. This raises both volatility ($\sigma^{\$} > \sigma$) and the effective risk premium in foreign currency.

Second, to maintain identical physical default probabilities across currencies, the FC pseudo firm must adjust its leverage. In particular, higher asset risk in foreign currency requires a lower leverage ratio (i.e., a lower strike $K^{\$}/A^{\$}$).

We compute default probabilities and credit spreads in the classical Merton framework. Default occurs when the pseudo firm's asset value falls below the face value of debt at maturity, i.e., $A_T < K$. Under lognormal dynamics, the physical default probability is given by

$$\mathbb{P}(A_T < K) = \Phi\left(-\frac{\log(A_t/K) + (\mu - \frac{1}{2}\sigma^2)(T-t)}{\sigma\sqrt{T-t}}\right), \tag{18}$$

with an analogous expression in foreign currency obtained by replacing $(\mu, \sigma)$ with $(\mu^{\$}, \sigma^{\$})$.

Debt is priced as risk-free debt minus a put option on the firm's assets, so that credit spreads satisfy

$$cs = -\frac{1}{T-t}\log\left(\frac{D_t}{K}\right) - r, \tag{19}$$

where $D_t$ depends on risk-neutral default probabilities and expected losses in default.

Combining these elements implies that cross-currency differences in credit spreads arise from differences in risk premia embedded in $(\mu^{\$}, \sigma^{\$})$, even though physical default risk is matched across currencies. In particular, higher effective risk premia and volatility in foreign currency translate into higher risk-neutral default probabilities and, ultimately, higher FC-denominated credit spreads relative to LC spreads.

## 3.2 Quantitative Implications

We calibrate the model to match the joint dynamics of the FTSE 100 index and the GBP/USD exchange rate over the sample period for which both LC and FC pseudo credit spreads are available. The calibration targets average returns, volatilities, and correlations in the data. In particular, we set the LC risk-free rate to $r = 0.019$, the equity risk premium to $\lambda_A = 0.041$, stock volatility to $\sigma = 0.14$, and exchange rate volatility to $\sigma_S = 0.10$. The correlation between equity and exchange rate returns is $\rho = 0.13$, and the currency risk premium is set to $\lambda_S = 0.02$. These values imply higher volatility and a higher effective risk premium for the USD-denominated asset. Table A.5 summarizes all parameter values.

We calibrate leverage such that the physical default probability is identical across currencies. Specifically, we set the LC face value of debt $K$ to match a one-year default probability of 5%, and then choose $K^{\$}$ to ensure $\mathbb{P}(A_T^{\$} < K^{\$}) = \mathbb{P}(A_T < K)$.

Figure 7 summarizes the model's implications. Panel (a) shows that USD-denominated credit spreads exceed their LC counterparts, consistent with the empirical evidence. This difference arises despite identical physical default probabilities, indicating that it reflects differences in the price of risk rather than the quantity of default risk.

Panels (b) and (c) illustrate the underlying mechanism. Because the USD-denominated asset is more volatile ($\sigma^{\$} > \sigma$), the FC pseudo firm must operate at lower leverage to match default probabilities (Panel b). This leverage adjustment ensures that physical default risk is identical across currencies. At the same time, the higher effective risk premium in USD increases risk-neutral default probabilities, as reflected in a larger wedge between risk-neutral and physical default probabilities (Panel c). This wedge captures the price of default risk and is the key driver of cross-currency spread differences.

The model highlights two channels that govern cross-currency credit spreads, as summarized by the decomposition:

$$\lambda_A^{\$} - \lambda_A = \lambda_S + \rho\sigma\sigma_S + \sigma_S^2. \tag{20}$$

First, the currency risk premium $\lambda_S$ directly increases the compensation required by investors holding USD-denominated assets. As shown in Panels (d)–(f), a higher $\lambda_S$ raises the effective risk premium in foreign currency, increases the risk-neutral default probability, and leads to higher USD credit spreads.

Second, the interaction between equity and exchange rate shocks, captured by $\rho\sigma\sigma_S$, amplifies downside risk in foreign currency. When $\rho > 0$, adverse equity shocks tend to coincide with currency depreciation, leading to more severe declines in the USD-denominated asset value. Panels (g)–(i) show that this amplification increases the risk premium and raises USD credit spreads, even though the associated increase in volatility requires lower leverage.

The convexity term $\sigma_S^2$ further contributes to the higher effective risk premium in foreign currency, reinforcing these effects.

Overall, while higher volatility in foreign currency tends to reduce leverage and compress credit spreads, this effect is dominated by the increase in risk premia. The model therefore reproduces the empirical finding that USD-denominated pseudo credit spreads exceed LC spreads, and provides a clear economic interpretation: cross-currency differences in credit spreads are driven by differences in risk premia, stemming from currency risk and its interaction with equity markets, rather than differences in physical default risk. These predictions yield testable implications that directly link cross-currency risk premia to observed credit spread differentials

# 4 Multi-Currency Credit Spreads Around The World

We study pseudo credit spreads across countries and currencies using an international panel of equity index options. We first describe the data and construction of local- and foreign-currency pseudo spreads. We then analyze the determinants of local-currency spreads and, subsequently, the drivers of pseudo quanto spreads, defined as the difference between USD- and local-currency spreads.

## 4.1 International Option Data and Country Coverage

We construct an international panel of LC and USD-denominated pseudo credit spreads. To this end, we assemble data on stock market indices with traded options across countries, as well as on USD-denominated exchange-traded funds (ETFs) that track these indices and have listed options.

Our country coverage builds on Du and Schreger (2016) and Kelly et al. (2016), which we extend to include Thailand, Malaysia, India, and China, reflecting the increasing availability of options data in recent years.

We obtain index levels and option prices from Refinitiv Datastream and OptionMetrics via Wharton Research Data Services (WRDS). Specifically, we use end-of-day put and call option data on local stock indices from Datastream (via Refinitiv Eikon) and on USD-denominated index-tracking ETFs from OptionMetrics. Details on data cleaning and filtering are provided in Appendix A.

Our final sample comprises 29 countries (8 emerging and 21 developed) as well as the Eurozone. Table 1 summarizes the coverage, including index identifiers, option tickers, currency denominations, sample periods, and the average number of option observations. Coverage varies substantially across countries and currencies, with earlier availability in local currency options and more recent expansion in USD-denominated ETF options.

Option markets tend to be more liquid in local currency, although USD-denominated ETF options are relatively liquid for several countries, including Brazil, Canada, China, Mexico, Singapore, and Malaysia. For each country, we construct aggregate pseudo spreads using the most liquid option market and all available option contracts that pass our filtering criteria.

To ensure comparability across countries, we restrict pseudo firms to have ex-ante default probabilities no higher than the historical Standard & Poor's CCC cumulative default rate. We then aggregate option-implied pseudo yields within each month using time-to-maturity weights to obtain country-level pseudo credit spreads at maturities of 3, 6, 12, and 24 months.

For 6-month (3, 12, 24 months) bonds, we restrict the option maturity to be within [91, 365] ([7,182], [182, 547], [365, 1095]) days.

To construct cross-currency counterparts, we match options across LC and USD markets such that the implied ex-ante default probability is identical. This procedure yields twin pseudo bonds, one in local currency and one in USD, with the same default risk but different risk premia.

Finally, we construct risk-free benchmark rates using option-implied box rates based on the put-call parity relation, following Brenner and Galai (1986), Van Binsbergen et al. (2022), and Diamond and Van Tassel (2021). When country-level box rates are unreliable due to limited liquidity (Australia, Brazil, Canada and Mexico), we use regional benchmarks or convert USD-implied rates into local currency using covered interest parity. Additional details are provided in Appendix A.

## 4.2 International Evidence on Multi-Currency Credit Spreads

Table 2 reports summary statistics for 6-month pseudo credit spreads across countries. A central finding is that foreign-currency (FC) spreads systematically exceed their LC counterparts. For developed economies (Panel A), the average LC spread is 3.44%, compared to 4.64% in USD, a difference of about 120 basis points. LC spreads range from 71bps (Netherlands) to 780bps (New Zealand), illustrating substantial cross-country heterogeneity.

Spreads are higher in emerging markets (Panel B), with average LC (FC) spreads of 5.32% (5.67%). While the ranking FC $>$ LC holds broadly, a few exceptions (e.g., Denmark, Greece, New Zealand, and Taiwan) highlight cross-country heterogeneity in currency risk exposure. These patterns are robust across maturities (3, 12, and 24 months), as reported in Appendix Tables A.6, A.7, and A.8.

Figure 8 illustrates the time-series dynamics of LC and FC spreads across regions. Although spreads co-move globally, there is substantial cross-regional heterogeneity in their response to macroeconomic events. In particular, FC spreads react more strongly to episodes involving

currency risk, such as the Brexit referendum in Europe. Consistent with this, Table 2 highlights that the correlation between LC and FC spreads varies widely across countries, ranging from 43% (Italy) to 97% (Greece), suggesting that FC spreads embed additional variation related to the interaction between default and exchange rate risk.

Panel A of Table 3 reports aggregate term structures of pseudo credit spreads. On average, the term structure is downward sloping. However, Figure 9 reveals substantial cross-country heterogeneity. In the figure, we plot the term structure of pseudo credit spreads for each country after normalizing by the 3-month spread, so that all curves start at zero. This scaling allows for a direct comparison of the shape of the term structure across countries. While the average pattern is downward sloping, the figure shows that some countries exhibit steeply upward-sloping term structures, whereas others display strongly downward-sloping profiles.

Panel B reports ex-ante default probabilities. By construction, default probabilities are identical across currencies, allowing us to isolate differences in credit spreads that arise purely from differences in risk premia. For 6-month maturities, average default probabilities are 8.54% in developed economies and 11.53% in emerging markets. Country-level statistics are reported in Appendix Table A.9.

## 4.3 Drivers of Local-Currency Credit Spreads

We examine the economic drivers of pseudo credit spreads denominated in LC. Our focus is on 3-month pseudo bonds, although the results are robust across maturities. Summary statistics for the explanatory variables are reported in Appendix Table A.11.

In column (1) of Table 4, we relate LC pseudo credit spreads to their fundamental components: the physical default probability ($P$) and the risk premium component ($Q - P$). The panel regression includes country fixed effects and exploits within-country time-series variation. Both components are highly significant and jointly explain 83.2% of the variation in spreads.

The estimated coefficient of 0.346 implies that a one percentage point increase in the physical default probability raises spreads by about 35 basis points. The effect of the risk premium is larger: a one-point increase in $Q - P$ increases spreads by approximately 55 basis points. This is consistent with the view that credit spreads reflect both expected default losses and compensation for bearing default risk (e.g., Gilchrist and Zakrajšek, 2012; Berndt et al., 2018; Culp et al., 2018).

In column (2), we examine the role of the underlying equity market. LC pseudo credit spreads are positively related to stock market volatility and negatively related to expected returns. This is consistent with the structural credit risk framework: higher volatility increases the likelihood that asset values fall below the default threshold, while higher expected returns improve firm fundamentals and reduce default risk.

Column (3) examines the role of exchange rate dynamics. A one percentage point increase in FX volatility is associated with an increase in spreads of about 30 basis points. In addition, spreads widen when the local currency depreciates, as indicated by the statistically significant negative coefficient on exchange rate returns, $-0.090$. These results suggest that currency risk is an important determinant of local credit spreads: depreciation and higher volatility increase uncertainty about future economic conditions and raise perceived default risk.

Column (4) shows that local and foreign risk-free rates are not significant predictors of pseudo credit spreads. This likely reflects the short maturity of the bonds considered, for which variation in the risk-neutral drift has a limited impact on spreads. Instead, spreads are primarily driven by country-specific fundamentals and risk premia.

Columns (5) to (7) examine the role of local and global macro-financial variables. We first consider local conditions in column (5). Higher inflation is associated with wider spreads, consistent with the view that inflation erodes purchasing power, increases uncertainty, and raises default risk. We also find that foreign exchange reserves are significantly related to pseudo spreads. The estimated coefficient implies that a one standard deviation increase in reserves is associated with a change in spreads of nearly 300 basis points, indicating a substantial economic effect.

The interpretation of this relationship is nuanced. On the one hand, higher reserves may signal greater policy credibility and stronger capacity of central banks to stabilize the currency and domestic financial conditions (e.g., Bank for International Settlements, 2023). On the other hand, reserve accumulation is often more pronounced in economies that are more exposed to external shocks or vulnerable to capital flow reversals. In this case, higher reserves may coincide with higher underlying credit risk. Our results are consistent with the former interpretation.

We next turn to global factors in columns (6) and (7). Pseudo spreads are negatively related to measures of real economic activity, such as the Chicago Fed National Activity Index (CFNAI), indicating that stronger economic conditions are associated with lower credit risk. In contrast, global risk factors, such as macroeconomic uncertainty (Jurado et al., 2015) and U.S. credit conditions, proxied by the Gilchrist and Zakrajšek (2012) GZ spread, are positively associated with local spreads. These findings highlight the importance of global financial conditions for local credit markets.

## 4.4 Drivers of Pseudo Quanto Spreads

We next examine the drivers of pseudo quanto spreads, defined as the difference between USD and LC pseudo credit spreads. Our framework implies that quanto spreads reflect cross-currency differences in the price of default risk, captured by differences in risk-neutral default probabilities ($Q^{\$} - Q$). Intuitively, they measure how default risk co-moves with investors' stochastic discount factor across currencies. Because risk premia depend on the level of default risk, both the physical default probability ($P$) and cross-currency differences in risk premia are expected to drive variation in pseudo quanto spreads.

Table 5 confirms these predictions. Both the physical default probability and the difference in risk-neutral default probabilities between USD and LC pseudo bonds significantly explain pseudo quanto spreads across all specifications, including pooled regressions, cross-sectional regressions with time fixed effects, and time-series regressions with country fixed effects. The relative importance of these components differs across dimensions: default risk plays a larger

role in the cross-section, whereas differences in risk premia dominate time-series variation. Consistent with this, the estimated coefficient on the risk premium component (0.492) is approximately three times larger than that on the physical default probability (0.168).

In Table 6, we examine whether the determinants of LC-denominated pseudo spreads also explain within-country variation in pseudo quanto spreads. Column (1) shows that lower LC equity returns and higher return volatility are associated with lower quanto spreads. This reflects the fact that these factors increase LC-denominated pseudo spreads, thereby narrowing the gap between USD and LC spreads. Conversely, column (2) shows that lower USD equity returns and higher volatility increase quanto spreads by raising USD-denominated pseudo spreads. These results highlight the asymmetric role of local and foreign risk factors in shaping the cross-currency pricing of credit risk.

Exchange rate dynamics further contribute to this asymmetry. Higher FX volatility increases the riskiness of USD-denominated claims relative to LC claims, thereby widening quanto spreads, although the economic magnitude is more moderate. In addition, the risk-free rate differential matters: higher USD interest rates are associated with lower quanto spreads, consistent with USD-denominated bonds being perceived as relatively safer.

Finally, we find that pseudo quanto spreads decrease with central bank FX reserves, stronger economic activity (as measured by the CFNAI), and greater macroeconomic uncertainty. These effects are consistent with the differential exposure of LC- and USD-denominated pseudo spreads to global risk factors and highlight the importance of international financial conditions in shaping cross-currency credit risk premia.

# 5 Information Content of the Pseudo Credit Spreads

We investigate the informational content of pseudo credit spreads for both the real economy and financial markets. Specifically, we assess whether pseudo spreads have predictive power for aggregate economic activity, local economic growth, and foreign exchange rate returns.

## 5.1 Predictability of Aggregate Economic Activity

We assess whether pseudo credit spreads contain predictive information about aggregate economic activity using the following panel regression specification estimated at the quarterly frequency:

$$\Delta Y_{t+1} = \alpha + \beta \Delta Y_t + \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_t + \varepsilon_{t+1}, \tag{21}$$

where $\Delta Y_{t+1}$ denotes the one-quarter-ahead growth rate of aggregate real GDP. As our baseline measure of global economic activity, we construct a quarterly series by averaging real GDP growth across countries (excluding the United States), using weights proportional to each country's average GDP over the sample period. For robustness, we verify that our results are consistent under alternative weighting schemes, including equal weights and specifications that include the United States in the cross-country average.

The main predictor is the country-level pseudo credit spread, derived from option-implied measures denominated in local currency (LC) and foreign currency (USD). Specifically, $\text{CS}_{i,t}^{LC}$ denotes the average LC pseudo spread for country $i$ in quarter $t$, while the quanto spread, defined as $\text{CS}_{i,t}^{\text{Quanto}} = \text{CS}_{i,t}^{\$} - \text{CS}_{i,t}^{LC}$, captures the cross-currency difference between USD- and LC-denominated pseudo spreads. Following Culp et al. (2018), we compute both spreads as the equally weighted average of option-implied credit spreads with maturities of 3, 6, 12, and 24 months. To account for potential serial correlation in the error terms, we compute standard errors using the Newey and West (1986) estimator with an optimally selected bandwidth.

In column (1) of Table 7, we find that $\text{CS}^{LC}$ significantly predicts future aggregate output growth with a negative sign. This result is consistent with previous evidence that widening credit spreads signal worsening economic conditions (e.g., Culp et al., 2018; Gilchrist and Zakrajšek, 2012). Regarding the economic magnitude, the estimated coefficient of column (1) implies that a one percentage point increase in the LC pseudo spread predicts a 0.023 percentage points decline in output growth, or about 0.1 percentage points on an annualized

basis. While the economic effect is modest—as one would expect from a single country-level spread forecasting a broad cross-country aggregate—it is statistically and economically meaningful. In contrast, column (2) shows that the pseudo quanto spread, $\text{CS}^{\text{Quanto}}$– which reflects how a country's currency co-moves with the global pricing kernel – does not significantly forecast real activity. Since pseudo quanto spreads primarily capture currency-related risk, they are less likely to contain information about aggregate economic fundamentals.

To assess the incremental predictive power of our pseudo spread measures, we control for two widely used U.S. credit-based indicators: the updated option-implied credit spread for the U.S. ($\text{CS}^{USA}$) and the GZ Spread of Gilchrist and Zakrajšek (2012). Given the high correlation between these two variables, we orthogonalize the GZ Spread with respect to $\text{CS}^{USA}$, as well as to the country-level pseudo spreads $\text{CS}^{LC}$ and $\text{CS}^{\$}$. Similarly, when $\text{CS}^{USA}$ is included as a control variable, we orthogonalize it with respect to the country-level pseudo spreads to mitigate multicollinearity concerns in the regression analysis.

We further include control variables to account for macroeconomic and monetary policy conditions. These controls comprise the term spread (10-year minus 3-month Treasury yield), the real federal funds rate, and the Macroeconomic Uncertainty Index of Jurado et al. (2015). As shown in columns (3) and (4) of Table 7, the coefficient on $\text{CS}^{LC}$ remains statistically significant even after controlling for these factors, indicating that country-level option-implied credit spreads contain predictive information beyond that captured by conventional U.S.-based indicators. Notably, both $\text{CS}^{USA}$ and the GZ Spread continue to be significant with the expected signs, reaffirming their role as important predictors of macroeconomic outcomes.

To better understand what drives the predictive power of local currency credit spreads, we decompose the spreads into two components: the expected quantity of credit risk and the associated risk premium. Specifically, we express the risk-neutral default probability $Q$ as the sum of the physical (real-world) default probability $P$ and the excess compensation $Q - P$, which captures the price of credit risk.

In practice, disentangling the expected default risk and the risk premium from bond or CDS spread data is challenging, as both components tend to comove and respond similarly to

shifts in market sentiment and macroeconomic conditions. To address this, prior studies have adopted model-based approaches. For instance, Gilchrist and Zakrajšek (2012) proxy default risk using the "distance to default" (DD) derived from the Merton (1974) model, while Berndt et al. (2018) rely on Moody's Analytics Expected Default Frequencies (EDF) as a forward-looking measure of firm-level conditional default probabilities.

Building on these insights, we apply a similar decomposition to our option-implied pseudo spreads. Columns (5) to (7) of Table 7 report that both the physical default probability $P$ and the credit risk premium $Q - P$ are significant predictors of future GDP growth. For example, based on Column (5), a 10-percentage-point increase in $P$ predicts a 0.158-percentage-point decline in next-quarter GDP growth, while a 10-point increase in the risk premium forecasts a 0.114-point contraction. The magnitudes are broadly similar, indicating that both components contribute meaningfully to the predictive power of pseudo credit spreads.

These findings confirm and extend the conclusions of Gilchrist and Zakrajšek (2012), who attribute the predictive content of credit spreads primarily to variation in the risk premium. In contrast, our results show that both the quantity and the price of credit risk are important for macroeconomic forecasting, even when using option-implied spreads in an international context.

Table A.12 demonstrates that our main results are robust to a range of alternative regression specifications. First, the findings hold regardless of whether aggregate economic growth is constructed using GDP-weighted or equally weighted country averages, indicating that the observed predictability is not driven by a small number of large economies. Second, the results are robust to the inclusion or exclusion of the United States in the construction of the aggregate series, suggesting that the predictive power of pseudo credit spreads extends beyond U.S.-specific dynamics. In addition, we confirm robustness across different forecast horizons and option maturities. Specifically, the results remain significant when predicting economic growth three months ahead using the physical default probability $P$ and credit risk premium $Q - P$ derived from options centered at the three-month horizon. Similarly, the findings persist when forecasting twelve-month-ahead growth using predictors constructed

from options across all maturities.

Taken together, our results highlight that option-implied credit spreads denominated in local currency provide valuable forward-looking information about future economic activity. This predictive power is both distinct from and complementary to that of traditional U.S.-based credit indicators and macro-financial controls. Moreover, decomposing these spreads shows that both expected credit losses and the compensation investors require for bearing credit risk contribute meaningfully to their forecasting ability. These findings suggest that pseudo spreads, derived from option markets across countries, can serve as a useful barometer of global macroeconomic conditions.

## 5.2 Country-Level Predictability of Economic Growth

We next examine the predictive power of pseudo credit spreads at the country level by estimating the following panel regression specification:

$$\Delta Y_{i,t+4} = \beta \Delta Y_{i,t} + \gamma_1 \mathrm{CS}_{i,t}^{LC} + \gamma_2 \mathrm{CS}_{i,t}^{\mathrm{Quanto}} + \delta \mathrm{Controls}_t + \alpha_i + \eta_t + \varepsilon_{i,t+4}, \tag{22}$$

where $\Delta Y_{i,t+4}$ denotes the one-year-ahead real GDP growth of country $i$. The specification includes country fixed effects ($\alpha_i$) to control for time-invariant heterogeneity across countries and time fixed effects ($\eta_t$) to control for aggregate conditions. Standard errors are clustered by both country and time to account for potential cross-sectional and temporal dependence in the residuals ($\varepsilon_{i,t+1}$).

Table 8 presents the results. Column (1) shows that the local currency pseudo credit spread, $\mathrm{CS}^{LC}$, significantly and negatively predicts a country's future economic growth. Quantitatively, a 100 basis point increase in $\mathrm{CS}^{LC}$ in quarter $t$ is associated with a decline in GDP growth of approximately 0.31 percentage points over the next four quarters. This effect is both statistically and economically meaningful.

The predictive power of $\text{CS}^{LC}$ remains robust across a variety of specifications. In particular, the results hold when controlling for standard macroeconomic predictors, across both advanced and emerging economies, and over different sample periods – including specifications that exclude the COVID-19 crisis. Moreover, the findings are robust to the inclusion of time fixed effects, which absorb global fluctuations in aggregate economic conditions. These results confirm that our option-implied pseudo credit spreads capture meaningful country-specific information not already reflected in conventional indicators.

Finally, columns (6) through (10) present the results from the decomposition into the physical default probability ($P$) and the credit risk premium ($Q - P$). Consistent with our aggregate-level findings, both components contribute significantly to the predictive power of the spreads. Notably, the contribution of the risk premium appears particularly strong among emerging markets, where risk pricing tends to be more volatile and information diffusion less efficient. These results underscore the value of our pseudo spread decomposition in capturing both the quantity and the price of credit risk as forward-looking indicators of economic activity.

## 5.3 Exchange Rate Predictability

While it is the local currency pseudo spreads that contain information about future real economic activity, we next show that the pseudo quanto spreads carry valuable information for predicting exchange rate movements. Our analysis proceeds by estimating the following panel regression specification:

$$\Delta s_{i,t+4} = \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t+4}, \tag{23}$$

where $\Delta s_{i,t+4}$ denotes the one-year-ahead exchange rate return of country $i$, with a positive $\Delta s$ indicating an appreciation of the country's local currency relative to the USD. The specification includes country fixed effects ($\alpha_i$) to control for time-invariant heterogeneity across countries and time fixed effects ($\eta_t$) to control for aggregate conditions. Standard

errors are clustered by both country and time to account for potential cross-sectional and temporal dependence in the residuals ($\varepsilon_{i,t+1}$). The results are presented in Table 9.

First, we find that a country's LC pseudo credit spread significantly predicts its currency return over a 12-month horizon. Based on Column (4), for example, a 100 basis point increase in $\text{CS}^{LC}$ implies an exchange rate return of about 0.33% over the next year. The positive relationship is statistically robust across various subsamples, particularly among emerging markets. A higher LC credit spread is thus associated with higher subsequent excess returns on the local currency relative to the U.S. dollar. This pattern is consistent with a risk premium channel: when investors require greater compensation for bearing corporate credit risk, this premium also forecasts stronger currency performance. In essence, LC credit spreads capture priced risk that influences both bond and currency returns.

Second, we show that the pseudo quanto credit spread statistically predict future currency returns with a positive sign. Based on Column (4), for example, a 100 basis point increase in $\text{CS}^{\text{Quanto}}$ implies an LC appreciation of about 0.25% over the next year. A higher pseudo quanto spread implies that bond investors require greater compensation in USD terms for bearing identical underlying credit risk. This reflects a situation in which the USD/LC exchange rate tends to depreciate in *bad times*–for instance, when the local equity market declines or the investor's pricing kernel rises. In such scenarios, USD pseudo bonds become less attractive, as losses on the local stock market are amplified when measured in USD, thereby accelerating the rise in default probability in bad times. As a result, investors demand a higher risk premium on USD credit spreads relative to LC spreads. Quanto credit spreads therefore rise for currencies that tend to depreciate more during global downturns, as these currencies are perceived to be riskier and must compensate investors with higher expected returns.

Our empirical findings support this interpretation. Currencies of countries with higher pseudo quanto spreads tend to experience greater future appreciation. To test the underlying mechanism more directly, we sort the sample based on the correlation between local stock market returns and the USD/LC exchange rate. Table 10 reports the results. We find that the pseudo quanto spread predicts future currency returns only when this correlation is high,

indicating a stronger link between currency depreciation and adverse local market outcomes. Similar results obtain when we sort countries by the correlation of their local stock returns with either U.S. equity returns (S&P 500) or U.S. consumption growth. These findings are consistent with a covariance-based risk premium: the predictive power of the pseudo quanto spread arises specifically when the local currency covaries negatively with the global pricing kernel.

The evidence is grounded in our structural model framework, in which the covariance between the pricing kernel and default risk, captured by parameter $\lambda_S$, raises both the pseudo quanto spread and the expected excess return on the local currency. A key feature of the model is that default probabilities are held constant across currencies, so differences in credit spreads purely reflect variation in the price of risk rather than in default expectations. This identification strategy enables us to isolate a clean measure of currency risk premia embedded in pseudo credit spreads, disentangled from confounding effects related to credit events.

Our findings contribute to the growing literature that uses asset prices denominated in multiple currencies to forecast exchange rates. Kremens and Martin (2019) construct a currency factor based on 2-year quanto equity index products, which capture the risk-neutral covariance between a currency and the S&P 500. They show that currencies that depreciate more during market downturns – i.e., those with a higher negative covariance with marginal utility – offer higher expected returns. Our approach differs in both construction and interpretation. We introduce a *credit-based* quanto spread that reflects the joint covariance of currency returns with the global pricing kernel and the local equity market. This measure leverages a broad cross-section of traded and liquid options across multiple maturities, making it both theoretically grounded and practically implementable.

Finally, our approach complements and extends the methodology of Della Corte et al. (2023), who construct a credit-implied risk premium using euro-area sovereign CDS spreads in multiple currencies. While their measure captures depreciation risk conditional on sovereign credit events, our analysis focuses on a broader set of countries and captures systematic risk pricing in normal times. Moreover, by relying on short-maturity pseudo credit spreads, we avoid some of the liquidity and regulatory distortions affecting long-dated CDS contracts.

Our broader cross-country coverage and emphasis on risk pricing rather than event-driven risk represent key contributions to both the asset pricing and currency forecasting literatures.

# 6 Conclusion

We develop an option-based framework to construct corporate credit spreads across currencies using traded equity and foreign exchange options. By construction, local- and foreign-currency (LC and FC) pseudo credit spreads embed identical physical default probabilities, allowing differences across currencies to isolate currency-specific variation in the pricing of default risk.

Our results yield three main findings. First, FC-denominated pseudo credit spreads are systematically higher and more volatile than their LC counterparts, despite identical default risk. This difference reflects variation in the price of default risk across currencies, driven by currency risk and its interaction with equity markets. Second, LC pseudo credit spreads are informative about real economic activity and predict both global and country-level GDP growth, with both expected default risk and risk premia contributing to their predictive content. Third, pseudo quanto spreads, capturing cross-currency differences in the pricing of default risk, forecast exchange rate movements.

Taken together, these findings suggest that currency denomination affects the pricing of credit risk, rather than its physical likelihood. More broadly, the option-based approach provides a way to construct comparable credit spread measures across currencies, overcoming limitations of bond data and enabling a consistent analysis of credit risk in an international setting.

## Table 1: International Options Data and Country Coverage

This table summarizes the international option markets used to construct local- and USD-denominated pseudo credit spreads. For each country or region, we report the underlying stock market index (ticker and option mnemonic), the currency denomination of the options, the sample start and end dates, the average number of available put options per month (as a proxy for market liquidity), and the average number of observations used to estimate option-implied box rates (based on a minimum $R^2$ threshold of 0.9999). The right-hand columns report the corresponding information for USD-denominated options on ETFs that track the same index. The sample builds on Du and Schreger (2016), Kelly et al. (2016), Du et al. (2018), and Diamond and Van Tassel (2021), and is extended to include Thailand, Malaysia, India, and China. Emerging market economies (as defined by the IMF) are shaded. Data are obtained from Refinitiv Datastream and OptionMetrics via WRDS.

| | | Local Currency Options | | | | | Foreign Currency Options | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Country / Region | Market Index | Option Name | Currency | Start-End | # Box Rate | # Puts | ETF | Currency | Start-End | # Puts |
| Australia | ASX 200 | AXJ | AUD | 2/2010 - 7/2024 | 144 | 1923 | EWA | USD | 2/2007 - 8/2023 | 146 |
| Belgium | BEL 20 | BBEL | EUR | 6/2011 - 9/2017 | 105 | 15 | EWK | USD | 9/2013 - 8/2023 | 10 |
| Brazil | BOVESPA | IBOV | BRL | 10/2018 - 5/2024 | 0 | 186 | EWZ | USD | 6/2006 - 8/2023 | 758 |
| Canada | S&P/TSX 60 | CSXO | CAD | 6/2019 - 12/2020 | 44 | 110 | EWC | USD | 5/2006 - 8/2023 | 123 |
| China | SSE 50 | SS50 | CNY | 4/2016 - 7/2024 | 50 | 169 | FXI | USD | 9/2004 - 8/2023 | 590 |
| Denmark | OMXC 25 | KC25 | DKK | 3/2018 - 6/2024 | 30 | 12 | - | - | - | - |
| Europe | STOXX 50 | GXE | EUR | 6/2002 - 7/2024 | 266 | 2147 | EZU | USD | 3/2008 - 8/2023 | 105 |
| France | CAC 40 | PXA | EUR | 12/2005 - 7/2024 | 261 | 418 | EWQ | USD | 9/2011 - 8/2023 | 78 |
| Germany | DAX 30 | DAX | EUR | 7/2004 - 7/2024 | 224 | 1094 | EWG | USD | 12/2006 - 8/2023 | 197 |
| Greece | FTSE 20 | AF20 | EUR | 6/2016 - 6/2024 | 82 | 45 | GREK | USD | 5/2020 - 8/2023 | 78 |
| Hong Kong | HANG SENG | HSII | HKD | 6/2007 - 6/2024 | 252 | 1087 | EWH | USD | 4/2006 - 8/2023 | 152 |
| India | NIFTY 50 | INIF | INR | 2/2010 - 7/2024 | 154 | 1260 | EPI | USD | 4/2008 - 8/2023 | 105 |
| Israel | TASE | TLVJ | ILS | 2/2010 - 6/2023 | 8 | 370 | - | - | - | - |
| Italy | MIB | SMIB | EUR | 4/2007 - 6/2024 | 240 | 600 | EWI | USD | 11/2016 - 8/2023 | 123 |
| Japan | NIKKEI 225 | NK20 | JPY | 6/2007 - 7/2024 | 328 | 1494 | EWJ | USD | 11/2016 - 8/2023 | 590 |
| Malaysia | KLCI | KLSE | MYR | 5/2012 - 6/2024 | 61 | 19 | EWM | USD | 11/2016 - 8/2023 | 87 |
| Mexico | MIECS200 | MMIP | MXN | 2/2016 - 7/2024 | 33 | 67 | EWW | USD | 12/2007 - 8/2023 | 351 |
| Netherlands | AEX | EOE | EUR | 10/2001 - 6/2024 | 190 | 455 | EWN | USD | 10/2013 - 8/2023 | 13 |
| Norway | OBX | OOBX | NOK | 1/2010 - 7/2024 | 38 | 176 | - | - | - | - |
| Poland | WIG 20 | WWIG | PLN | 7/2013 - 7/2024 | 125 | 224 | EPOL | USD | 9/2017 - 5/2019 | 18 |
| Singapore | MSCI Singapore | SGSG | SGD | 5/2011 - 11/2015 | 41 | 39 | EWS | USD | 11/2016 - 8/2023 | 102 |
| South Korea | KOSPI 200 | K200 | KRW | 5/2012 - 7/2024 | 5 | 583 | EWY | USD | 7/2007 - 8/2023 | 309 |
| Spain | IBEX 35 | IBEI | EUR | 5/2007 - 6/2007 | 104 | 768 | EWP | USD | 8/2007 - 8/2023 | 94 |
| Sweden | OMXS 30 | OS30 | SEK | 6/2007 - 6/2024 | 8 | 331 | EWD | USD | 9/2007 - 8/2023 | 52 |
| Switzerland | SMI | SMI | CHF | 2/2005 - 7/2024 | 226 | 1160 | EWL | USD | 7/2008 - 8/2023 | 276.5 |
| Taiwan | TSEC | TMTX | TWD | 2/2010 - 6/2024 | 70 | 312 | EWT | USD | 9/2016 - 8/2023 | 239 |
| Thailand | SET 50 | TFXS | THB | 5/2011 - 7/2024 | 48 | 90 | THD | USD | 3/2014 - 8/2023 | 70 |
| Turkey | XU 100 | XUIO | TRY | 2/2019 - 6/2024 | 21 | 340 | TUR | USD | 6/2013 - 8/2023 | - |
| United Kingdom | FTSE 100 | ESX | GBP | 6/2004 - 7/2024 | 1203 | 2075 | EWU | USD | 11/2016 - 8/2023 | 255 |
| United States | SPY | SPX | USD | 1/1996 - 8/2023 | 210 | 10751 | - | - | - | - |

Table 2: Local- and Foreign-Currency Pseudo Credit Spreads (6-Month)

This table reports summary statistics of 6-month pseudo credit spreads by country in local (LC) and foreign (USD) currency. LC pseudo bonds are constructed from put options on domestic stock market indices, while USD-denominated pseudo bonds use options on exchange-traded funds (ETFs) tracking the same indices. When USD (LC) option data are unavailable, we use the corresponding synthetic series. Credit spreads are expressed in percentage terms. The final columns report (i) the correlation between LC and USD spreads and (ii) the correlation between local equity returns and USD/LC exchange rate changes. Option maturities are restricted to 91-365 days. Data are monthly from 2003 to 2024 and sourced from Refinitiv Datastream and OptionMetrics via WRDS. Details on construction and filtering are provided in Appendices A and B.

**Panel A: Developed countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{r_A,r_S}$ |
| Australia | 193 | 4.14 | 3.88 | 2.32 | 1.42 | 8.23 | 193 | 6.10 | 5.46 | 3.18 | 2.69 | 11.53 | 0.75 | 0.47 |
| Beligium | 8 | 2.07 | 1.92 | 1.12 | 0.87 | 4.38 | 8 | 3.68 | 3.67 | 0.68 | 2.83 | 4.58 | 0.52 | 0.25 |
| Canada | 208 | 4.72 | 4.78 | 1.79 | 2.21 | 7.21 | 208 | 5.46 | 4.67 | 2.96 | 2.35 | 11.02 | 0.70 | 0.56 |
| Denmark | 1 | 8.83 | 8.83 | 0.00 | 8.83 | 8.83 | 1 | 7.94 | 7.94 | 0.00 | 7.94 | 7.94 | | 0.15 |
| Euro Area | 182 | 3.42 | 2.35 | 2.92 | 0.21 | 7.48 | 172 | 5.74 | 4.96 | 3.87 | 0.79 | 12.67 | 0.83 | 0.27 |
| France | 132 | 2.01 | 0.59 | 2.39 | 0.05 | 6.58 | 126 | 3.05 | 1.67 | 3.16 | 0.08 | 9.85 | 0.61 | 0.24 |
| Germany | 196 | 1.60 | 0.95 | 1.92 | 0.02 | 5.70 | 186 | 3.16 | 2.14 | 2.84 | 0.44 | 8.55 | 0.75 | 0.23 |
| Greece | 40 | 7.65 | 7.18 | 2.56 | 3.92 | 11.85 | 40 | 6.36 | 5.97 | 2.15 | 3.20 | 10.21 | 0.97 | 0.33 |
| Hong Kong | 172 | 2.09 | 1.02 | 2.78 | 0.02 | 7.49 | 163 | 3.07 | 2.46 | 2.99 | 0.36 | 8.42 | 0.78 | 0.17 |
| Italy | 150 | 1.58 | 0.84 | 1.99 | 0.27 | 5.38 | 140 | 2.39 | 1.86 | 2.31 | 0.05 | 5.99 | 0.43 | 0.30 |
| Japan | 197 | 1.95 | 1.58 | 1.74 | 0.32 | 5.02 | 182 | 2.35 | 1.88 | 2.04 | 0.49 | 5.85 | 0.70 | -0.44 |
| Netherlands | 194 | 1.57 | 0.71 | 2.03 | 0.08 | 6.02 | 184 | 3.08 | 2.29 | 2.76 | 0.30 | 9.19 | 0.72 | 0.18 |
| Norway | 89 | 4.52 | 3.80 | 2.84 | 1.03 | 10.32 | 82 | 9.30 | 8.64 | 5.31 | 3.66 | 21.99 | 0.69 | 0.48 |
| New Zealand | 28 | 7.80 | 7.23 | 2.56 | 4.24 | 12.29 | 28 | 7.56 | 6.72 | 2.47 | 4.46 | 11.70 | 0.94 | - |
| Singapore | 77 | 4.41 | 4.20 | 1.81 | 1.89 | 8.12 | 77 | 3.74 | 3.61 | 0.98 | 2.13 | 5.27 | 0.63 | 0.52 |
| South Korea | 191 | 5.11 | 5.01 | 3.08 | 0.58 | 11.06 | 192 | 5.44 | 4.48 | 3.45 | 2.16 | 12.64 | 0.41 | 0.46 |
| Spain | 160 | 5.49 | 4.81 | 2.77 | 2.56 | 11.67 | 160 | 6.31 | 5.21 | 3.99 | 2.16 | 14.85 | 0.77 | 0.35 |
| Sweden | 117 | 5.97 | 5.45 | 2.78 | 2.45 | 11.60 | 114 | 8.85 | 7.80 | 4.62 | 3.32 | 17.46 | 0.66 | 0.26 |
| Switzerland | 157 | 2.23 | 1.35 | 2.67 | 0.08 | 7.05 | 147 | 3.89 | 2.41 | 3.69 | 0.35 | 11.87 | 0.83 | -0.08 |
| Taiwan | 81 | 6.15 | 6.07 | 2.65 | 1.25 | 11.23 | 81 | 4.56 | 4.19 | 1.65 | 2.33 | 7.99 | 0.58 | 0.53 |
| United Kingdom | 218 | 2.95 | 2.13 | 2.37 | 0.78 | 7.51 | 208 | 3.96 | 3.37 | 2.31 | 1.23 | 8.53 | 0.73 | 0.21 |
| All | 2,791 | 3.44 | 2.81 | 2.92 | 0.12 | 8.83 | 2,692 | 4.64 | 3.81 | 3.64 | 0.51 | 11.45 | 0.72 | - |

**Panel B: Emerging countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{A,S}$ |
| Brazil | 205 | 6.74 | 5.56 | 4.19 | 3.15 | 17.58 | 207 | 7.06 | 6.01 | 4.59 | 3.08 | 13.69 | 0.91 | 0.64 |
| Chile | 78 | 5.63 | 5.55 | 1.86 | 2.61 | 8.90 | 78 | 5.51 | 5.16 | 1.94 | 2.77 | 8.78 | 0.68 | - |
| China | 157 | 4.31 | 4.04 | 1.75 | 1.82 | 7.70 | 161 | 4.05 | 3.80 | 1.63 | 1.91 | 7.30 | 0.73 | 0.32 |
| Colombia | 7 | 3.70 | 3.31 | 1.62 | 1.92 | 6.97 | 7 | 6.93 | 5.72 | 3.52 | 3.61 | 13.18 | 0.86 | - |
| India | 156 | 2.14 | 1.39 | 3.60 | 0.17 | 5.22 | 146 | 3.22 | 2.68 | 2.59 | 0.59 | 8.35 | 0.52 | 0.56 |
| Indonesia | 45 | 7.12 | 6.78 | 2.44 | 3.38 | 12.03 | 49 | 7.28 | 7.07 | 2.98 | 2.58 | 12.69 | 0.74 | - |
| Malaysia | 71 | 6.69 | 6.22 | 2.93 | 3.17 | 11.56 | 71 | 4.46 | 4.04 | 1.58 | 2.69 | 7.28 | 0.48 | 0.39 |
| Mexico | 188 | 5.04 | 4.75 | 3.02 | 1.49 | 11.08 | 188 | 5.15 | 4.52 | 2.88 | 2.28 | 10.73 | 0.70 | 0.54 |
| Poland | 91 | 2.74 | 2.11 | 1.92 | 0.71 | 6.77 | 84 | 5.11 | 4.37 | 3.35 | 0.90 | 11.42 | 0.78 | 0.55 |
| South Africa | 170 | 8.32 | 7.89 | 3.56 | 3.66 | 12.31 | 170 | 8.69 | 7.86 | 4.45 | 4.34 | 16.77 | 0.87 | - |
| Thailand | 78 | 5.39 | 4.70 | 2.78 | 1.90 | 9.73 | 96 | 5.45 | 4.77 | 2.46 | 2.47 | 9.54 | 0.57 | 0.48 |
| Turkey | 115 | 4.87 | 4.33 | 2.71 | 1.51 | 8.81 | 115 | 5.62 | 5.32 | 2.11 | 2.94 | 8.98 | 0.58 | 0.28 |
| All | 1,361 | 5.32 | 4.84 | 3.58 | 0.90 | 11.04 | 1,372 | 5.67 | 4.93 | 3.54 | 1.76 | 11.53 | 0.78 | - |

Table 3: Cross-Currency Pseudo Credit Spreads Across Maturities (Aggregate)

This table reports aggregate pseudo credit spreads and ex-ante default probabilities across currencies and maturities. Panel A presents credit spreads in local (LC) and foreign (USD) currency for maturities of 3, 6, 12, and 24 months, averaged across countries within advanced and emerging market groups. Panel B reports the corresponding physical default probabilities. LC pseudo bonds are constructed from options on domestic stock market indices, while USD-denominated pseudo bonds use options on exchange-traded funds (ETFs) tracking the same indices. When necessary, missing observations are replaced with the corresponding synthetic series. Option maturities are restricted to 7-182, 91-365, 182-547, and 365-1095 days for 3-, 6-, 12-, and 24-month horizons, respectively. Credit spreads and default probabilities are expressed in percentage terms. Data are monthly from 2003 to 2024 and sourced from Refinitiv Datastream and OptionMetrics via WRDS. Details are provided in Appendices A and B.

**Panel A: Credit Spread**

| | Local Currency | | | | | | Foreign Currency | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | Corr |
| **3-month** | | | | | | | | | | | | | |
| Advanced | 3,453 | 3.85 | 2.65 | 3.72 | 0.44 | 10.68 | 3,332 | 7.04 | 4.61 | 9.44 | 1.31 | 18.31 | 0.26 |
| Emerging | 1,513 | 6.03 | 5.16 | 4.56 | 0.76 | 13.89 | 1,507 | 6.08 | 5.25 | 4.24 | 1.72 | 12.69 | 0.69 |
| **6-month** | | | | | | | | | | | | | |
| Advanced | 2,791 | 3.44 | 2.81 | 2.92 | 0.12 | 8.83 | 2,692 | 4.64 | 3.81 | 3.64 | 0.51 | 11.45 | 0.72 |
| Emerging | 1,361 | 5.32 | 4.84 | 3.58 | 0.90 | 11.04 | 1,372 | 5.67 | 4.93 | 3.54 | 1.76 | 11.53 | 0.78 |
| **12-month** | | | | | | | | | | | | | |
| Advanced | 2,119 | 3.25 | 2.82 | 2.83 | 0.10 | 8.04 | 2,057 | 4.02 | 3.28 | 3.42 | 0.29 | 10.83 | 0.63 |
| Emerging | 1,019 | 4.49 | 3.93 | 3.08 | 0.68 | 10.19 | 1,014 | 4.80 | 4.16 | 2.91 | 1.38 | 10.33 | 0.76 |
| **24-month** | | | | | | | | | | | | | |
| Advanced | 1,461 | 3.65 | 4.26 | 5.05 | 0.32 | 9.50 | 1,403 | 4.90 | 3.86 | 3.94 | 0.66 | 13.55 | 0.37 |
| Emerging | 725 | 3.17 | 3.98 | 3.17 | 0.55 | 10.20 | 716 | 5.18 | 4.49 | 3.36 | 1.52 | 10.58 | 0.70 |

**Panel B: Ex-ante Default Probabilities**

| | Local Currency | | | | | | Foreign Currency | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | Corr |
| **3-month** | | | | | | | | | | | | | |
| Advanced | 3,445 | 8.19 | 7.61 | 4.48 | 1.87 | 16.71 | 3,468 | 8.21 | 7.61 | 4.48 | 1.90 | 16.71 | 0.9996 |
| Emerging | 1,527 | 9.92 | 9.01 | 5.00 | 3.36 | 19.97 | 1,532 | 9.95 | 9.00 | 5.03 | 3.36 | 20.11 | 0.9999 |
| **6-month** | | | | | | | | | | | | | |
| Advanced | 2,789 | 8.54 | 7.83 | 6.14 | 0.51 | 19.76 | 2,790 | 8.54 | 7.86 | 6.14 | 0.49 | 19.76 | 0.9998 |
| Emerging | 1,376 | 11.53 | 11.31 | 4.84 | 3.66 | 20.41 | 1,376 | 11.54 | 11.31 | 4.83 | 3.66 | 20.41 | 0.9999 |
| **12-month** | | | | | | | | | | | | | |
| Advanced | 2,124 | 9.85 | 9.50 | 7.47 | 0.28 | 23.44 | 2,125 | 9.86 | 9.50 | 7.47 | 0.30 | 23.43 | 1.0000 |
| Emerging | 1,023 | 12.01 | 12.01 | 5.58 | 2.61 | 21.25 | 1,023 | 12.01 | 12.01 | 5.57 | 2.61 | 21.25 | 1.0000 |
| **24-month** | | | | | | | | | | | | | |
| Advanced | 1,459 | 16.55 | 17.38 | 9.15 | 0.41 | 30.89 | 1,467 | 16.54 | 17.32 | 9.15 | 0.42 | 30.91 | 1.0000 |
| Emerging | 725 | 14.66 | 14.49 | 7.70 | 1.05 | 27.17 | 725 | 14.66 | 14.49 | 7.70 | 1.05 | 27.17 | 1.0000 |

Table 4: Drivers of Local-Currency Pseudo Credit Spreads

This table reports panel regressions of 3-month pseudo credit spreads in local currency (LC) on a set of economic determinants. The physical and risk-neutral default probabilities are denoted by $P$ and $Q$, respectively, and are computed for 3-month pseudo bonds. The data are quarterly, constructed as averages of monthly observations within each quarter. All specifications include country fixed effects. The $t$-statistics, reported in parentheses, are computed using standard errors clustered at the country and quarter levels. Details on the construction of local variables are provided in Section 2, while global variables are described in Section 4.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Dependent Variable: Local-Currency Pseudo Credit Spread | | | | | | |
| | Risk decomposition | Stock index moments | FX moments | Risk-free rates | Local conditions | Global conditions | |
| Default Probability (P) | 0.346*** | | | | | | |
| | (12.38) | | | | | | |
| Default Premium (Q - P) | 0.549*** | | | | | | |
| | (12.96) | | | | | | |
| Expected Return (LC) | | -0.370** | | | | | |
| | | (-2.54) | | | | | |
| Return Volatility (LC) | | 0.421*** | | | | | |
| | | (3.35) | | | | | |
| FX Return (USD per LC) | | | -0.090** | | | | |
| | | | (-2.05) | | | | |
| FX Volatility | | | 0.300*** | | | | |
| | | | (3.94) | | | | |
| LC Risk-free Rate | | | | 0.113 | | | |
| | | | | (0.85) | | | |
| USD Risk-free Rate | | | | -0.058 | | | |
| | | | | (-0.25) | | | |
| Term Spread | | | | 0.004 | | | |
| | | | | (1.07) | | | |
| Foreign Reserves (USD) | | | | | -0.026*** | | |
| | | | | | (-3.26) | | |
| Local Inflation | | | | | 0.167** | | |
| | | | | | (2.20) | | |
| CFNAI | | | | | | -0.013*** | |
| | | | | | | (-2.82) | |
| Macro Uncertainty | | | | | | 0.058*** | |
| | | | | | | (3.88) | |
| GZ Spread | | | | | | | 0.024*** |
| | | | | | | | (4.20) |
| EBP | | | | | | | -0.006 |
| | | | | | | | (-0.67) |
| Constant | -0.009*** | 0.020** | 0.017*** | 0.037*** | 0.334*** | -0.004 | -0.013 |
| | (-2.73) | (2.18) | (2.67) | (4.73) | (3.71) | (-0.31) | (-0.93) |
| Observations | 1,743 | 1,256 | 1,617 | 1,533 | 1,326 | 1,745 | 725 |
| R-squared | 0.832 | 0.351 | 0.464 | 0.414 | 0.442 | 0.487 | 0.583 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Table 5: Decomposition of Pseudo Quanto Spreads

This table reports regression results decomposing the pseudo quanto spread, defined as the difference between USD- and local currency (LC)-denominated 3-month pseudo credit spreads. The explanatory variables are the physical default probability ($P$) and a measure of the default risk premium, captured by the difference in risk-neutral default probabilities ($Q$) between USD and LC pseudo bonds. All probabilities refer to pseudo bonds with a 3-month maturity. The data are quarterly and computed as the average of monthly observations within each quarter. Regressions include country and/or time fixed effects. The $t$-statistics are reported in parentheses and are based on standard errors clustered at the quarter and/or country level. Variable definitions are provided in Section 4.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Pooled | | | Cross section | | | Time series | | |
| Default Probability (P) | 0.469*** | | 0.530*** | 0.476*** | | 0.536*** | 0.168*** | | 0.288*** |
| | (3.53) | | (6.00) | (3.54) | | (6.11) | (3.49) | | (7.73) |
| USD Q - LC Q | | 0.415*** | 0.568*** | | 0.418*** | 0.571*** | | 0.492*** | 0.551*** |
| | | (13.52) | (9.70) | | (11.99) | (9.45) | | (18.25) | (19.32) |
| Constant | -0.018* | 0.016* | -0.029*** | -0.018* | 0.016* | -0.030*** | 0.007* | 0.016*** | -0.009*** |
| | (-1.77) | (1.89) | (-4.50) | (-1.82) | (1.86) | (-4.62) | (1.71) | (22.07) | (-2.71) |
| Observations | 1,692 | 1,692 | 1,692 | 1,691 | 1,691 | 1,691 | 1,692 | 1,692 | 1,692 |
| R-squared | 0.530 | 0.155 | 0.812 | 0.548 | 0.167 | 0.823 | 0.778 | 0.875 | 0.909 |
| Country FE | No | No | No | No | No | No | Yes | Yes | Yes |
| Time FE | No | No | No | Yes | Yes | Yes | No | No | No |
| Clustering by country | Yes | Yes | Yes | Yes | Yes | Yes | No | No | No |
| Clustering by time | Yes | Yes | Yes | No | No | No | Yes | Yes | Yes |

Table 6: Drivers of Pseudo Quanto Spreads

This table reports panel regressions of pseudo quanto spreads on a set of risk factors. The pseudo quanto spread is defined as the difference between USD and LC 3-month pseudo credit spreads. The data are quarterly, constructed as averages of monthly observations within each quarter. All specifications include country fixed effects. The $t$-statistics, reported in parentheses, are computed using standard errors clustered at the country and quarter levels. Details on the construction of local variables are provided in Section 2, and global variables are described in Section 4.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Dependent Variable: Pseudo Quanto Spread | | | | | | |
| | Stock index moments | | FX moments | Risk-free rates | Local conditions | Global conditions | |
| Expected Return (LC) | 0.359*** | | | | | | |
| | (4.82) | | | | | | |
| Return Volatility (LC) | -0.115** | | | | | | |
| | (-2.12) | | | | | | |
| Expected Return (USD) | | -0.175*** | | | | | |
| | | (-5.90) | | | | | |
| Return Volatility (USD) | | 0.398*** | | | | | |
| | | (5.06) | | | | | |
| FX Return (USD per LC) | | | -0.011 | | | | |
| | | | (-0.70) | | | | |
| FX Volatility | | | 0.002*** | | | | |
| | | | (5.81) | | | | |
| USD - LC Risk-free Rate | | | | -0.265*** | | | |
| | | | | (-7.33) | | | |
| Term Spread | | | | -0.000 | | | |
| | | | | (-0.29) | | | |
| Foreign Reserves (USD) | | | | | -0.027*** | | |
| | | | | | (-7.50) | | |
| Local Inflation | | | | | 0.039 | | |
| | | | | | (1.05) | | |
| CFNAI | | | | | | -0.005*** | |
| | | | | | | (-3.99) | |
| Macro Uncertainty | | | | | | -0.012** | |
| | | | | | | (-2.04) | |
| GZ Spread | | | | | | | 0.004 |
| | | | | | | | (1.36) |
| EBP | | | | | | | -0.002 |
| | | | | | | | (-0.33) |
| Constant | 0.020*** | -0.030*** | 0.006* | 0.019*** | 0.323*** | 0.030*** | 0.012 |
| | (3.32) | (-3.47) | (1.94) | (20.01) | (8.13) | (6.34) | (1.59) |
| Observations | 1,205 | 1,206 | 1,564 | 1,486 | 1,286 | 1,692 | 720 |
| R-squared | 0.801 | 0.414 | 0.777 | 0.789 | 0.791 | 0.768 | 0.747 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 7: Predictability of Aggregate GDP Growth

This table reports the results of the following predictive regression:

$$\Delta Y_{t+1} = \alpha + \beta \Delta Y_t + \gamma_1 \mathrm{CS}_{i,t}^{LC} + \gamma_2 \mathrm{CS}_{i,t}^{\mathrm{Quanto}} + \delta \mathrm{Controls}_t + \varepsilon_{t+1},$$

where $\Delta Y_{t+1}$ reflects the one-quarter-ahead real GDP growth averaged across countries (excluding the US), with weights given by the mean GDP over the sample period. The main variables of interest in Panel A are the local currency (LC) pseudo credit spread for country $i$ in quarter $t$, denoted by $\mathrm{CS}_{i,t}^{LC}$, and the difference between $\mathrm{CS}_{i,t}^{USD}$ and $\mathrm{CS}_{i,t}^{LC}$, denoted by $\mathrm{CS}_{i,t}^{\mathrm{Quanto}}$. In Panel B, the main variables of interest are the default probability ($P$) and the default risk premium, measured as the difference between the physical ($P$) and risk-neutral ($Q$) default probabilities. All measures are centered around the 3-month maturity to match our measures with the forecast horizon. The controls include the (updated, LC) quarterly SPX pseudo spread of Culp et al. (2018) denoted by 'CS USA', the term spread, the Macroeconomic Uncertainty Index of Jurado et al. (2015), the real Federal Funds rate (FFR), and the 'GZ Spread' of Gilchrist and Zakrajšek (2012) available up to 2015. We adjust the standard errors using the Newey and West (1987) kernel, where the bandwidth is selected optimally to account for potential serial correlation across residuals ($\varepsilon_{t+1}$), and further control for the lag of aggregate economic growth. The tables report the regression coefficients, which are multiplied by 100, as well as the $t$-stats in parenthesis.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Pseudo credit spreads | | | | Risk decomposition | | |
| | | | Controlling for CNV | Controlling for GZ | | Controlling for CNV | Controlling for GZ |
| | Full sample | Full sample | Full sample | Up to 2015 | Full sample | Full sample | Up to 2015 |
| CS LC | -2.342** | -2.714** | -10.568*** | -6.834*** | | | |
| | (-2.21) | (-2.44) | (-8.82) | (-15.44) | | | |
| CS Difference (USD - LC) | | 0.095 | 0.254 | 0.133 | | | |
| | | (0.17) | (0.49) | (0.52) | | | |
| Default Probability | | | | | -1.575*** | -3.832*** | -1.811*** |
| | | | | | (-3.62) | (-8.68) | (-8.40) |
| Default Premium (Q - P) | | | | | -1.142*** | -3.453*** | -1.763*** |
| | | | | | (-2.71) | (-7.98) | (-7.88) |
| CS US | | | -0.796*** | -0.331*** | | -0.788*** | -0.243*** |
| | | | (-15.87) | (-15.17) | | (-15.93) | (-10.40) |
| Term Spread | | | 0.402*** | -0.079*** | | 0.337*** | -0.026 |
| | | | (10.60) | (-2.75) | | (9.26) | (-0.79) |
| Macro Uncertainty | | | 4.475*** | 0.497 | | 3.965*** | -1.054*** |
| | | | (11.61) | (1.62) | | (10.92) | (-3.43) |
| FFR | | | | -0.125*** | | | -0.088*** |
| | | | | (-7.06) | | | (-4.38) |
| GZ Spread | | | | -0.769*** | | | -0.658*** |
| | | | | (-19.09) | | | (-15.26) |
| Constant | 0.850*** | 0.875*** | -3.043*** | 1.037*** | 0.971*** | -2.433*** | -2.433*** |
| | (13.23) | (12.78) | (-9.23) | (5.18) | (13.09) | (-7.70) | (-7.70) |
| Observations | 1,770 | 1,718 | 1,659 | 730 | 1,743 | 1,634 | 1,634 |
| R-squared | 0.051 | 0.052 | 0.181 | 0.681 | 0.056 | 0.185 | 0.185 |

## Table 8: Predictability of Country-level GDP Growth

This table reports the panel results of the following predictive regression:

$$\Delta Y_{i,t+4} = \beta \Delta Y_{i,t} + \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_t + \alpha_i + \eta_t + \varepsilon_{i,t+4},$$

where $\Delta Y_{i,t+4}$ the one-year-ahead real GDP growth for country $i$. The main variables of interest in Panel A are the local currency (LC) pseudo credit spread for country $i$ in quarter $t$, denoted by $\text{CS}_{i,t}^{LC}$, and the difference between $\text{CS}_{i,t}^{USD}$ and $\text{CS}_{i,t}^{LC}$, denoted by $\text{CS}_{i,t}^{\text{Quanto}}$. In Panel B, the main variables of interest are the default probability ($P$) and the default risk premium, measured as the difference between the physical ($P$) and risk-neutral ($Q$) default probabilities. These variables are computed as the equally weighted average of the measures at 3-month, 6-month, 1-year, and 2-year horizons. The controls include the (updated, LC) quarterly SPX pseudo spread of Culp et al. (2018) denoted by 'CS USA', the term spread, and the Macroeconomic Uncertainty Index of Jurado et al. (2015). We include country fixed effects and cluster the standard errors at the country and time level. Columns (5) and (10) additionally include time fixed effects. The table reports the regression coefficients, which are multiplied by 100, as well as the $t$-stats in parenthesis.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | Pseudo credit spreads | | | | | Risk decomposition | | | | |
| | Full sample | AE | EM | No Covid | Full sample | Full sample | AE | EM | No Covid | Full sample |
| CS LC | -31.010*** | -29.933*** | -32.608*** | -21.348*** | -9.731*** | | | | | |
| | (-4.09) | (-4.04) | (-3.15) | (-3.30) | (-3.56) | | | | | |
| CS Difference (USD - LC) | 2.166 | 0.538 | 1.104 | -0.042 | -1.158 | | | | | |
| | (0.50) | (0.06) | (0.23) | (-0.01) | (-0.38) | | | | | |
| Default Probability | | | | | | -9.830*** | -9.378*** | -10.171*** | -7.664*** | -0.214 |
| | | | | | | (-3.72) | (-3.31) | (-2.85) | (-3.65) | (-0.19) |
| Default Premium (Q - P) | | | | | | -7.566*** | -4.154 | -9.348** | -6.118*** | -2.739* |
| | | | | | | (-2.94) | (-0.96) | (-2.17) | (-2.92) | (-1.95) |
| CS US | -0.950* | -0.901* | -0.889 | -0.149 | | -0.833* | -0.907* | -0.573 | -0.049 | |
| | (-1.92) | (-1.95) | (-1.29) | (-0.53) | | (-1.82) | (-1.93) | (-0.90) | (-0.20) | |
| Term Spread | 1.230*** | 0.934** | 2.073*** | 1.123** | | 1.061** | 0.807** | 1.776*** | 1.037** | |
| | (2.67) | (2.45) | (2.91) | (2.43) | | (2.40) | (2.16) | (2.68) | (2.30) | |
| Macro Uncertainty | 13.869** | 12.622** | 16.794** | 2.477 | | 11.694** | 11.140** | 13.320** | 0.708 | |
| | (2.38) | (2.36) | (2.41) | (0.80) | | (2.10) | (2.14) | (2.08) | (0.26) | |
| Constant | -9.821* | -8.850** | -12.213* | -1.151 | 2.487*** | -7.810 | -7.730* | -8.755 | 0.482 | 2.140*** |
| | (-1.98) | (-2.00) | (-2.00) | (-0.42) | (15.15) | (-1.65) | (-1.77) | (-1.55) | (0.20) | (14.75) |
| Observations | 1,538 | 1,050 | 488 | 1,423 | 1,564 | 1,514 | 1,031 | 483 | 1,399 | 1,544 |
| R-squared | 0.251 | 0.199 | 0.319 | 0.228 | 0.722 | 0.239 | 0.184 | 0.301 | 0.230 | 0.728 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | No | No | No | No | Yes | No | No | No | No | Yes |

## Table 9: Exchange Rate Predictability

This table reports the panel results of the following predictive regression:

$$\Delta s_{i,t+4} = \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t+4},$$

where $\Delta s_{i,t+4}$ denotes the one-year-ahead exchange rate return of country $i$, with an increase in the log exchange rate $s$ indicates an appreciation of the country's local currency (LC) relative to the USD. The main variables of interest are the local currency (LC) pseudo credit spread for country $i$ in quarter $t$, denoted by $\text{CS}_{i,t}^{LC}$, and the difference between $\text{CS}_{i,t}^{USD}$ and $\text{CS}_{i,t}^{LC}$, denoted by $\text{CS}_{i,t}^{\text{Quanto}}$. These variables are computed as the equally weighted average of the credit spreads at 3-month, 6-month, 1-year, and 2-year horizons. The controls include each country's real GDP growth, its level of foreign reserves, and its year-on-year inflation rate. Columns (5) and (6) presents results for advanced (AE) and emerging economies (EM) separately. Column (7) excludes the Covid 19 crisis. We include country and time fixed effects, and cluster the standard errors at the country and time level. The table reports the regression coefficients as well as the $t$-stats in parenthesis.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Full sample | Full sample | Full sample | Full sample | AE | EM | No Covid |
| CS LC | 0.285*** | | 0.326*** | 0.325*** | 0.090 | 0.766*** | 0.351*** |
| | (2.80) | | (3.05) | (3.08) | (0.67) | (5.45) | (3.29) |
| CS Difference (USD - LC) | | 0.190*** | 0.210*** | 0.248*** | 0.408*** | 0.216*** | 0.283*** |
| | | (2.73) | (3.17) | (3.94) | (3.15) | (3.12) | (4.33) |
| GDP Growth | | | | 0.026 | 0.111 | 0.030 | 0.119 |
| | | | | (0.19) | (0.50) | (0.27) | (0.41) |
| FX Reserves | | | | 0.021* | 0.022** | -0.035 | 0.025** |
| | | | | (1.91) | (2.13) | (-1.14) | (2.34) |
| Inflation (YOY) | | | | 0.821*** | 0.964*** | 0.541*** | 0.864*** |
| | | | | (6.66) | (5.94) | (3.17) | (6.69) |
| Constant | -0.038*** | -0.027*** | -0.043*** | -0.291** | -0.283** | 0.287 | -0.350*** |
| | (-7.67) | (-24.32) | (-7.81) | (-2.37) | (-2.39) | (0.81) | (-2.87) |
| Observations | 1,569 | 1,564 | 1,564 | 1,271 | 862 | 406 | 1,180 |
| R-squared | 0.615 | 0.619 | 0.623 | 0.629 | 0.693 | 0.622 | 0.631 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Local controls | No | No | No | Yes | Yes | Yes | Yes |

Table 10: Exchange Rate Predictability by Currency Characteristics

This table reports cross-sectional differences in exchange rate predictability. It presents the panel results of the following predictive regression by currency characteristics:

$$\Delta s_{i,t+4} = \gamma_1 \mathrm{CS}_{i,t}^{LC} + \gamma_2 \mathrm{CS}_{i,t}^{\mathrm{Quanto}} + \delta \mathrm{Controls}_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t+4},$$

where $\Delta s_{i,t+4}$ denotes the one-year-ahead exchange rate return of country $i$, with an increase in the log exchange rate $s$ indicates an appreciation of the country's local currency (LC) relative to the USD. In Columns (1) and (2), countries are sorted according to their correlation between local stock market returns and USD/LC exchange rate returns. In Columns (3) and (4), countries are sorted according to their correlation between SP&500 returns and USD/LC exchange rate returns. In Columns (5) and (6), countries are sorted according to their correlation between US consumption growth and USD/LC exchange rate returns. The main variables of interest are the local currency (LC) pseudo credit spread for country $i$ in quarter $t$, denoted by $\mathrm{CS}_{i,t}^{LC}$, and the difference between $\mathrm{CS}_{i,t}^{USD}$ and $\mathrm{CS}_{i,t}^{LC}$, denoted by $\mathrm{CS}_{i,t}^{\mathrm{Quanto}}$. These variables are computed as the equally weighted average of the credit spreads at 3-month, 6-month, 1-year, and 2-year horizons. The controls include each country's real GDP growth, its level of foreign reserves, and its year-on-year inflation rate. We include country and time fixed effects, and cluster the standard errors at the time level. The table reports the regression coefficients as well as the $t$-stats in parenthesis.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Corr with LC index | | Corr with SP500 | | Corr with US consumption | |
| | Low | High | Low | High | Low | High |
| CS LC | -0.000 | 0.445*** | -0.360** | 0.627*** | -0.087 | 0.700*** |
| | (-0.00) | (4.17) | (-2.29) | (7.45) | (-0.72) | (6.27) |
| CS Difference (USD - LC) | -0.026 | 0.428*** | -0.063 | 0.293*** | 0.109 | 0.647*** |
| | (-0.23) | (5.43) | (-0.50) | (4.69) | (1.21) | (4.72) |
| GDP Growth | -0.205 | 0.113 | -0.074 | 0.336 | -0.204 | 0.342** |
| | (-1.21) | (0.99) | (-0.69) | (1.25) | (-1.28) | (2.14) |
| FX Reserves | 0.022** | 0.044** | 0.025* | 0.007 | 0.026** | -0.022 |
| | (2.31) | (2.38) | (1.92) | (0.37) | (2.02) | (-1.03) |
| Inflation (YOY) | 0.708*** | 0.750*** | 0.627*** | 0.875*** | 0.915*** | 0.733*** |
| | (3.31) | (5.17) | (3.52) | (4.87) | (4.86) | (4.57) |
| Constant | -0.278** | -0.559*** | -0.298* | -0.165 | -0.337** | 0.152 |
| | (-2.58) | (-2.71) | (-1.99) | (-0.80) | (-2.26) | (0.66) |
| Observations | 561 | 694 | 628 | 628 | 624 | 641 |
| R-squared | 0.813 | 0.655 | 0.705 | 0.693 | 0.757 | 0.671 |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Local controls | Yes | Yes | Yes | Yes | Yes | Yes |

Figure 1: Empirical Credit Spreads of Two-Year SPX Pseudo Bonds (United States)

This figure presents credit spreads of two-year pseudo bonds in the United States. Pseudo bonds are constructed as risk-free debt minus put options on the S&P 500 Index (SPX). Investment-grade (IG) and high-yield (HY) ratings are assigned by mapping the ex-ante default probabilities of pseudo bonds, computed from the empirical distribution of SPX returns, into Moody's rating categories. See Appendix A for details. Panel (a) compares the historical IG and HY credit spreads reported in Culp et al. (2018) (labeled CNV) with our replicated series, extended to 2022 (labeled AJPS). Panel (b) compares our replicated IG and HY credit spread indices constructed using either box rates inferred from put-call parity (Van Binsbergen et al., 2022) or the risk-free rates of Gürkaynak et al. (2007) (labeled GSW). SPX option data are from OptionMetrics. Shaded vertical bars denote NBER recessions. The data are monthly and span 1996 to 2023.

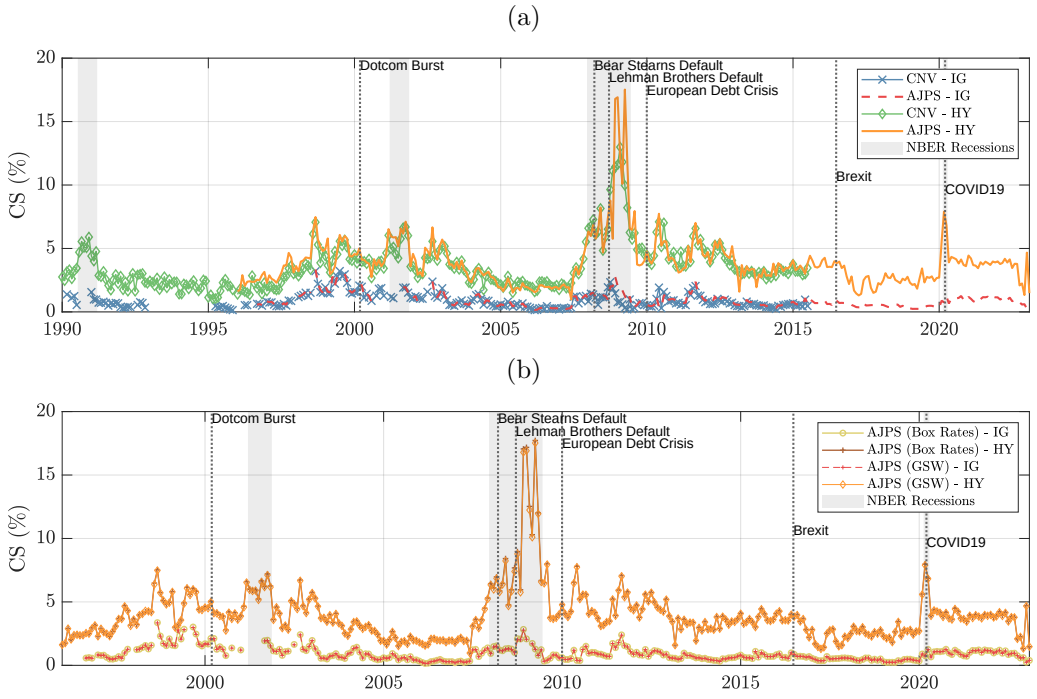


Figure 2: Empirical Credit Spreads of Six-Month ESX Pseudo Bonds (United Kingdom)

This figure plots six-month pseudo credit spreads and default probabilities for the U.K. Local-currency (GBP) spreads constructed from put options on the FTSE100 index (ESX), while foreign-currency (USD) spreads are constructed from USD-denominated ETF options tracking the same index. For six-month bonds, option maturities are restricted to 91-365 days (see Appendix A). Panel (a) shows local- and foreign-currency credit spreads. Panel (b) reports the corresponding ex-ante default probabilities, which are nearly identical across currencies by construction. Panel (c) reports the number of options used to construct each series. The data are monthly from 2005 to 2024. Shaded areas denote recessions.

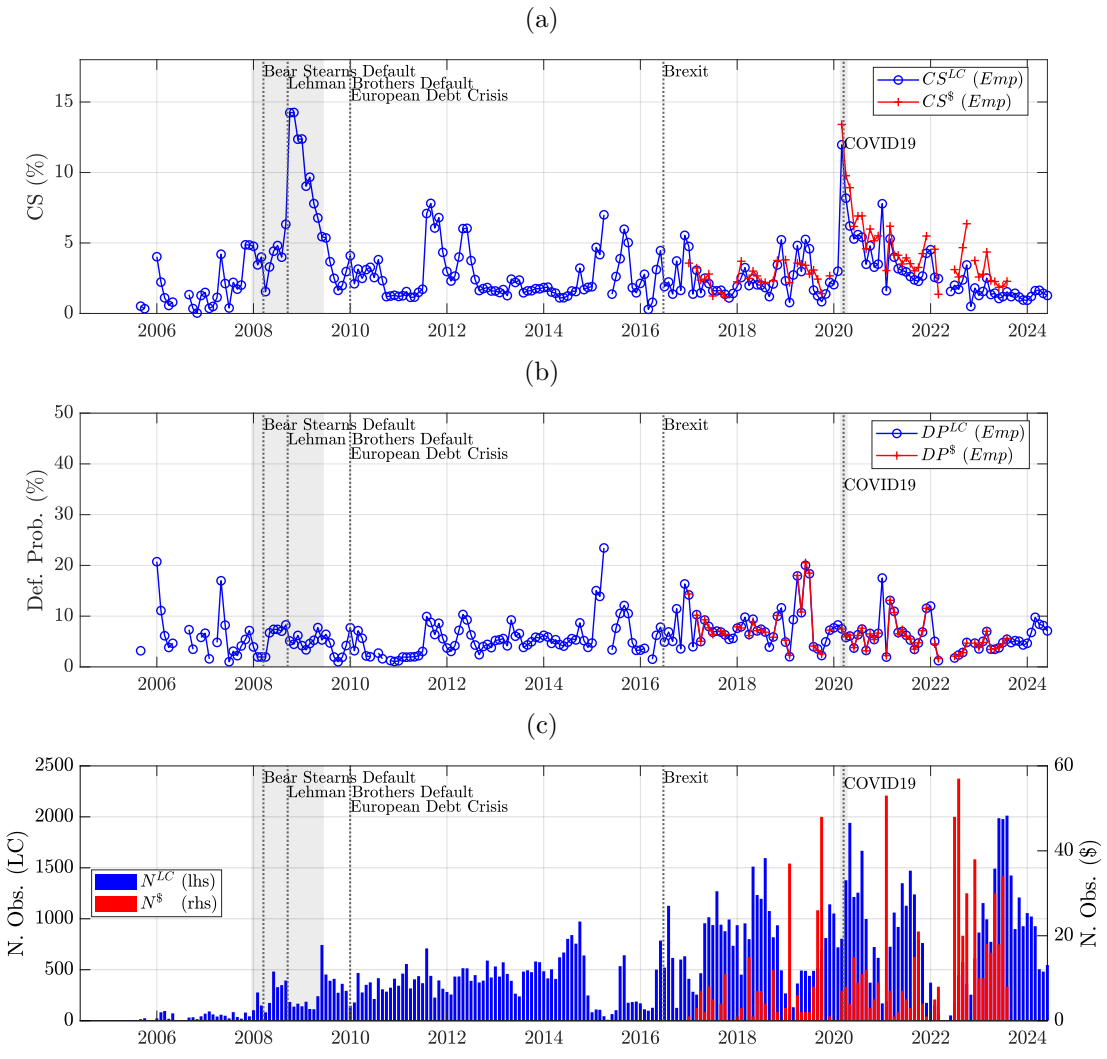


Figure 3: Synthetic Credit Spreads of Six-Month ESX Pseudo Bonds

This figure compares six-month pseudo credit spreads constructed from option data with their synthetic counterparts. Local-currency (GBP) spreads are derived from FTSE100 index options, while foreign-currency (USD) spreads are derived from USD-denominated ETF options tracking the same index. Synthetic series are constructed using the Black-Scholes-Merton model applied to the corresponding synthetic index in foreign or local currency. Option maturities are restricted to 91-365 days (see Appendices A and B). Panel (a) shows local-currency spreads and their synthetic counterparts. Panel (b) shows foreign-currency spreads and their synthetic counterparts. Panel (c) reports the combined series of local- and foreign-currency spreads. The data are monthly from 2003 to 2024. Shaded areas denote recessions.

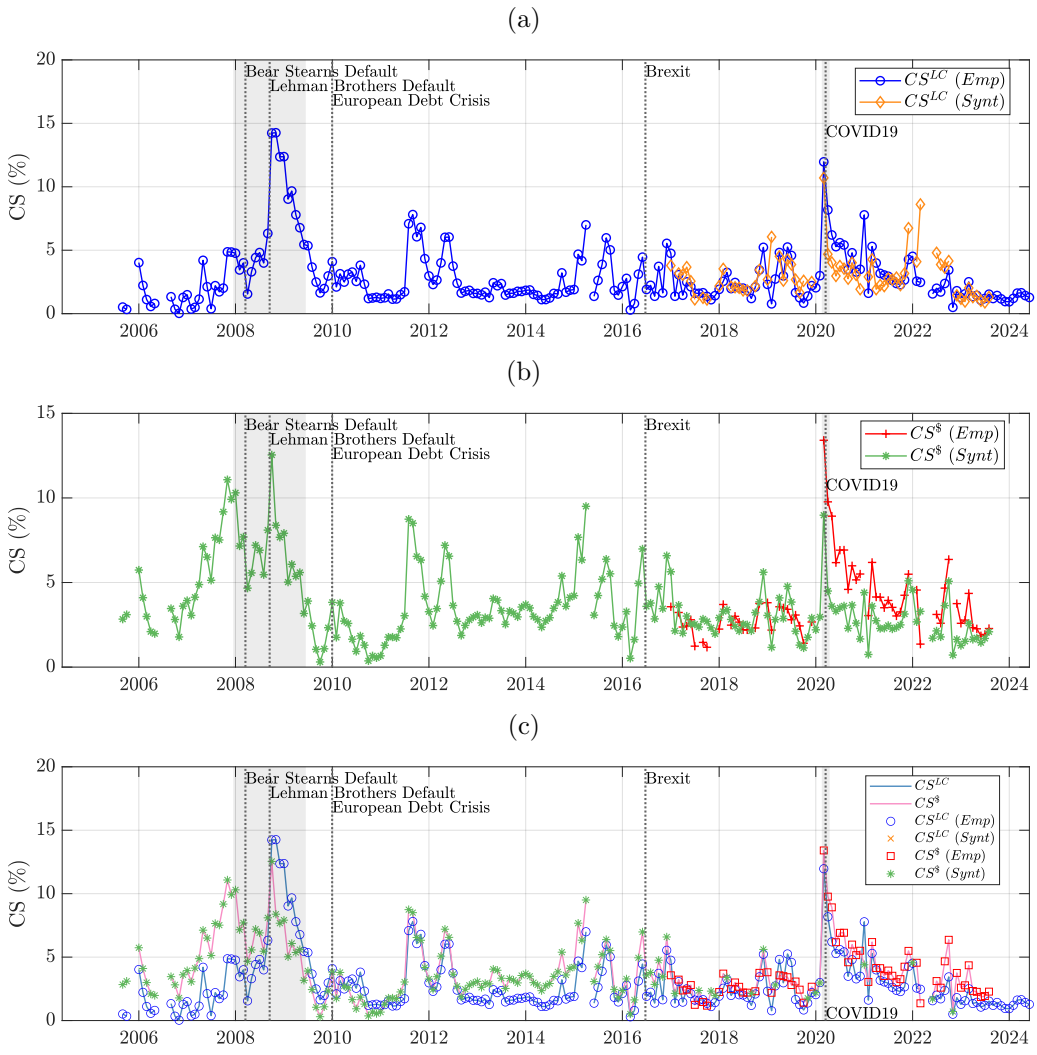


Figure 4: Credit Spreads of Six-Month ESX Pseudo Bonds - By Currency

This figure compares six-month pseudo credit spreads in local (GBP) and foreign (USD) currency. Local-currency spreads are constructed from FTSE100 index options (ESX), while foreign-currency spreads are constructed from USD-denominated ETF options tracking the same index. Synthetic series are obtained using the Black-Scholes-Merton model applied to the corresponding synthetic index in foreign or local currency. Option maturities are restricted to 91-365 days (see Appendices A and B). Panel (a) shows local-currency spreads and their synthetic counterparts. Panel (b) reports the ratio of local- to foreign-currency spreads. Panel (c) shows the spread differential between foreign- and local-currency credit spreads. The data are monthly from 2003 to 2024. Shaded areas denote recessions.

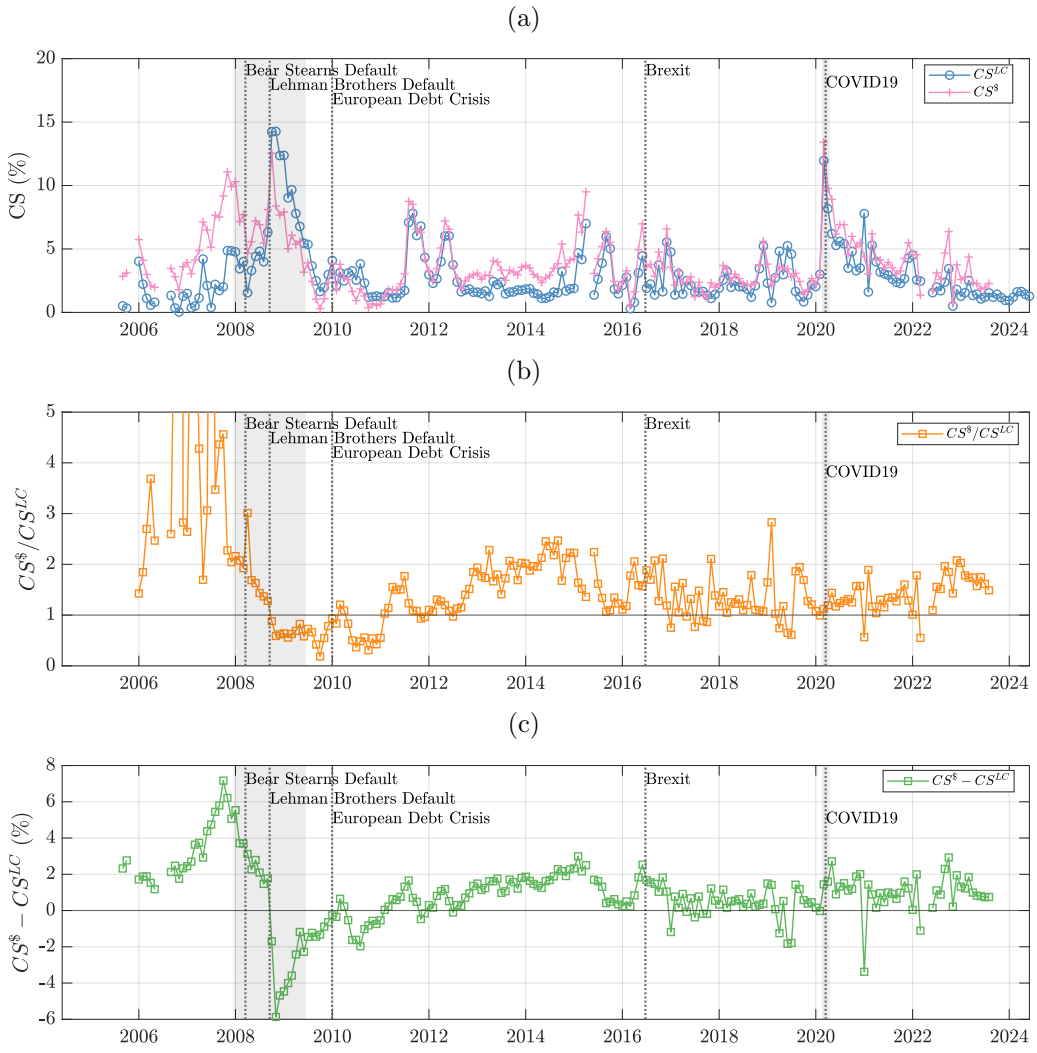


Figure 5: Default probabilities, volatility, and leverage: United Kingdom.

This figure reports default probabilities, implied volatilities, and leverage for six-month pseudo bonds in local (GBP) and foreign (USD) currency. Local-currency series are constructed from FTSE100 index options (ESX), while foreign-currency series are constructed from USD-denominated ETF options tracking the same index. Synthetic series are obtained using the Black-Scholes-Merton model applied to the corresponding synthetic index in foreign or local currency. Physical ($P$) default probabilities are estimated from historical return distributions, while risk-neutral ($Q$) default probabilities are inferred from option prices using the Black-Scholes-Merton model. Option maturities are restricted to 91-365 days (see Appendices A and B). Panel (a) reports the ratio of risk-neutral to physical default probabilities in local and foreign currency. Panel (b) shows implied volatilities. Panel (c) reports implied leverage ratios. The data are monthly from 2003 to 2024. Shaded areas denote recessions.

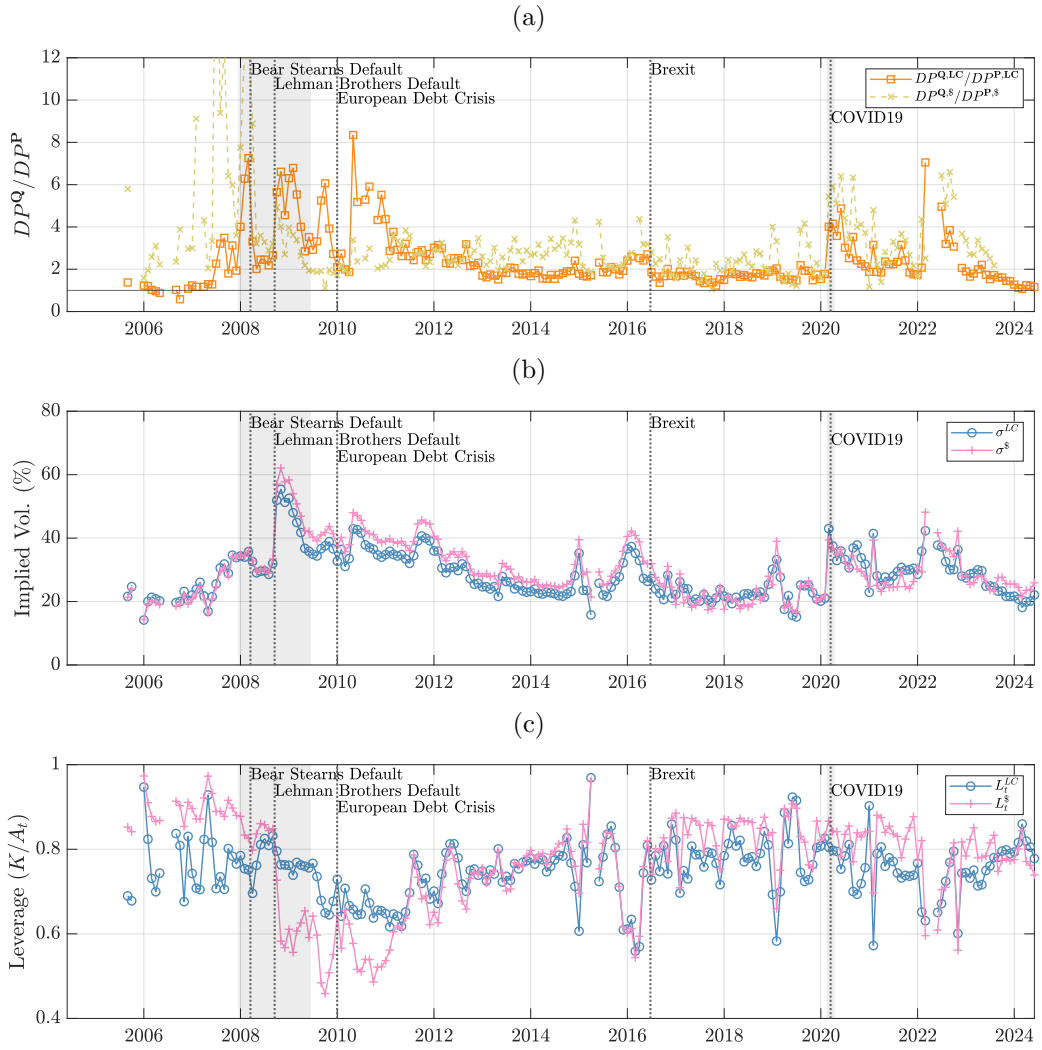


Figure 6: Quanto Spreads and Risk Premia

This figure plots the relation between the pseudo quanto spread, defined as the difference between foreign- and local-currency credit spreads, and the corresponding cross-currency difference in risk premia, measured as the difference in risk-neutral default probabilities. Local-currency (GBP) pseudo bonds are constructed from FTSE100 index options (ESX), while foreign-currency (USD) pseudo bonds are constructed from USD-denominated ETF options tracking the same index. Synthetic series are obtained using the Black-Scholes-Merton model applied to the corresponding synthetic index in foreign or local currency. Risk-neutral default probabilities are inferred from option prices. Option maturities are restricted to 91-365 days (see Appendices A and B). The data are monthly from 2003 to 2024.

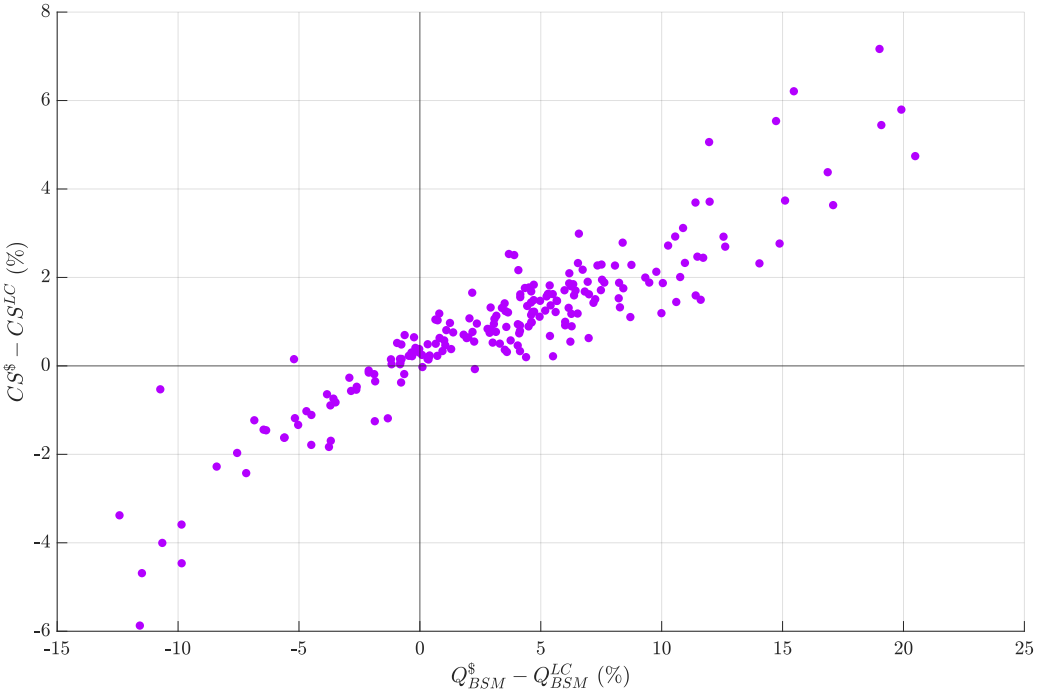


Figure 7: Cross-Currency Credit Spreads: Model-Implied Levels and Drivers

This figure illustrates the model-implied cross-currency differences in pseudo credit spreads and their economic drivers. Panels (a)-(c) show how credit spreads, leverage, and risk-neutral default probabilities vary with the level of default risk. Panels (d)-(f) examine the role of the currency risk premium, while Panels (g)-(i) analyze the impact of the correlation between the local stock market index and the USD-GBP exchange rate. Local-currency (GBP) measures are shown with dashed red lines, and foreign-currency (USD) measures with solid blue lines. Model parameters are calibrated as described in Table A.5.

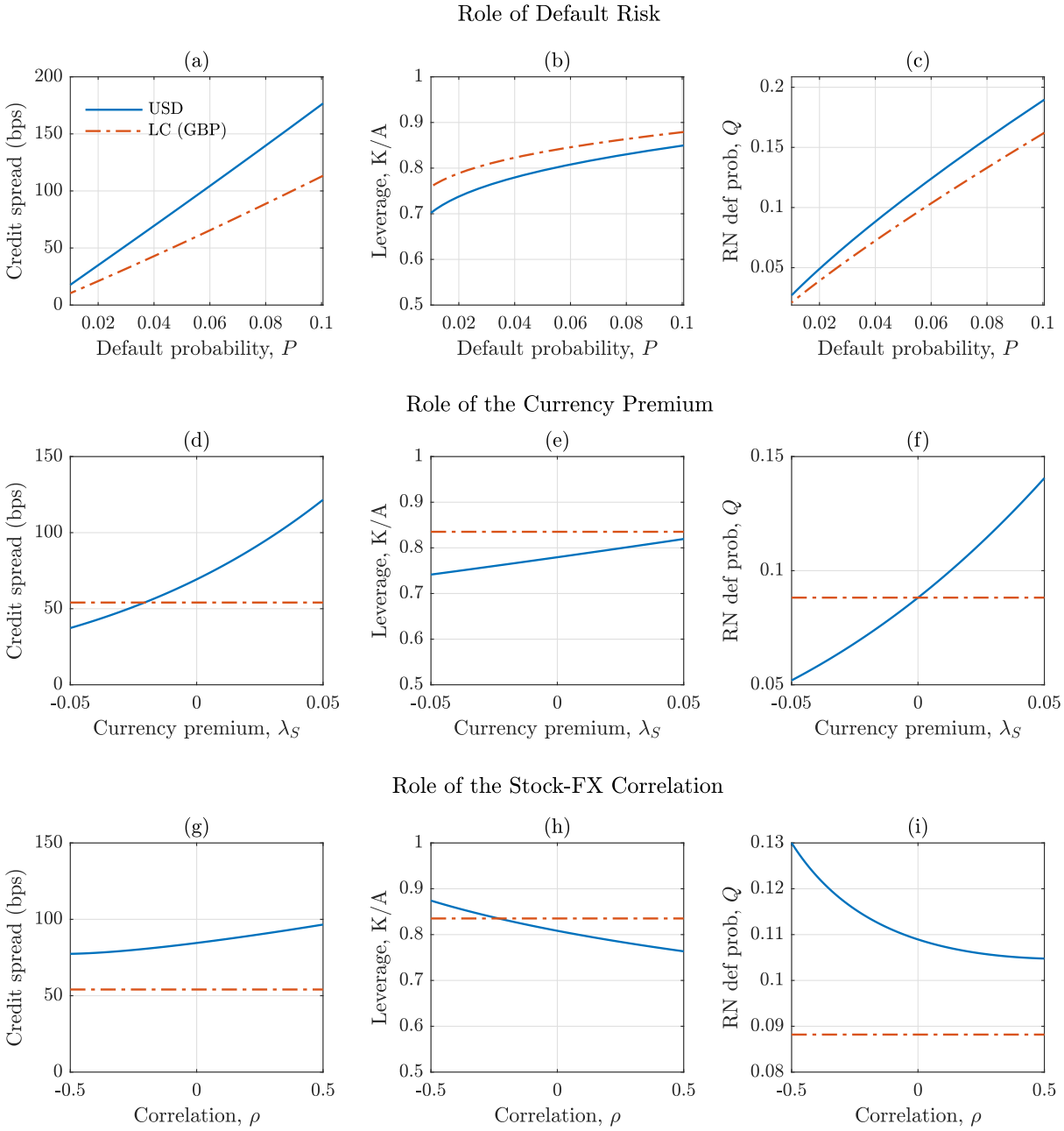


Figure 8: Regional Dynamics of Local- and Foreign-Currency Pseudo Credit Spreads (6-Month)

This figure plots regional GDP-weighted averages of 6-month pseudo credit spreads in local (LC) and foreign (USD) currency. Panel (a) shows LC spreads, and Panel (b) shows USD-denominated spreads for three regions: Europe, Asia-Pacific, and the Americas. LC pseudo bonds are constructed from options on domestic stock market indices, while USD-denominated pseudo bonds use options on exchange-traded funds (ETFs) tracking the same indices. Option maturities are restricted to 91-365 days. The series are computed as GDP-weighted averages across countries within each region. Data are monthly from 2003 to 2024 and sourced from Refinitiv Datastream, OptionMetrics via WRDS, and the IMF (for GDP weights). Shaded areas denote NBER recessions. Countries included for Europe are Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Norway, Poland, United Kingdom, Spain, Sweden, Switzerland and Turkey; for Asia-Pacific: China, India, Japan, South Korea, Malaysia, Singapore and Thailand; for Americas: Brazil, Canada, Chile, Colombia, Mexico. Details are provided in Appendices A and B.

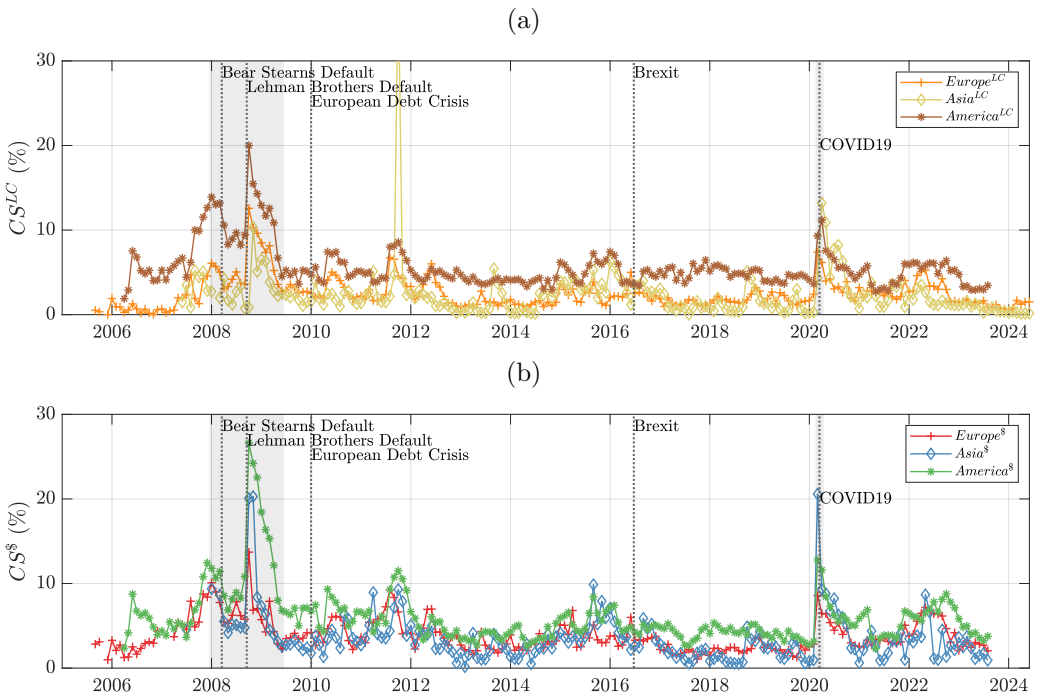
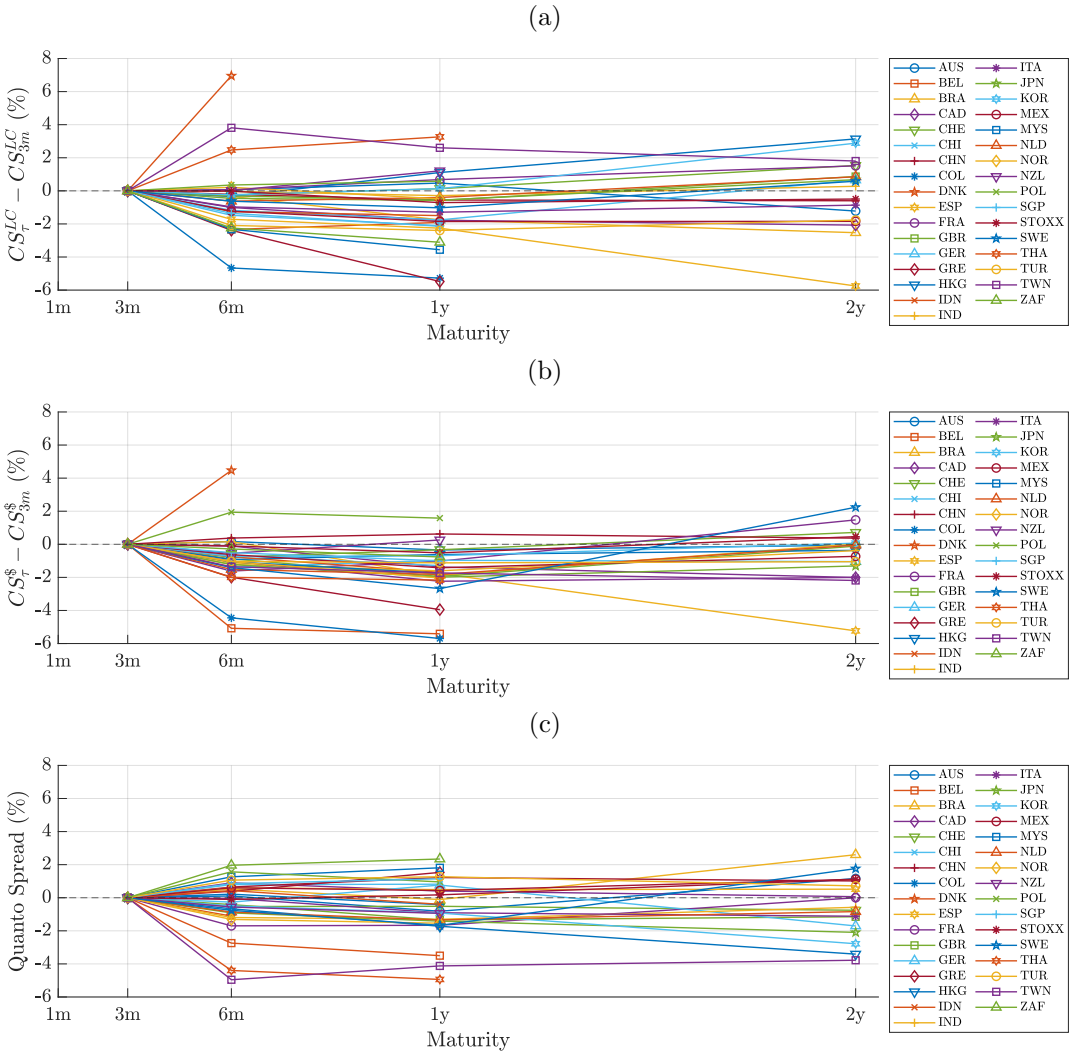


Figure 9: Cross-Country Term Structures of Pseudo Credit Spreads

This figure plots cross-country term structures of pseudo credit spreads in local (LC) and foreign (USD) currency. Panel (a) shows LC spreads and Panel (b) shows USD-denominated spreads, both normalized by subtracting the corresponding 3-month spread for each country, so that all curves start at zero. This normalization isolates differences in the slope of the term structure across countries. Panel (c) reports the term structure of pseudo quanto spreads (USD minus LC), normalized relative to the 3-month quanto spread. LC pseudo bonds are constructed from options on domestic stock market indices, while USD-denominated pseudo bonds use options on exchange-traded funds (ETFs) tracking the same indices. Option maturities are restricted to 7-182, 91-365, 182-547, and 365-1095 days for 3-, 6-, 12-, and 24-month horizons, respectively. Data are monthly from 2003 to 2024 and sourced from Refinitiv Datastream and OptionMetrics via WRDS. Details are provided in Appendices A and B.



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INTERNET APPENDIX to

**"Option-Implied Local Currency Credit Spreads"**

(Not for publication)

This Internet Appendix presents supplementary results that complement the main body of the paper.

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# A Estimation of Empirical Credit Spreads

We describe in detail our procedure for replicating the construction of empirical pseudo credit spreads. This involves explaining the data sources (Section A.1), estimation of expected returns (Section A.2) and their volatility (Sections A.3), the estimation of ex-ante default probabilities (Section A.4), the estimation of riskless rates (Section A.5), and the aggregation of credit spreads into investment grade and high yield indices for the U.S (Section A.6) and country-level indices for other countries (Section A.7).

## A.1 ETF and Index Options Data

We undertake a comprehensive search for data on international stock market indices with traded options, as well as on exchange-traded funds (ETFs) denominated in U.S. dollars that track these indices and have listed options. Our sample construction begins with the set of emerging and developed markets identified in Du and Schreger (2016) and Kelly et al. (2016). Consistent with prior literature, we find that options on local-currency stock indices are standard European-style contracts, whereas options on the corresponding USD-denominated ETFs are American-style.

We obtain index and options price and trade data from Refinitiv (formerly Thomson Reuters, now LSEG) Datastream and from OptionMetrics via Wharton Research Data Services (WRDS). Specifically, we retrieve end-of-day put and call option data on international stock indices from Datastream, accessed through Refinitiv Eikon, and on USD-denominated index-tracking ETFs from OptionMetrics. For each option contract, the data include mid price, strike price, expiration date, exercise style, trading volume, open interest, implied volatility, and the closing price of the underlying asset. We use this options data to estimate option-implied interest rates net of credit and convenience yields (i.e., box rates) as well as pseudo-bond yields.

To estimate pseudo-bond yields from European options, we apply the data filters recommended by Culp et al. (2018) and Constantinides et al. (2013). Specifically, we exclude: (i) duplicate observations; (ii) quotes with zero bid prices or zero open interest; (iii) options whose prices imply negative interest rates under put-call parity; (iv) options whose prices imply negative volatility when conditioning on put-call-parity-implied interest rates and dividend yields; (v) options with implied volatilities more than one standard deviation from the average of their moneyness peer group (bins of width 0.05); (vi) options for which put-call

parity implies interest rates more than one standard deviation from the peer group average; and (vii) options with less than seven days to maturity. Following Culp et al. (2018), we retain deep out-of-the-money options, as they are essential for estimating prices of high-credit-quality pseudo-bonds. When multiple quotes exist for contracts with identical terms but different prices, we retain the quote with the implied volatility closest to that of options with similar moneyness. If OptionMetrics reports a missing or zero implied volatility, we impute it using the Black-Scholes-Merton model.

To estimate pseudo-bond yields from American options, we apply less stringent filters. We retain options with more than seven days to maturity and non-zero open interest. We exclude only those options that violate the put-call parity bounds for American options, using zero-coupon rates from Gürkaynak et al. (2007) as inputs.

Table 1 summarizes the final options data used in this study. For each country or region, we report the name, the ticker of the corresponding stock market index, the mnemonic of the option series on the index, the currency denomination of the options, the sample start and end dates, and the average number of available option observations per month. The subsequent columns present the same information for USD-denominated options on ETFs that track the respective country's stock market index.

## A.2 Forecasting Expected Returns

For a given forecast horizon $\tau$, asset growth $A_{t+\tau}/A_t$ is modeled as the sum of an expected and an unexpected component:

$$\ln(A_{t+\tau}/A_t) = \mu_{t,\tau} + \sigma_{t,\tau}\varepsilon_{t+\tau}, \tag{A.1}$$

where $\mu_{t,\tau}$ is the time-$t$ expected log return on the local market index over horizon $\tau$ and $\varepsilon_{t+\tau}$ is a standardized shock scaled by asset return volatility $\sigma_{t,\tau}$.

Following Culp et al. (2018), we estimate $\mu_{t,\tau}$ using the index's dividend yield for the U.S. We use end-of-month data on the S&P 500 index and dividend distributions from CRSP covering 1946-2023. Expected returns are forecasted using the dividend-to-price ratio $D_t/P_t$ in the following expanding-window regression:

$$\ln(A_{t+\tau}/A_t) = a_{t,\tau} + b_{t,\tau}D_t/P_t + u_{t,\tau}, \qquad t = 0, 1, 2, \ldots T - \tau, \tag{A.2}$$

where $D_t/P_t$ is proxied as the difference between one-year cumulative value-weighted total and capital returns, minus one. The predicted expected return is then given by $\widehat{\mu}_{t,\tau} = \widehat{a}_{t,\tau} + \widehat{b}_{t,\tau} D_t/P_t$.

For non-SPX indices, we estimate the time-$t$ expected return parameter $\mu_{t,\tau}$ for some forecast horizon $\tau$ by fitting an AR(1) model to the realized returns of the pseudo-firm's asset price process (i.e., the return on the market index $A_t$). We use the entire history of monthly returns up until month $t$, to avoid any look-ahead bias. In a AR(1) model, returns evolve as follows:

$$\ln(A_{t+\tau}/A_t) = \beta_0 + \beta_1 \ln(A_{t-1+\tau}/A_{t-1}) + \varepsilon_t, \tag{A.3}$$

where $\varepsilon_t$ represents the residuals. The parameters of the AR(1) model, $\beta_0$ and $\beta_1$ are estimated using the full history of past returns. We require a minimum of 5 years of monthly data to ensure reliable estimates. We use the estimated parameters and the time series of returns to iteratively forecast and accumulate returns over the desired $\tau$-month horizon.

## A.3 Volatility Estimation

We estimate the time-$t$ expected return volatility $\sigma_{t,\tau}$ for some forecast horizon $\tau$ by fitting a GARCH(1,1) model to the realized demeaned returns of the pseudo-firm's asset price process. As in the AR(1) case for the expected return, we use the entire history of monthly returns up until month $t$, to avoid any look-ahead bias. In a GARCH(1,1) model, the volatility evolves as follows:

$$\sigma_t^2 = \omega + \beta \sigma_{t-1}^2 + \alpha \eta_{t-1}^2, \tag{A.4}$$

where $\eta_t$ represents the return residuals. The parameters of the GARCH(1,1) model, $\alpha$, $\beta$, and $\omega$ are estimated using the full history of past returns. We require a minimum of 5 years of monthly data to ensure reliable volatility estimates. We use the estimated parameters and the time series of filtered variances to iterate the variance over the desired $\tau$-month horizon based on the following equation:

$$\mathbb{E}_t\left[\hat{\sigma}_{t,\tau}^2\right] = (\alpha+\beta)^\tau \left(\sigma_t^2 - \frac{\omega}{1-\alpha-\beta}\right) + \frac{\omega}{1-\alpha-\beta}. \tag{A.5}$$

## A.4 Estimating Ex-Ante Default Probabilities

We assign an expected physical default probability to each pseudo-bond in our sample, based on the dynamics of the underlying asset and the pseudo-firm's debt-to-asset ratio. These

default probabilities serve two key purposes. First, they allow us to match pseudo-debt contracts on the same index across currencies by default risk. Second, for the S&P 500, they enable the allocation of pseudo-debt contracts to appropriate credit rating buckets, as detailed in Section A.6.

For each pseudo-firm $i$, identified by strike price $K_i$, the time-$t$ ex-ante default probability over horizon $\tau$ is defined as:

$$p_{i,t}(\tau) = \mathbb{P}\left[A_{t,\tau} < K_i \mid \mathcal{F}_t\right], \tag{A.6}$$

where $A_{t,\tau}$ denotes predicted asset growth over forecast horizon $\tau$, based on estimates of the expected return $\mu_{t,\tau}$ and asset volatility $\sigma_{t,\tau}$ for the same horizon.

To compute the physical default probability over horizon $\tau$, we first construct the empirical distribution of historical shocks, defined as $\widehat{\varepsilon}_{t,\tau} = \left(\ln\left(A_{t+\tau}/A_t\right) - \widehat{\mu}_{t,\tau}\right)/\widehat{\sigma}_{t,\tau}$. The estimation of $\widehat{\mu}_{t,\tau}$ and $\widehat{\sigma}_{t,\tau}$ is described in Sections A.2 and A.3, respectively. Using the empirical shock distribution, we estimate the physical default probability for pseudo-firm $i$ as $\widehat{p}_{i,t}(\tau) = \mathbb{P}\left[A_{t,\tau} < K_i \mid \mathcal{F}_t\right] = \mathbb{P}\left[\widehat{\varepsilon}_{t,\tau} < X_{i,t} \mid \mathcal{F}_t\right]$, where $X_{i,t} = \left(\ln(K_i/A_t) - \widehat{\mu}_{t,\tau}\right)/\widehat{\sigma}_{t,\tau}$. This probability is computed as the in-sample frequency of historical shocks falling below the threshold $X_{i,t}$, i.e., $\widehat{p}_{i,t}(\tau) = n\left(\widehat{\varepsilon}_{t,\tau} < X_{i,t}\right)/n\left(\widehat{\varepsilon}_{t,\tau}\right)$, where $n(\cdot)$ denotes the number of observations satisfying the condition.

More specifically, to determine the ex-ante default probability at each time $t$, we construct a time series of shocks $\widehat{\varepsilon}_{s,\tau} = \left(\ln(A_{s+\tau}/A_s) - \widehat{\mu}_{s,\tau}\right)/\widehat{\sigma}_{s,\tau}$ for all $s + \tau < t$. Practically, this requires re-estimating $\widehat{\mu}_{s,\tau}$ and $\widehat{\sigma}_{s,\tau}$ at each time $s < t-\tau$ using an expanding window, as additional data become available for the predictive regressions, and the AR(1) and GARCH(1,1) models. The ex-ante default probability is then given by the fraction of historical shocks that fall below the current threshold, i.e., $\widehat{\varepsilon}_{s,\tau} < \widehat{X}_{i,t}$.

Due to the discrete nature of how empirical default probabilities are assigned, there exists a minimum strike value $\underline{K}$ such that for all $K < \underline{K}$, the estimated empirical default probability would be exactly zero. However, the only scenario where a pseudo-firm would have a true default probability of zero is when it has no leverage, i.e., when $K = 0$.

Given this, we add the theoretical zero-leverage point with zero default probability to the observed strike prices $K_i$, and their default probabilities $DP_i$. With this, we then assign an adjusted empirical default probability by linearly interpolating the closest points to the left and to the right of to each observed pseudo-firm's leverage.

## A.5 Risk-Free Rates

We estimate local-currency (LC) risk-free rates using options on the domestic stock market index. Specifically, we follow Brenner and Galai (1986), Van Binsbergen et al. (2022), and Diamond and Van Tassel (2021) in inferring implied interest rates from the put-call parity relation applied to European-style options on the local stock market index. The resulting rates, commonly referred to as box rates, are considered free of credit and convenience yield components.[7]

Put-call parity is a no-arbitrage condition that relates the prices of European put and call options with the same strike price ($K$) and maturity ($T$) to the spot price of the underlying asset ($i_t$) and the present value of the strike. The relation is given by:

$$p_t(K,T) - c_t(K,T) = e^{-r(T-t)}K - i_t, \tag{A.7}$$

where $p_t(K,T)$ and $c_t(K,T)$ denote the prices of the put and call, respectively, and $r$ is the continuously compounded risk-free interest rate over the interval $[t,T]$.

The empirical counterpart to Equation (A.7), which we use to infer implied interest rates, is a pooled cross-sectional regression estimated for a given maturity $T$ across all available strikes $K_i$, $i = 1,\ldots,K$:

$$p_{i,t}(T) - c_{i,t}(T) = \alpha_t(T) + \beta_t(T)K_i + u_{i,t}(T), \tag{A.8}$$

where $p_{i,t}(T)$ and $c_{i,t}(T)$ denote the mid-prices of put and call options with strike $K_i$ and maturity $T$. The error term $u_{i,t}(T)$ is assumed to be i.i.d. with zero mean and conditionally mean-independent of strike: $E[u_{i,t}(T) \mid K_i] = 0$. Under this assumption, the OLS slope coefficient $\widehat{\beta}_t(T)$ has a one-to-one mapping to the implied interest rate via: $\widehat{r}_{t,T} = -1/(T-t)\log\widehat{\beta}_t(T)$.

In contrast to Van Binsbergen et al. (2022) and Diamond and Van Tassel (2021), we use daily data rather than the median of intraday estimates, which reduces the volatility of our box rate series. Regression (A.8) is estimated using options with more than two weeks to expiration. We retain implied box rates from regressions with an $R^2$ of at least 0.9999 – a slightly lower threshold than the 0.99999 used by Diamond and Van Tassel (2021), which has negligible impact on the resulting implied credit spreads. To construct a daily term

[7] Following Van Binsbergen et al. (2022), we further limit the sample for box rate estimation to option contracts with more than 21 days to maturity.

structure of box rates over a finer maturity grid, we linearly interpolate estimated box rates for the available maturities.

For some countries, liquidity of LC index options is insufficient to reliably estimate country-specific box rates. For that reason, we construct regional box rate indices for the Euro area, non-Euro European countries, and Asian economies.

In the first case, we replace the country-specific box rate denominated in EUR with a regional box rate index derived as a simple average of the box rates for time $t$ and maturity $\tau$ for Belgium, Spain, France, Germany, Italy, the Netherlands and the STOXX index.

To construct the European regional box rate index, we translate the LC box rate index of Belgium, Switzerland, Denmark, Spain, France, the UK, Germany, Italy, the Netherlands, Norway, Poland, the STOXX100 index, Sweden and Turkey into USD denominated box rates using the covered interest parity (CIP) condition following Du and Schreger (2016). Even though CIP was violated across most currencies following the 2008 Global Financial Crisis (GFC), this allows us to infer the relevant, effective funding rate that can be used as a benchmark for the computation of credit spreads (Augustin et al., 2024). Thus, we obtain the risk-free counterpart using the following relation:

$$\widehat{r}^{\$}_{t,T} = \widehat{r}^{LC}_{t,T} - \rho_{t,T}, \tag{A.9}$$

where $\rho_{t,T} = (T-t)^{-1}(f_{t,T}/s_t)$ is the log forward premium defined as the difference between the log forward rate $f_{t,T}$ and the log exchange rate $s_t$. To construct the forward premium, we use the forward rates, spot rates, and days to settlement obtained from Bloomberg. Table A.2 summarizes data availability for the forward rates. When an option cannot be matched with a forward contract of equivalent maturity, we linearly interpolate the forward rate to reflect the options' time-to-maturity. Once we have USD box rates for all the European economies, we take their simple average and translate them back to each country LC using $\widehat{r}^{LC}_{t,T} = \widehat{r}^{\$}_{t,T} + \rho_{t,T}$. We use the European regional box rate index for all European countries in our sample outside the Eurozone: Denmark, the UK, Norway, Poland, Sweden, Switzerland and Turkey.

Finally, we take a similar approach to create the Asian regional box rate index, but using the LC-denominated box rates for China, Hong Kong, India, Japan, South Korea, Malaysia, Singapore, Thailand and Taiwan.

In a few instances, LC box rates are unreliable or unavailable for our sample period (Australia, Brazil, Canada and Mexico). In those cases, we use the USD-denominated box rate estimated from options on the S&P500 index and then convert them to a LC risk-free rate using the CIP condition as described above.

Country-specific risk-free rates in foreign currency (i.e., USD) are constructed using box rates estimated from USD-denominated SPX options written on the S&P500 index.

Table A.3 presents summary statistics for the box rates in LC and FC at the monthly frequency. The last three columns of the Table indicate if the box rate is obtained directly from the options on the local index, from the options on the local index but converted in the appropriate currency using the CIP condition, or obtained from applying the CIP condition to the US box rates.

## A.6 Credit Spreads and Aggregation to IG and HY Indices

For the U.S., we generate high-yield (HY) and investment-grade (IG) indices of pseudo-bond yields. We allocate pseudo-bonds to the IG or HY category based on their individual credit ratings (Aaa/Aa, A/Baa, or Ba, B, Caa-C) and days-to-maturity.

We assign a pseudo credit rating to each pseudo-bond by matching its ex-ante default probability, computed as described in Section A.4, with a credit rating category provided by Moody's 2022 Annual Default Study Report (Moody's, 2022). Exhibit 39 in Moody's (2022) provides average cumulative global default rates by letter rating for various default horizons, ranging from one year to 20 years. These default rates are computed from 1970 to 2022. Since pseudo bonds are mostly computed for short maturities, we primarily rely on the 1-year and 2-year cumulative default probabilities, which we report in Table A.4 for convenience.

Regarding the mapping of maturities, we follow Culp et al. (2018). Hence, the three-month, six-month, and 12-month indices are based on options with maturities ranging from 7 days to 6 months, three months to 12 months, and six months to 18 months, respectively. The 2-year horizon index uses options that are strictly more than one year to maturity.

The pseudo bonds are assigned to the IG category if their credit rating is Baa or higher. Otherwise, pseudo bonds are assigned to the HY category. We construct all indices at the monthly frequency and aggregate all pseudo-yields available at the end of a given month within a given credit category (HY or IG) to compute a weighted average pseudo yield.

Specifically, to compute a weighted average, we define auxiliary weights based on the distance between an option's time to maturity $T$ and a target maturity $\bar{T}$, say 2 years. The auxiliary weight is defined as:

$$\tilde{\omega}_{i,T,\bar{T}} = \phi\left(\frac{T-\bar{T}}{30Days}\right), \tag{A.10}$$

where we scale by 30 to account for the monthly frequency of our data and where $\phi(\cdot)$ is the standard normal distribution function. The final weights are standardized using

$$\omega_{i,T,\bar{T}} = \frac{\tilde{\omega}_{i,T,\bar{T}}}{\sum_i^n \tilde{\omega}_{i,T,\bar{T}}}. \tag{A.11}$$

## A.7 Country-Level Aggregation of Credit Spreads

For countries other than the U.S., we construct aggregate pseudo credit spreads representing the credit risk of the basked of firms in each country's stock market index. We restrict pseudo firms to have an ex-ante empirical default probability no higher than the Standard&Poor's "CCC Global Corporate Average Cumulative Default Rate" between 1981 and 2023.

We construct pseudo credit spreads with maturities equal to 3 months, 6 months, 1 year, and 2 years. For each of these maturity buckets, we use options with maturities ranging between 7 days and 6 months, 3 months and 1 year, 6 months and 18 months,and 1 year and 3 years, respectively. As described in Section A.6, we aggregate country credit spreads at the monthly frequency and combine all pseudo-yields available within a given month to compute a time-to-maturity weighted average pseudo yield.

# B Estimation of Synthetic Credit Spreads

We detail the procedure used to construct synthetic pseudo credit spreads. When option data in one of the currencies is insufficiently liquid, we might generate synthetic put option prices on the index or ETF denominated in the other currency. This requires computing the necessary inputs to the Black-Scholes option pricing formula, as described in Sections B.1 and B.2. We then aggregate the resulting synthetic option prices to construct country-level credit spread indices in the same fashion as we do in Section A.7.

To illustrate our framework, let's assume that options data on the ETF denominated in USD–the foreign currency–are not readily available, while those on the main stock market index denominated in local currency are.

## B.1 Synthetic Strikes, Riskless Rates, and Dividend Yields

We compute the synthetic FC-denominated credit spreads using pseudo bond prices $\widehat{B}_t^{\$}(K^{FC}, T)$, computed as

$$\widehat{B}_t^{\$}(K^{\$}, T) = K^{\$}\widehat{Z}_t^{\$}(T) - \widehat{P}_t^{\$}(K^{\$}, T), \tag{B.1}$$

where the put price is computed using the Black-Scholes-Merton option pricing formula (Black and Scholes, 1973)

$$\widehat{P}_t^{\$}(K^{\$}, \tau) = BSM(A_t^{\$}, K^{\$}, \tau, \widehat{r}_{t,\tau}^{\$}, \widehat{\sigma}_{t,\tau}^{\$}, d_{t,\tau}^{\$}). \tag{B.2}$$

For each option in our sample, we construct a twin option in foreign currency. We obtain the foreign currency denominated underlying counterpart by multiplying the local currency stock market index with the exchange rate, $A_t^{\$} = A_t \cdot S_t$, where $S_t$ denotes the exchange rate expressed in units of FC per LC.[8] The time to maturity $\tau$ and the dividend yields are fixed to be identical for both twins. We compute the riskless rate in FC by applying the covered interest rate parity condition to the riskless arte denominated in LC, as described in Section A.5. We construct the implied volatility in FC by using a combination of the twin option's implied volatility in LC and the implied volatility of the options on the exchange rate, as

[8] As reflected in Table A.2, we could have directly used prices of the stock market indices tracking the local stock market index in FC. We use a synthetic underlying asset to remainconsistent with our model in Section B.2.

per Section B.2. Finally, we select the firm's level of debt (i.e. the strike $K^{\$}$) such that the probability of default is the same in both currencies. Specifically, we want to ensure that:

$$\widehat{p}_{i,t}(\tau) = \mathbb{P}\left[A_{t,\tau} < K_i \mid \mathcal{F}_t\right] \equiv \widehat{p}^{\$}_{j,t}(\tau) = \mathbb{P}\left[A^{\$}_{t,\tau} < K^{\$}_j \mid \mathcal{F}_t\right]. \tag{B.3}$$

The ex-ante default probability in FC is computed following the description in Section A.2, but applied to the stock index in FC.

## B.2 Synthetic Foreign Currency Volatility Estimations

In those cases where foreign currency-denominated options are unavailable, we need to derive a synthetic option-implied volatility denominated in foreign currency. Let $A_t$ and $A^{\$}_t$ denote a country's stock market index valued in LC and foreign currency FC, respectively, and $S_t$ is the exchange rate expressed in units of FC per LC. Absent any arbitrage opportunities, $A^{\$}_t = A_t S_t$. We derive the dynamics of $A^{\$}_t$ using the dynamics of $A_t$ and $S_t$:

$$\begin{aligned} dA_t &= \mu A_t dt + \sigma A_t dW_t \\ dS_t &= \mu^S S_t dt + \sigma^S S_t dW^S_t, \end{aligned}$$

where the Brownian shocks are correlated with correlation coefficient $\rho$ such that $dW^S_t = \rho dW_t + \sqrt{1-\rho^2} dW^{\perp}_t$. Using Ito's lemma, we derive the dynamics of $A^{\$}_t$, which evolve as:

$$\begin{aligned} \mathrm{d}A^{\$}_t &= A_t S_t \mathrm{d}S_t/S_t + A_t S_t \mathrm{d}A_t/A_t + A_t S_t \mathrm{d}S_t/S_t \mathrm{d}A_t/A_t \\ &= A_t S_t \left[\mu^S\, dt + \sigma^S \left(\rho dW_t + \sqrt{1-\rho^2} dW^{\perp}_t\right)\right] + A_t S_t \left(\mu dt + \sigma dW_t\right) + A_t S_t \rho\sigma\sigma^S dt \\ &= A^{\$}_t \left[\left(\mu^S + \mu + \rho\sigma\sigma^S\right) \mathrm{d}t + \left(\sigma + \rho\sigma^S\right) \mathrm{d}W_t + \sigma^S \sqrt{1-\rho^2} dW^{\perp}_t\right] \\ &= A^{\$}_t \left[\left(\mu^S + \mu + \rho\sigma\sigma^S\right) \mathrm{d}t + \sigma^{\$} \mathrm{d}W^{\$}_t\right], \end{aligned}$$

where $W^{\$}_t$ is a Brownian motion defined by

$$\mathrm{d}W^{\$}_t := \frac{1}{\sigma^{\$}} \left[\left(\sigma + \rho\sigma^S\right) \mathrm{d}W_t + \sigma^S \sqrt{1-\rho^2} dW^{\perp}_t\right],$$

with

$$\left(\sigma^{\$}\right)^2 = \left(\sigma^S\right)^2 + (\sigma)^2 + 2\rho\sigma\sigma^S, \tag{B.4}$$

which we can compute using implied volatilities of foreign exchange and stock index options. We use at-the-money implied volatilities of exchange rate options to estimate $\sigma_S$. To estimate $\sigma$, we rely on local currency options with similar moneyness to avoid biases associated with differences in implied volatility smiles. If necessary, we also maturity-match the implied volatilities on the exchange-rate options by interpolating along the maturity axis. At-the-money implied volatilities of European options are directly available from Bloomberg. The correlation between exchange rate returns and asset returns is obtained using a 5-year rolling window.[9]

## B.3 Matching Pseudo Bonds Across Currencies

The ex-ante default probabilities from empirical CSs in LC (FC) does not necessarily coincide with those from CSs in FC (LC). More explicitly, when the empirical default probability associated with LC (FC) empirical CSs is not equal to that from the empirical default probability of FC (LC) empirical CSs, we cannot confidently use the synthetic estimates to substitute the missing empirical observations.

To overcome this empirical limitation, we refine the selection of pseudo bonds in FC (LC) that enter in the index computation when we consider the LC (FC) credit spread index. Using the LC (FC) credit spread index as benchmark, we select the subset of pseudo bonds with ex-ante default probabilities and maturities within absolute differences of $\theta_{DP}$ and $\theta_{\tau}$, respectively. We then take maturity-weighted average as described in Section A.6 of this smaller subset of pseudo firms to create our default-probability-matched indices. In our empirical implementation, we use $\theta_{DP} = 50$ bps, and $\theta_{\tau} = 91$ days.

Using this method, we can generate two sets of pseudo credit spreads, depending on what currency-denomination we use as benchmark: LC or FC (USD). We select the currency benchmark for each country based on the highest number of observation for the CS index time series after filling as many missing empirical estimates with their synthetic counterparts as possible. Table A.13 presents what benchmark currency we use for each country and maturity in our empirical implementation.

[9] Our results are similar when we use dynamic conditional correlations (Engle, 2002).

# C A Structural Framework for Pseudo Credit Spreads

This appendix shows that pseudo credit spreads closely track firm-level credit spreads in a structural model. While levels differ due to risk premia, the two series exhibit a tight, near-linear relationship. This supports the interpretation of pseudo spreads as a meaningful proxy for corporate credit risk.

## C.1 Firm and Pseudo Credit Spreads in the Merton Model

Within the Merton framework, we simulate a firm's asset dynamics under the physical measure $P$ and price securities under the risk-neutral measure $Q$. We then construct a pseudo firm with a balance sheet calibrated to match the firm's physical default probability. This setup allows us to compare credit spreads and risk-neutral-to-physical default probability ratios ($Q/P$) between the pseudo and underlying firm. We proceed in several steps.

1. *Simulate asset dynamics under the physical measure.*

   Under $P$, the firm's asset value follows a geometric Brownian motion,

   $$dA_t/A_t = \mu_A\, dt + \sigma_A\, dW_t. \tag{C.1}$$

   We simulate this process at a daily frequency using the standard discretization:

   $$A_{t+\Delta} = A_t \exp\Big[(\mu_A - \tfrac{1}{2}\sigma_A^2)\Delta + \sigma_A\sqrt{\Delta}\,\varepsilon_t\Big], \tag{C.2}$$

   where $\varepsilon_t \sim \mathcal{N}(0,1)$ and $\Delta = 1/252$.

2. *Calibrate the face value of debt.*

   The firm issues zero-coupon debt with face value $K$ maturing at horizon $T$. To maintain a stationary leverage ratio, we assume that the face value grows at the same rate as expected asset growth:

   $$K_t = K_0 e^{\mu_A t}. \tag{C.3}$$

3. *Equity and debt valuation.*

Under the risk-neutral measure $Q$, define

$$d_1 = \frac{\ln(A_t/K_t) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}, \qquad d_2 = d_1 - \sigma_A\sqrt{T}. \tag{C.4}$$

The Merton (1974) pricing formulas for equity and debt are

$$E_t = A_t\,\Phi(d_1) - K_t\,e^{-rT}\,\Phi(d_2), \tag{C.5}$$

$$B_t = K_t e^{-rT} - \big[K_t\,\Phi(-d_2) - A_t\,\Phi(-d_1)\big]. \tag{C.6}$$

The continuously compounded yield and credit spread are given by

$$y_t = -\frac{1}{T}\ln\left(\frac{B_t}{K_t}\right), \qquad s_t = y_t - r. \tag{C.7}$$

4. *Compute default probabilities under $P$ and $Q$.*

   The physical default probability at horizon $T$ is

$$\mathrm{PD}_t^{(P)} = \Phi\left(\frac{\ln(K_t/A_t) - (\mu_A - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right), \tag{C.8}$$

   and the corresponding risk-neutral probability is

$$\mathrm{PD}_t^{(Q)} = \Phi\left(\frac{\ln(K_t/A_t) - (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right). \tag{C.9}$$

5. *Construct the pseudo firm.*

   *(a) Pseudo asset.* The pseudo firm's asset is defined as the equity of the underlying firm:

$$A_t^{(\mathrm{ps})} = E_t. \tag{C.10}$$

   *(b) Pseudo-asset dynamics under $P$.* Because the pseudo asset equals the firm's equity, its dynamics are implied by the equity dynamics in the Merton model. Using the elasticity relation

$$\eta_t = \frac{A_t}{E_t}\Phi(d_1), \tag{C.11}$$

the pseudo asset's drift and volatility under $P$ are

$$\mu_{A,t}^{(\mathrm{ps})} = r + \eta_t(\mu_A - r), \qquad \sigma_{A,t}^{(\mathrm{ps})} = \eta_t \sigma_A, \tag{C.12}$$

so both moments are time-varying and increase with leverage.

*(c) Matching physical default probabilities.* We choose the pseudo firm's face value $K_t^{(\mathrm{ps})}$ so that its physical default probability matches that of the underlying firm:

$$\Phi\left(\frac{\ln(K_t^{(\mathrm{ps})}/A_t^{(\mathrm{ps})}) - (\mu_{A,t}^{(\mathrm{ps})} - \frac{1}{2}(\sigma_{A,t}^{(\mathrm{ps})})^2)T}{\sigma_{A,t}^{(\mathrm{ps})}\sqrt{T}}\right) = \Phi\left(\frac{\ln(K_t/A_t) - (\mu_A - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right). \tag{C.13}$$

6. *Value the pseudo firm and compute its credit spread.*

We value the pseudo firm by applying the Merton model to $(A_t^{(\mathrm{ps})}, K_t^{(\mathrm{ps})})$. In the baseline case, we abstract from an equity volatility risk premium and set risk-neutral volatility equal to physical volatility, $\sigma_t^{(Q)} = \sigma_{A,t}^{(\mathrm{ps})}$. As an extension, we allow for $\sigma_t^{(Q)} > \sigma_{A,t}^{(\mathrm{ps})}$.

Define

$$d_1^{(\mathrm{ps})} = \frac{\ln(A_t^{(\mathrm{ps})}/K_t^{(\mathrm{ps})}) + (r + \frac{1}{2}(\sigma_t^{(Q)})^2)T}{\sigma_t^{(Q)}\sqrt{T}}, \qquad d_2^{(\mathrm{ps})} = d_1^{(\mathrm{ps})} - \sigma_t^{(Q)}\sqrt{T}. \tag{C.14}$$

The pseudo firm's debt value is then

$$B_t^{(\mathrm{ps})} = K_t^{(\mathrm{ps})}e^{-rT} - \Big[K_t^{(\mathrm{ps})}\Phi(-d_2^{(\mathrm{ps})}) - A_t^{(\mathrm{ps})}\Phi(-d_1^{(\mathrm{ps})})\Big]. \tag{C.15}$$

Its yield and credit spread are

$$y_t^{(\mathrm{ps})} = -\frac{1}{T}\ln\left(\frac{B_t^{(\mathrm{ps})}}{K_t^{(\mathrm{ps})}}\right), \qquad s_t^{(\mathrm{ps})} = y_t^{(\mathrm{ps})} - r. \tag{C.16}$$

The corresponding physical and risk-neutral default probabilities are

$$\mathrm{PD}_t^{(P,\mathrm{ps})} = \Phi\left(\frac{\ln(K_t^{(\mathrm{ps})}/A_t^{(\mathrm{ps})}) - (\mu_{A,t}^{(\mathrm{ps})} - \frac{1}{2}(\sigma_{A,t}^{(\mathrm{ps})})^2)T}{\sigma_{A,t}^{(\mathrm{ps})}\sqrt{T}}\right), \tag{C.17}$$

$$\mathrm{PD}_t^{(Q,\mathrm{ps})} = \Phi\left(\frac{\ln(K_t^{(\mathrm{ps})}/A_t^{(\mathrm{ps})}) - (r - \frac{1}{2}(\sigma_t^{(Q)})^2)T}{\sigma_t^{(Q)}\sqrt{T}}\right). \tag{C.18}$$

We then compute

$$\left(\frac{Q}{P}\right)_{\text{firm}} = \frac{\text{PD}_t^{(Q)}}{\text{PD}_t^{(P)}}, \qquad \left(\frac{Q}{P}\right)_{\text{pseudo}} = \frac{\text{PD}_t^{(Q,\text{ps})}}{\text{PD}_t^{(P,\text{ps})}}. \tag{C.19}$$

## C.2 Simulation Evidence

To study the relation between credit spreads and pseudo credit spreads, we repeat Steps 1–6 for $N$ simulated firms. In each simulation, we generate a 10-year asset path with initial value $A_0 = 100$, drift $\mu_A = 7\%$, volatility $\sigma_A = 25\%$, and risk-free rate $r = 3\%$. The initial face value of debt $K_0$ is calibrated so that the average physical default probability over the horizon equals 10%.

Figure A.1 reports time-series dynamics for a representative firm. Panels A and B show the evolution of asset, equity, and debt values for the firm and its pseudo counterpart. Panel C plots their default probabilities, which coincide by construction, while Panel D shows the joint dynamics of credit spreads. Despite differences in levels, the two spreads exhibit highly similar time-series variation.

Figure A.2 summarizes results across $N = 100$ simulated firms. Panel A compares credit spreads, and Panel B compares risk-neutral-to-physical default probability ratios ($Q/P$). Across simulations, pseudo-firm spreads and $Q/P$ ratios closely track those of the underlying firm. The tight, near-linear relationship between the two indicates that pseudo credit spreads provide an accurate representation of the firm's underlying credit conditions.

## C.3 Accounting for a volatility risk premium

As an extension, we allow risk-neutral volatility to exceed physical volatility, consistent with the data. Specifically, we scale risk-neutral volatility by a factor of 1.5, so that $\sigma_t^{(Q)} = 1.5\,\sigma_{A,t}^{(\text{ps})}$.[10]

The results show that both credit spreads and $Q/P$ ratios are higher for the pseudo firm. While matching physical default probabilities anchors the pseudo firm to the same underlying fundamentals as the firm, higher risk-neutral volatility amplifies the risk premium embedded in bond prices.

[10] Bollerslev et al. (2009) report a risk-neutral variance on the SPX of 33.23% and a physical variance of 14.93% (Table 1, p. 4478), implying a ratio of volatilities of approximately $\sqrt{33.23/14.93} \approx 1.5$.

As a result, pseudo-firm credit spreads and $Q/P$ ratios remain tightly linked to those of the underlying firm but are larger in magnitude. Overall, incorporating a volatility risk premium is important for generating economically meaningful credit risk premia and elevated risk-neutral default probabilities.

# D Reconciling Firm- and Index-Level Credit Spreads

This appendix examines how pseudo credit spreads differ when the underlying asset is defined at the firm level versus the aggregate level. A common intuition is that individual firms face greater idiosyncratic volatility, which lowers their asset Sharpe ratios and, in turn, their credit spreads. Under this logic, for a given level of default risk, credit spreads based on a diversified market index should exceed those of individual firms.

This prediction contrasts with the empirical findings of Culp et al. (2018), who document that index credit spreads are, in fact, lower than firm-level spreads (see Figure 2). We show that the Merton model reconciles this apparent tension: while higher idiosyncratic volatility reduces risk-neutral default probabilities, it also increases the severity of default states and hence expected losses. This loss-given-default channel can dominate, generating higher firm-level credit spreads despite lower asset Sharpe ratios.

## D.1 Firm and Index Dynamics

Consider an individual firm $i$ whose asset value evolves under the physical measure $P$ according to

$$\frac{dS_{i,t}}{S_{i,t}} = \mu\, dt + \sigma_M\, dB_t^P + \sigma_\varepsilon\, dB_{i,t}^P,$$

where $B_t^P$ is a common (systematic) Brownian motion and $B_{i,t}^P$ is firm-specific. The total asset volatility of firm $i$ is therefore

$$\sigma_S^2 := \sigma_M^2 + \sigma_\varepsilon^2.$$

Aggregating across $N$ such firms yields an index with dynamics

$$\frac{dI_t}{I_t} = \mu\, dt + \sigma_M\, dB_t^P + \frac{\sigma_\varepsilon}{N} \sum_{i=1}^{N} dB_{i,t}^P.$$

Since idiosyncratic shocks diversify away, the index volatility is

$$\sigma_I^2 := \sigma_M^2 + \frac{\sigma_\varepsilon^2}{N} < \sigma_S^2 \qquad (N > 1).$$

The individual firm and the aggregate index share the same drift $\mu$ but differ in volatility due to diversification. As a result, the asset Sharpe ratio is higher for the index:

$$\mathrm{SR}_I = \frac{\mu - r}{\sigma_I} > \frac{\mu - r}{\sigma_S} = \mathrm{SR}_S.$$

As emphasized by Chen et al. (2009), credit spreads increase with the asset Sharpe ratio (see Equation 6). It would therefore appear that, for a given level of default risk, the credit spread of an index should exceed that of an individual firm. We now show that this conclusion relies on the restrictive assumption of constant loss given default (LGD), and can reverse once LGD is allowed to vary endogenously.

## D.2 Case I: Constant LGD

Suppose that the firm and the index are calibrated to have the same physical default probability over horizon $T$, given by $\Phi(-d_2^{(P)})$. The only difference between them is asset volatility, which affects their Sharpe ratios. We can therefore directly compare their implied credit spreads.

Under the risk-neutral measure $Q$, the default probability is

$$\mathrm{PD}^{(Q)} = \Phi(-d_2^{(Q)}), \qquad d_2^{(Q)} = \frac{\ln(K/A_0) - (r - \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} = d_2^{(P)} - \mathrm{SR}\sqrt{T}.$$

Holding $d_2^{(P)}$ fixed, a higher asset Sharpe ratio (such as that of the index) implies a lower $d_2^{(Q)}$ and therefore a higher risk-neutral default probability.

When LGD is assumed to be constant, the credit spread is

$$s = -\frac{1}{T}\ln\Big(1 - \mathrm{PD}^{(Q)}\,\mathrm{LGD}\Big). \tag{D.1}$$

Hence, the higher $\mathrm{PD}^{(Q)}$ of the index directly translates into a higher credit spread. This is the mechanism emphasized in Chen et al. (2009).

However, this prediction stands in contrast to the empirical findings of Culp et al. (2018), whose Figure 2 shows that firm-level credit spreads exceed index spreads. We show next that this tension disappears once the assumption of constant LGD is relaxed.

## D.3 Case II: Endogenous LGD

Consider the risk-neutral pricing equation for a zero-coupon bond with face value $K$ maturing at $T$,

$$B_0 = e^{-rT}\,\mathbb{E}^Q[\min(A_T, K)]\,.$$

Using $\min(A_T, K) = K - (K - A_T)^+$, this can be written as

$$B_0 = Ke^{-rT} - e^{-rT}\,\mathbb{E}^Q\left[(K - A_T)^+\right].$$

Define the risk-neutral loss given default as

$$\mathrm{LGD}^{(Q)} = \mathbb{E}^Q\left[\frac{K - A_T}{K}\,\middle|\,A_T < K\right],$$

which captures the expected fractional loss conditional on default. Then

$$\mathbb{E}^Q[(K - A_T)^+] = K\,\mathrm{PD}^{(Q)}\,\mathrm{LGD}^{(Q)}.$$

Substituting yields

$$B_0 = Ke^{-rT}\left(1 - \mathrm{PD}^{(Q)}\mathrm{LGD}^{(Q)}\right).$$

Let $y$ satisfy $B_0 = Ke^{-yT}$ and define the credit spread $s = y - r$. Then

$$s = -\frac{1}{T}\ln\!\left(1 - \mathrm{PD}^{(Q)}\,\mathrm{LGD}^{(Q)}\right),$$

which mirrors the constant-LGD expression in Equation (D.1) but now features endogenous $\mathrm{LGD}^{(Q)}$.

In the Merton model, $\mathrm{LGD}^{(Q)}$ depends on asset volatility through $d_1^{(Q)}$ and $d_2^{(Q)}$:

$$\mathrm{LGD}^{(Q)} = 1 - \frac{A_0e^{rT}}{K}\frac{\Phi(-d_1^{(Q)})}{\Phi(-d_2^{(Q)})} = 1 - \frac{A_0e^{rT}}{K}\frac{\Phi(-d_2^{(Q)} - \sigma\sqrt{T})}{\Phi(-d_2^{(Q)})},$$

where $d_1^{(Q)} = d_2^{(Q)} + \sigma\sqrt{T}$.

An increase in volatility $\sigma$ lowers the ratio

$$\frac{\Phi(-d_2^{(Q)} - \sigma\sqrt{T})}{\Phi(-d_2^{(Q)})},$$

thereby increasing $\text{LGD}^{(Q)}$. Intuitively, higher volatility increases the dispersion of $A_T$, making default realizations occur deeper in the left tail and raising expected losses.

Overall, higher idiosyncratic volatility affects credit spreads through two opposing channels. On the one hand, it lowers the asset Sharpe ratio and thus reduces the risk-neutral default probability $\text{PD}^{(Q)}$, compressing spreads. On the other hand, it increases the loss given default $\text{LGD}^{(Q)}$, which raises spreads. Figure A.3 illustrates these mechanisms for maturities of $T = 5$ years (top panels) and $T = 2$ years (bottom panels). For low to moderate volatility, the Sharpe-ratio channel dominates and spreads decline with volatility. When volatility is sufficiently high, the LGD channel strengthens and can dominate, leading to higher firm-level spreads relative to index spreads. This reversal is more pronounced at shorter maturities, where LGD is more sensitive to volatility.

As an additional exercise, we replicate Figure 2 of Culp et al. (2018) within the model. Specifically, we simulate an economy with 3,000 firms and compare the average firm-level credit spread to the spread implied by the aggregate index. Rating buckets are defined using annual physical default probabilities $\text{PD}^{(P)}$, calibrated to match the default frequencies reported in **?**. The results, reported in Figure A.4, show that the model generates lower index spreads than firm-level spreads across all rating categories, consistent with the data.

# E Data Appendix

**Indices and ETFs returns and dividend yield.** We download price and dividend data for the primary stock indices of each country in our sample. For the majority of countries, we find also find price and dividend data on the ETF on the MSCI country index, in USD. When the dividend data is unavailable, we download total returns and back out the dividends using the total returns and ex-dividend returns. The daily time series are downloaded from Datastream. Columns (4), (5), and (6) in Table A.2 present show data availability for the LC stock indices, and columns (7) and (8) for the FC stock indices. Note that the last row of the Table describes the downloading ticker format for each time series. The starting date of each country's time series in LC varies greatly across the sample. The data on the US stock market dates back to 1871, but for the majority of the countries, we only have data dating from the early 1980s. For the FC indices, most ETFs were not traded before the mid-to-late 1990s. This data is notably used to estimate the ex-ante probability of default of pseudo debt as described in Section A.4.

**Spot exchange rates.** We obtain the last spot exchange rate from Bloomberg. The local currency time series ticker is expressed in units of USD and writes "USD$CCY$ Curncy". Our spot exchange rate data spans twenty currency pairs at a daily frequency. Table A.2 lists the various exchange rates used in our analysis; note that we use the CNH (offshore market Chinese Yuan), not the CNY, to represent the Renminbi value as there are trading restrictions on the latter.

**Forward exchange rate.** The forward points and days-to-maturity are downloaded from Bloomberg. This data spans twenty currency pairs at a daily frequency, for contract maturities of 1, 3, 6,12, 18, 24, and 36 months. Table A.2 columns (2) and (3) present information on data availability. The last row gives information on how to build the downloading tickers for the various forward maturities. The forward points $fp$ are from Bloomberg, they can be positive or negative. They are used to compute the forward exchange rate $F$ as per the following formula, $F = S + (fp/10^{ff})$, where the forward factor $ff$ varies across currencies. Typically, the forward factor is 4, but it can be 2 (India, Japan, Thailand), or 0 (South Korea and Taiwan). We use forward exchange rates to compute the risk-free rates based on the covered interest rate parity as in Du et al. (2018), we describe this in equation (A.9). Note that the dating convention of the forward contracts is also heterogeneous, the year is assumed to have either 360 or 365 days, depending on the country. For example, if the convention is 360, the forward basis for a contract with 27 days-to-maturity is computed as $\rho = (360/27)(\ln(F) - \ln(S))$.

**Options on the exchange rates.** Put options on the exchange rates are available on Bloomberg, they are quoted in terms of implied volatility. We download the daily implied volatilities for various maturities of at-the-money options as it allows us to avoid considerations related to the volatility smile. Data availability is described in Table A.2, column (1) and the downloading ticker is constructed as per instructions on the last row of the table. The implied volatilities of the exchange rate options are used to obtain the synthetic implied volatility of the stock index in the missing currency as per equation (B.4).

**Options on ETF and stock indices.** We retrieve end-of-day put and call option data from Refinitiv Eikon and Option metrics WRDS. Table 1 lists the countries, the underlying index of the option, and the currency in which the option is priced. Options in local currency are plain vanilla European options, whereas the foreign-currency options are American-type options. Our unbalanced sample spans from October 2001 to June 2023, except for options on the S&P500, which starts in 1996. Observations include the contract bid and ask prices, strike price, expiration date, exercise style, trading volume, open interest, implied volatility, and the closing price of the underlying security. The data cleaning procedure is described in Section A.1.

# F Derivations of the Model of Local and Foreign Currency Credit Spreads

## F.1 Fundamental Equation of Asset Pricing in Continuous Time

We here verify that

$$\mathbb{E}_t\left[\frac{d(M_tX_t)}{M_tX_t}\right] = 0 \tag{D.2}$$

for any process whose return is given by $\frac{dX_t}{X_t}$, where $\mathbb{E}$ is the expectation operator (under $\mathbb{P}$) and $M_t$ is the stochastic discount factor (SDF) that prices assets in LC.

This equation should hold for any asset (or strategy), including an investment in the risk-free bond $B_t$, whose return is given by

$$\frac{dB_t}{B_t} = rdt, \tag{D.3}$$

where $r$ denotes the risk-free interest rate in LC.

We indeed have

$$\mathbb{E}_t\left[\frac{d(M_tB_t)}{M_tB_t}\right] = \underbrace{\mathbb{E}\left[\frac{dM_t}{M_t}\right]}_{-rdt} + \underbrace{\mathbb{E}\left[\frac{dB_t}{B_t}\right]}_{rdt} + \underbrace{\mathbb{E}\left[\frac{dM_t}{M_t}\frac{dB_t}{B_t}\right]}_{0} = 0, \tag{D.4}$$

which verifies that Equation (D.2) holds.

## F.2 Expected Return on the Currency Trade

Applying Itô's Lemma on $f(M_t, S_t, B_t^\$) = M_t(1/S_t)B_t^\$$ in Equation (**??**), we obtain (ignoring time subscripts for convenience):

$$\begin{aligned} df(M,S,B^\$) = {} & \frac{B^\$}{S}\,dM - \frac{MB^\$}{S^2}\,dS + \frac{M}{S}\,dB^\$ \\ & + \frac{1}{2}\left(2M\frac{B^\$}{S^3}(dS)^2 + 0(dM)^2 + 0(dB^\$)^2\right) \\ & - \frac{1}{S^2}B^\$dMdS + \frac{1}{S}dMdB^\$ - M\frac{1}{S^2}dSdB^\$. \end{aligned} \tag{D.5}$$

After taking expectations, we obtain

$$\begin{aligned}\mathbb{E}_t\left[df(M,S,B^{\$})\right] = \mathbb{E}_t\left[\frac{B^{\$}}{S}\,dM\right] - \mathbb{E}_t\left[\frac{MB^{\$}}{S^2}\,dS\right] + \mathbb{E}_t\left[\frac{M}{S}\,dB^{\$}\right] \\ + \underbrace{\mathbb{E}_t\left[M\frac{B^{\$}}{S^3}(dS)^2\right]}_{M\frac{B^{\$}}{S}\sigma_S^2 dt} - \mathbb{E}_t\left[\frac{1}{S^2}B^{\$}dMdS\right] \\ + \underbrace{\mathbb{E}_t\left[\frac{1}{S}dMdB^{\$}\right]}_{0} - \underbrace{\mathbb{E}_t\left[M\frac{1}{S^2}dSdB^{\$}\right]}_{0}.\end{aligned} \tag{D.6}$$

Dividing the equation above by $M(1/S)B^{\$}$ yields

$$\mathbb{E}_t\left[\frac{df(M,S,B^{\$})}{M(1/S)B^{\$}}\right] = \underbrace{\mathbb{E}_t\left[\frac{dM}{M}\right]}_{-rdt} - \mathbb{E}_t\left[\frac{dS}{S}\right] + \underbrace{\mathbb{E}_t\left[\frac{dB^{\$}}{B^{\$}}\right]}_{r^{\$}dt} + \sigma_S^2 dt - \mathbb{E}_t\left[\frac{dM}{M}\frac{dS}{S}\right]. \tag{D.7}$$

Finally, after re-arranging, we obtain

$$\mathbb{E}_t\left[\frac{dS}{S}\right] = (r^{\$} - r + \sigma_S^2)dt - \mathbb{E}_t\left[\frac{dM}{M}\frac{dS}{S}\right]. \tag{D.8}$$

Table A.1: **Existing Bond Indices in Domestic and Foreign Currency.** This table presents the availability of bond indices in domestic and foreign currency (USD) covering a determined country, currency or region. It presents the name of one of the providers of the Country or foreign currency bond index, when available; the domicile of the firms issuing the bonds in the index; what credit ratings are considered in the index construction; the number of constituent bonds as of February 2026; and the average maturity (or duration) of the corresponding bond index. Note: Special subscriptions are required to get lacking information for iBoxx indices.

| **Country / Region** | **Index Provider** | | **Issuer Domicile** | | **Ratings Covered** | | **N. Bonds** | | **Avg. Maturity (yrs)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| | LC | USD | LC | USD | LC | USD | LC | USD | LC | USD |
| Australia | Bloomberg | x | Global | x | IG | x | 297 | x | 4.96 | x |
| Brazil | B3 | iBoxx | Country | Country | AAA | IG & HY | 57 | 141 | *No Info* | *Subs. Needed* |
| Canada | Bloomberg | x | Global | x | IG | x | 1160 | x | 7.60 | x |
| Chile | x | iBoxx | x | Country | x | IG & HY | x | 68 | x | *Subs. Needed* |
| China | FTSE | FTSE | Country | Country | IG | A+ / BB | 386 | 242 | 3.31 | 7.15 |
| Colombia | x | iBoxx | x | Country | x | IG & HY | x | 41 | x | *Subs. Needed* |
| Denmark | S&P | x | Global | x | IG | x | 2 | x | 0.77 | x |
| Euro Area | Bloomberg | x | Global | x | IG | x | 4064 | x | 5.22 | x |
| Great Britain | Bloomberg | x | Global | x | IG | x | 934 | x | 8.61 | x |
| Hong Kong | iBoxx | iBoxx | Asia-Pacific | Country | IG | IG & HY | 399 | 158 | *Subs. Needed* | *Subs. Needed* |
| India | Nifty | iBoxx | Country | Country | AAA | IG & HY | 6 | 98 | 0.23 | *Subs. Needed* |
| Indonesia | IBPA | iBoxx | Country | Country | IG & HY | IG & HY | 256 | 54 | *No Info* | *Subs. Needed* |
| Japan | Bloomberg | x | Global | x | IG | x | 202 | x | 4.08 | x |
| Malaysia | FTSE | iBoxx | Global | Country | IG & HY | IG & HY | 567 | 23 | 6.57 | *Subs. Needed* |
| Mexico | S&P | iBoxx | Country | Country | IG & HY | IG & HY | 242 | 155 | 6.44 | *Subs. Needed* |
| New Zealand | S&P | iBoxx | Global | Country | IG | IG & HY | 103 | 25 | 3.42 | *Subs. Needed* |
| Norway | Bloomberg | x | Global | x | IG | x | 4 | x | 5.49 | x |
| Poland | x | iBoxx | x | Country | x | IG & HY | x | 3 | x | *Subs. Needed* |
| Singapore | iBoxx | x | Global | x | AAA / BB | x | 204 | x | 3.82 (Duration) | x |
| South Africa | x | iBoxx | x | Country | x | IG & HY | x | 38 | x | *Subs. Needed* |
| South Korea | FTSE | iBoxx | Global | Country | IG & HY | IG & HY | 1813 | 202 | 3.32 | *Subs. Needed* |
| Sweden | S&P | x | Global | x | IG | x | 99 | x | 2.84 | x |
| Switzerland | Bloomberg | x | Global | x | IG | x | 346 | x | 4.77 | x |
| Taiwan | Taipei Exchange | iBoxx | Country | Country | IG & HY | IG & HY | *No Info* | 19 | *No Info* | *Subs. Needed* |
| Thailand | x | iBoxx | x | Country | x | IG & HY | x | 35 | x | *Subs. Needed* |
| Turkey | x | iBoxx | x | Country | x | IG & HY | x | 67 | x | *Subs. Needed* |

## Table A.2: Data Source

In this table, we list our sample of countries, their exchange rate, the name of their primary stock market index and their data availability. Data pertaining to exchange rates, such as the at-the-money implied volatility of exchange rate options, the forward exchange rate, and the days-to-maturity of the forward exchange rate contracts, are sourced from Bloomberg. We obtain implied volatilities and forward rates for contracts ranging from 1-month to 3-years to maturity. We source price index, total index returns and associated dividend yields from Eikon Refinitiv (Datastream). The tickers associated with these time series are described on the last row of the table.

| | | | | | | Local Index - LC | | | Local Index - USD ETF | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | (1) | (2) | (3) | | (4) | (5) | (6) | (7) | (8) |
| Country | Exchange rate | IV ATM | Forward | Forward DTM | Index Name | Price index | Total Return | Dividend | Price index | Dividend |
| Australia | AUD/USD | ✓ | ✓ | ✓ | S&P/ASX 200 | ✓ | ✓ | - | ✓ | ✓ |
| Belgium | EUR/USD | ✓ | ✓ | ✓ | Belgium 20 | ✓ | ✓ | - | ✓ | ✓ |
| Brazil | BRL/USD | ✓ | ✓ | ✓ | BOVESPA | - | ✓ | ✓ | ✓ | ✓ |
| Canada | CAD/USD | ✓ | ✓ | ✓ | S&P/TSX 60 INDEX | ✓ | ✓ | ✓ | ✓ | ✓ |
| China | CNY/USD | ✓ | ✓ | ✓ | CHINAAMC CHINA 50 ETF | ✓ | - | ✓ | ✓ | ✓ |
| Denmark | DKK/USD | ✓ | ✓ | ✓ | OMXC 25 CAP | ✓ | ✓ | - | ✓ | ✓ |
| Euro area | EUR/USD | ✓ | ✓ | ✓ | EURO STOXX 50 | ✓ | ✓ | ✓ | ✓ | ✓ |
| France | EUR/USD | ✓ | ✓ | ✓ | FRANCE CAC 40 | ✓ | ✓ | - | ✓ | ✓ |
| Germany | EUR/USD | ✓ | ✓ | ✓ | DAX PERFORMANCE (XETRA) | ✓ | ✓ | - | ✓ | ✓ |
| Greece | EUR/USD | ✓ | ✓ | ✓ | FTSE/ATHEX LARGE CAP | ✓ | ✓ | - | ✓ | ✓ |
| Hong Kong | HKD/USD | ✓ | ✓ | ✓ | HANG SENG | ✓ | ✓ | ✓ | ✓ | ✓ |
| India | INR/USD | ✓ | ✓ | ✓ | CNX NIFTY(50) | ✓ | ✓ | - | ✓ | ✓ |
| Israel | ILS/USD | ✓ | ✓ | ✓ | TEL AVIV SE TA-35 | ✓ | - | - | ✓ | ✓ |
| Italy | EUR/USD | ✓ | ✓ | ✓ | FTSE MIB INDEX | ✓ | ✓ | ✓ | ✓ | ✓ |
| Japan | JPY/USD | ✓ | ✓ | ✓ | NIKKEI 225 STOCK AVERAGE | ✓ | ✓ | - | ✓ | ✓ |
| Malaysia | MYR/USD | ✓ | ✓ | ✓ | FTSE BURSA MALAYSIA KLCI | ✓ | ✓ | ✓ | ✓ | ✓ |
| Mexico | MXN/USD | ✓ | ✓ | ✓ | MEXDER-IPC INDEX | ✓ | - | ✓ | ✓ | ✓ |
| Norway | NOK/USD | ✓ | ✓ | ✓ | OSLO SE OBX | ✓ | ✓ | - | ✓ | ✓ |
| Poland | PLN/USD | ✓ | ✓ | ✓ | WARSAW GENERAL INDEX 20 | ✓ | ✓ | - | ✓ | ✓ |
| Singapore | SGD/USD | - | - | - | MSCI SINGAPORE | - | - | - | - | - |
| South Korea | KRW/USD | ✓ | ✓ | ✓ | KOREA SE KOSPI 200 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Spain | EUR/USD | ✓ | ✓ | ✓ | MEFF-MINI IBEX 35 INDEX | - | - | ✓ | ✓ | ✓ |
| Sweden | SEK/USD | ✓ | ✓ | ✓ | OMX STOCKHOLM 30 (OMXS30) | ✓ | ✓ | - | ✓ | ✓ |
| Switzerland | USD/CHF | ✓ | ✓ | ✓ | SWISS MARKET (SMI) | ✓ | ✓ | - | ✓ | ✓ |
| Taiwan | TWD/USD | ✓ | - | - | TAIWAN SE WEIGHED TAIEX | ✓ | - | ✓ | ✓ | ✓ |
| Thailand | TRY/USD | ✓ | ✓ | ✓ | BANGKOK S.E.T. 50 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Turkey | THB/USD | ✓ | ✓ | ✓ | BIST NATIONAL 30 | ✓ | ✓ | ✓ | - | - |
| United Kingdom | GBP/USD | ✓ | ✓ | ✓ | FTSE 100 | ✓ | ✓ | ✓ | ✓ | ✓ |
| Ticker structure | CCYUSD | USDCCYV | CCY[MAT] | CCY[MAT] | | [Index Name] | [Index Name] | [Index Name] | ISHARE MSCI [Country] | |
| MAT=1M,3M,6M | BGN Curncy | [MAT] | Curncy | Curncy | | PRICE | TOT | DIVIDEND | ETF ([PRICE INDEX] | |
| 1Y,18M,2Y,3Y | PX LAST | BGN Curncy | PX LAST | DAYS TO MTY | | INDEX | RETURN | YIELD | or [DIVIDEND YIELD]) | |
| | | **Bloomberg** | | | | | **Datastream** | | | |

Table A.3: Local and Foreign Box Rate Indices – 3-Month Horizon

This table reports the summary statistics for 3-month box rates estimates. Due to the illiquidity of options data for most of the countries, we create regional indices as described in Section A.5. CIP refers to the covered interest rate parity deviation proxied by the 3-month forward basis. We proxy foreign currency (USD) box rates for the economies in our sample as the one constructed using options on the S&P500 index.

**Panel A: Developed Countries**

| Country | Index Type | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. |
|---|---|---|---|---|---|---|---|
| Australia | SPX box rate + CIP | 332 | 0.041 | 0.046 | 0.020 | 0.003 | 0.070 |
| Belgium | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Canada | SPX box rate + CIP | 332 | 0.026 | 0.022 | 0.017 | 0.004 | 0.055 |
| Euro Area | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| France | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Germany | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Greece | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Hong Kong | Asian index | 205 | 0.010 | 0.008 | 0.011 | -0.004 | 0.031 |
| Italy | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Japan | Asian index | 194 | -0.001 | -0.001 | 0.012 | -0.024 | 0.015 |
| Netherlands | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Singapore | Asian index | 103 | 0.009 | 0.013 | 0.049 | 0.000 | 0.032 |
| South Korea | Asian index | 58 | 0.029 | 0.028 | 0.022 | 0.005 | 0.052 |
| Spain | Eurozone index | 250 | 0.011 | 0.005 | 0.016 | -0.005 | 0.044 |
| Sweden | Europe index | 55 | 0.009 | 0.004 | 0.014 | -0.004 | 0.041 |
| Switzerland | Europe index | 210 | 0.002 | 0.000 | 0.011 | -0.008 | 0.026 |
| Taiwan | Asian index | 140 | -0.007 | -0.002 | 0.018 | -0.043 | 0.015 |
| United Kingdom | Europe index | 213 | 0.017 | 0.009 | 0.019 | 0.004 | 0.057 |

**Panel B: Emerging Countries**

| Country | Index Type | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. |
|---|---|---|---|---|---|---|---|
| Brazil | SPX box rate + CIP | 295 | 0.109 | 0.104 | 0.053 | 0.027 | 0.205 |
| China | Asian index | 96 | 0.026 | 0.027 | 0.017 | 0.003 | 0.052 |
| India | Asian index | 169 | 0.065 | 0.064 | 0.017 | 0.039 | 0.097 |
| Malaysia | Asian index | 142 | 0.026 | 0.025 | 0.011 | 0.010 | 0.045 |
| Mexico | SPX box rate + CIP | 310 | 0.086 | 0.073 | 0.060 | 0.031 | 0.219 |
| Poland | Europe index | 133 | 0.028 | 0.020 | 0.023 | 0.003 | 0.073 |
| Thailand | Asian index | 156 | 0.020 | 0.018 | 0.014 | -0.001 | 0.043 |
| Turkey | Europe index | 29 | 0.188 | 0.117 | 0.128 | 0.088 | 0.453 |

**Panel C: Foreign (SPX) Box Rates**

| Country | Index Type | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. |
|---|---|---|---|---|---|---|---|
| United States | SPX box rate | 250 | 0.019 | 0.012 | 0.016 | 0.003 | 0.053 |

Table A.4: Moody's Historical Default Probabilities 1970-2022

In this table, we report the Moody's U.S. average cumulative issuer-weighted default rates from 1970 to 2022 for a horizon of 1 and 2 years for credit rating categories ranging from Aaa/Aa to Caa-C. Source: Moody's.

| Rating/Year | 1 | 2 |
|---|---|---|
| Aaa/Aa | 0.0% | 0.05% |
| A/Baa | 0.1% | 0.25% |
| Ba | 0.9% | 2.5% |
| B | 3.2% | 7.7% |
| Caa-C | 9.0% | 16.2% |

Table A.5: Model Calibration.

This table reports parameter values in the model calibration. Values are annualized when applicable.

| **Parameter** | **Notation** | **Values** |
|---|---|---|
| *Panel A: Risk-free rates and exchange rate* | | |
| Risk-free rate in LC | $r$ | 0.019 |
| Risk-free rate in USD | $r^{\$}$ | 0.014 |
| Exchange rate (USD per unit of GBP) | $S_t$ | 1 |
| Currency risk premium | $\lambda_S$ | 0.02 |
| Exchange rate return volatility | $\sigma_S$ | 0.1 |
| Expected exchange rate return | $\mu_S = r^{\$} - r + \sigma_S^2 + \lambda_S$ | 0.025 |
| *Panel B: Stock index in local currency (GBP)* | | |
| Stock index price in LC | $A_t$ | 100 |
| Expected stock index return | $\mu$ | 0.06 |
| Stock market risk premium | $\lambda_A$ | 0.041 |
| Correlation between LC stock index and exchange rate | $\rho$ | 0.13 |
| Stock index return volatility | $\sigma$ | 0.14 |
| Face debt value | $K$ | set s.t. $\mathbb{P} = 0.05$ |
| Debt maturity | $T - t$ | 1 |
| *Panel C: Stock index in USD* | | |
| Stock index price in USD | $A_t^{\$} = A_t \cdot S_t$ | 100 |
| Expected stock index return | $\mu^{\$} = \mu + \mu_S + \rho\sigma\sigma_S$ | 0.087 |
| Stock market risk premium | $\lambda_A^{\$} = \mu_A^{\$} - r^{\$}$ | 0.073 |
| Stock index return volatility | $\sigma^{\$} = \sqrt{\sigma^2 + \sigma_S^2 + 2\rho\sigma_S\sigma}$ | 0.182 |
| Face debt value | $K^{\$}$ | set s.t. $\mathbb{P}^{\$} = \mathbb{P}$ |

## Table A.6: Local and Foreign Currency Pseudo Credit Spreads – 3-Month Horizon

This table presents summary statistics of the 3-month pseudo credit spreads by country in local and foreign currency. Pseudo bonds in local currency (LC) are constructed from put options on the corresponding domestic stock market index, while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks each of them. When an observation is missing, it is replaced by the synthetic counterpart of the empirical time series. For three-month bonds, we restrict the option maturity to be within [7, 182] days. See Appendices A and B for details. The units are in percentage terms: for example, the average LC credit spread for all developed countries is 3.85%. The last two columns report the correlation between the LC and USD credit spreads, and the correlation between the LC stock index and USD/LC exchange rate returns. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

**Panel A: Developed Countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{r_A,r_S}$ |
| Australia | 195 | 4.08 | 2.93 | 3.56 | 0.88 | 10.72 | 195 | 5.93 | 5.04 | 3.91 | 2.52 | 12.90 | 0.84 | 0.47 |
| Belgium | 27 | 4.40 | 3.39 | 3.52 | 0.07 | 13.09 | 27 | 8.76 | 8.06 | 5.39 | 0.86 | 18.60 | 0.88 | 0.25 |
| Canada | 210 | 5.72 | 5.42 | 2.51 | 2.59 | 10.46 | 210 | 5.56 | 4.63 | 3.50 | 2.31 | 12.57 | 0.54 | 0.56 |
| Denmark | 9 | 1.88 | 0.91 | 2.35 | 0.18 | 7.21 | 4 | 3.47 | 3.63 | 2.89 | 0.26 | 6.34 | 0.22 | 0.15 |
| Euro Area | 205 | 3.43 | 2.16 | 3.52 | 0.57 | 11.52 | 195 | 5.84 | 4.49 | 4.11 | 1.39 | 14.67 | 0.72 | 0.27 |
| France | 208 | 1.95 | 1.09 | 2.21 | 0.26 | 6.61 | 198 | 4.67 | 3.77 | 3.45 | 1.12 | 10.66 | 0.48 | 0.24 |
| Germany | 223 | 2.78 | 1.88 | 2.85 | 0.34 | 8.07 | 210 | 4.55 | 3.43 | 3.82 | 1.27 | 11.19 | 0.77 | 0.23 |
| Greece | 39 | 10.03 | 9.32 | 4.22 | 2.21 | 16.40 | 39 | 8.35 | 7.52 | 2.87 | 4.71 | 13.88 | 0.89 | 0.33 |
| Hong Kong | 199 | 2.43 | 1.52 | 2.91 | 0.08 | 7.85 | 192 | 4.00 | 3.38 | 3.26 | 0.86 | 9.56 | 0.80 | 0.17 |
| Israel | 120 | 4.30 | 2.11 | 6.62 | 0.51 | 18.66 | 107 | 47.44 | 47.66 | 22.53 | 11.89 | 87.71 | -0.12 | 0.40 |
| Italy | 187 | 2.55 | 1.65 | 2.89 | 0.52 | 7.91 | 177 | 3.41 | 2.77 | 2.89 | 0.18 | 9.84 | 0.34 | 0.30 |
| Japan | 205 | 2.26 | 1.59 | 2.32 | 0.51 | 5.24 | 189 | 3.57 | 3.09 | 2.89 | 0.81 | 9.22 | 0.75 | -0.44 |
| Netherlands | 220 | 2.20 | 1.15 | 3.13 | 0.35 | 8.81 | 210 | 4.60 | 3.76 | 3.11 | 1.29 | 10.95 | 0.54 | 0.18 |
| Norway | 174 | 4.31 | 3.61 | 2.86 | 1.15 | 9.46 | 164 | 10.35 | 9.34 | 6.30 | 2.88 | 20.78 | 0.60 | 0.48 |
| New Zealand | 38 | 7.78 | 7.80 | 2.46 | 4.02 | 12.22 | 38 | 8.11 | 8.47 | 2.35 | 4.21 | 11.84 | 0.79 | - |
| Singapore | 82 | 5.77 | 5.54 | 2.48 | 2.45 | 11.13 | 82 | 4.24 | 4.00 | 1.50 | 2.26 | 6.82 | 0.60 | 0.52 |
| South Korea | 193 | 5.36 | 5.11 | 3.35 | 1.08 | 11.96 | 194 | 6.18 | 5.22 | 4.60 | 2.48 | 13.62 | 0.37 | 0.46 |
| Spain | 181 | 7.21 | 6.15 | 4.33 | 2.42 | 17.19 | 181 | 7.43 | 5.81 | 5.28 | 2.70 | 18.74 | 0.80 | 0.35 |
| Sweden | 184 | 6.60 | 5.52 | 4.40 | 1.61 | 14.25 | 180 | 10.26 | 8.84 | 5.80 | 3.14 | 20.99 | 0.73 | 0.26 |
| Switzerland | 200 | 2.47 | 1.85 | 2.53 | 0.30 | 6.90 | 203 | 4.67 | 3.36 | 3.63 | 1.54 | 11.56 | 0.64 | -0.08 |
| Taiwan | 132 | 2.34 | 1.60 | 2.30 | 0.18 | 6.90 | 125 | 5.92 | 5.31 | 2.90 | 2.34 | 12.00 | 0.65 | 0.53 |
| United Kingdom | 222 | 3.40 | 2.33 | 3.00 | 0.91 | 8.71 | 212 | 4.84 | 3.98 | 3.14 | 1.50 | 11.32 | 0.75 | 0.21 |
| All | 3,453 | 3.85 | 2.65 | 3.72 | 0.44 | 10.68 | 3,332 | 7.04 | 4.61 | 9.44 | 1.31 | 18.31 | 0.26 | - |

**Panel B: Emerging Countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{A,S}$ |
| Brazil | 205 | 7.08 | 5.56 | 5.14 | 2.94 | 21.00 | 207 | 6.90 | 5.28 | 5.89 | 2.54 | 16.23 | 0.86 | 0.64 |
| Chile | 95 | 7.10 | 6.98 | 2.93 | 2.28 | 12.86 | 95 | 6.19 | 6.03 | 2.45 | 2.51 | 11.01 | 0.79 | - |
| China | 157 | 4.52 | 4.16 | 2.53 | 0.58 | 9.37 | 164 | 3.67 | 3.25 | 1.83 | 1.57 | 8.23 | 0.55 | 0.32 |
| Colombia | 10 | 8.37 | 7.37 | 2.93 | 5.47 | 15.74 | 10 | 11.38 | 11.74 | 2.89 | 5.88 | 16.12 | 0.64 | - |
| India | 173 | 2.17 | 1.78 | 1.58 | 0.47 | 4.88 | 163 | 4.44 | 3.80 | 3.00 | 1.71 | 9.09 | 0.79 | 0.56 |
| Indonesia | 65 | 8.38 | 8.25 | 3.00 | 3.33 | 12.69 | 70 | 8.04 | 7.67 | 3.58 | 3.18 | 14.09 | 0.43 | - |
| Malaysia | 81 | 9.01 | 7.87 | 5.60 | 3.63 | 21.16 | 81 | 5.52 | 5.04 | 2.73 | 2.59 | 10.84 | 0.48 | 0.39 |
| Mexico | 189 | 6.27 | 5.97 | 4.14 | 1.53 | 14.32 | 189 | 5.78 | 4.77 | 3.91 | 2.27 | 12.90 | 0.64 | 0.54 |
| Poland | 125 | 2.38 | 1.65 | 2.10 | 0.59 | 7.32 | 117 | 3.17 | 2.21 | 2.63 | 0.50 | 8.84 | 0.81 | 0.55 |
| South Africa | 180 | 10.57 | 10.14 | 3.94 | 5.36 | 17.24 | 180 | 8.97 | 8.15 | 5.02 | 3.41 | 17.96 | 0.70 | - |
| Thailand | 113 | 2.92 | 1.89 | 3.55 | 0.34 | 8.57 | 111 | 7.45 | 7.14 | 3.88 | 2.70 | 13.50 | 0.71 | 0.48 |
| Turkey | 120 | 6.96 | 6.48 | 3.79 | 1.40 | 13.15 | 120 | 6.64 | 6.44 | 2.98 | 3.05 | 11.58 | 0.59 | 0.28 |
| All | 1,513 | 6.03 | 5.16 | 4.56 | 0.76 | 13.89 | 1,507 | 6.08 | 5.25 | 4.24 | 1.72 | 12.69 | 0.69 | - |

## Table A.7: Local and Foreign Currency Pseudo Credit Spreads – 12-Month Horizon

This table presents summary statistics of the 12-month pseudo credit spreads by country in local and foreign currency. Pseudo bonds in local currency (LC) are constructed from put options on the corresponding domestic stock market index, while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks each of them. When an observation is missing, it is replaced by the synthetic counterpart of the empirical time series. For 1-years bonds, we restrict the option maturity to be within [182,547] days. See Appendices A and B for details. The units are in percentage terms: for example, the average LC credit spread for all developed countries is 3.25%. The last two columns report the correlation between the LC and USD credit spreads, and the correlation between the LC stock index and USD/LC exchange rate returns. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

**Panel A: Developed Countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{r_A,r_S}$ |
| Australia | 170 | 4.55 | 4.30 | 2.49 | 0.98 | 9.12 | 170 | 5.59 | 4.49 | 3.00 | 2.29 | 11.39 | 0.40 | 0.47 |
| Belgium | 2 | 2.49 | 2.49 | 1.45 | 1.47 | 3.52 | 2 | 3.35 | 3.35 | 0.20 | 3.21 | 3.50 | -1.00 | 0.25 |
| Canada | 154 | 3.95 | 3.92 | 1.46 | 1.67 | 6.47 | 154 | 4.19 | 3.70 | 2.39 | 1.75 | 8.51 | 0.58 | 0.56 |
| Euro Area | 152 | 2.72 | 1.74 | 2.91 | 0.02 | 7.94 | 142 | 5.33 | 4.03 | 4.57 | 0.54 | 11.62 | 0.89 | 0.27 |
| France | 94 | 2.63 | 2.79 | 1.98 | 0.04 | 6.37 | 94 | 3.65 | 3.59 | 2.71 | 0.11 | 8.57 | 0.83 | 0.24 |
| Germany | 140 | 1.02 | 0.52 | 1.51 | 0.01 | 3.56 | 135 | 3.58 | 2.82 | 3.63 | 0.35 | 12.95 | 0.24 | 0.23 |
| Greece | 11 | 4.55 | 4.29 | 2.00 | 2.19 | 9.11 | 11 | 4.40 | 4.43 | 1.86 | 2.18 | 8.06 | 0.96 | 0.33 |
| Hong Kong | 181 | 3.54 | 3.25 | 2.01 | 1.00 | 7.21 | 188 | 3.38 | 3.02 | 2.16 | 1.31 | 7.61 | 0.58 | 0.17 |
| Italy | 133 | 1.26 | 0.84 | 1.18 | 0.20 | 3.69 | 124 | 1.17 | 0.61 | 1.51 | 0.06 | 4.73 | 0.38 | 0.30 |
| Japan | 137 | 1.69 | 1.33 | 1.55 | 0.10 | 4.35 | 126 | 1.59 | 1.20 | 1.57 | 0.26 | 4.00 | 0.85 | -0.44 |
| Netherlands | 160 | 1.79 | 0.91 | 2.26 | 0.07 | 6.21 | 151 | 2.78 | 2.12 | 2.77 | 0.16 | 9.08 | 0.86 | 0.18 |
| Norway | 19 | 3.82 | 3.81 | 1.59 | 1.43 | 7.16 | 17 | 8.31 | 9.21 | 3.30 | 3.85 | 12.45 | 0.18 | 0.48 |
| New Zealand | 7 | 8.99 | 7.95 | 2.75 | 5.94 | 12.65 | 7 | 8.37 | 7.89 | 2.69 | 5.36 | 11.80 | 0.88 | - |
| Singapore | 38 | 3.63 | 3.72 | 1.75 | 1.42 | 7.23 | 38 | 3.24 | 3.09 | 1.06 | 1.79 | 5.47 | 0.60 | 0.52 |
| South Korea | 192 | 5.49 | 4.71 | 4.14 | 0.96 | 12.91 | 194 | 5.49 | 4.19 | 4.19 | 1.34 | 15.15 | 0.37 | 0.46 |
| Spain | 60 | 4.95 | 4.03 | 3.34 | 2.03 | 13.65 | 60 | 5.66 | 4.18 | 4.20 | 1.61 | 14.30 | 0.77 | 0.35 |
| Sweden | 89 | 5.57 | 5.44 | 2.36 | 2.23 | 10.17 | 86 | 7.58 | 6.40 | 3.99 | 2.81 | 14.68 | 0.62 | 0.26 |
| Switzerland | 101 | 2.60 | 1.63 | 2.40 | 0.07 | 6.28 | 91 | 4.34 | 3.68 | 3.47 | 0.21 | 10.24 | 0.75 | -0.08 |
| Taiwan | 69 | 4.94 | 4.92 | 2.33 | 0.24 | 8.14 | 69 | 4.19 | 4.08 | 1.48 | 2.18 | 6.53 | 0.61 | 0.53 |
| United Kingdom | 210 | 2.82 | 1.77 | 2.58 | 0.28 | 7.30 | 198 | 2.89 | 2.42 | 2.49 | 0.11 | 7.76 | 0.83 | 0.21 |
| All | 2,119 | 3.25 | 2.82 | 2.83 | 0.10 | 8.04 | 2,057 | 4.02 | 3.28 | 3.42 | 0.29 | 10.83 | 0.63 | - |

**Panel B: Emerging Countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{A,S}$ |
| Brazil | 201 | 5.32 | 4.27 | 3.28 | 2.15 | 12.67 | 203 | 5.01 | 4.15 | 2.80 | 2.00 | 11.32 | 0.78 | 0.64 |
| Chile | 30 | 5.00 | 4.52 | 2.10 | 2.54 | 9.11 | 30 | 4.90 | 4.69 | 1.78 | 2.46 | 8.40 | 0.70 | - |
| China | 155 | 3.97 | 3.74 | 1.85 | 1.82 | 7.28 | 155 | 4.29 | 4.12 | 1.43 | 2.32 | 6.74 | 0.64 | 0.32 |
| Colombia | 2 | 3.09 | 3.09 | 0.05 | 3.06 | 3.12 | 2 | 5.68 | 5.68 | 1.68 | 4.49 | 6.88 | -1.00 | - |
| India | 145 | 1.88 | 1.26 | 1.97 | 0.18 | 5.24 | 135 | 2.84 | 1.97 | 2.27 | 0.39 | 7.10 | 0.82 | 0.56 |
| Indonesia | 8 | 6.88 | 7.20 | 1.54 | 4.03 | 8.81 | 8 | 6.34 | 5.66 | 2.82 | 3.51 | 12.80 | -0.62 | - |
| Malaysia | 31 | 5.45 | 5.27 | 1.66 | 3.16 | 8.02 | 31 | 3.77 | 3.38 | 1.53 | 2.19 | 6.49 | 0.67 | 0.39 |
| Mexico | 187 | 4.42 | 3.89 | 3.30 | 1.23 | 9.99 | 187 | 4.36 | 3.75 | 2.91 | 1.60 | 12.44 | 0.75 | 0.54 |
| Poland | 49 | 2.96 | 2.35 | 1.67 | 1.09 | 5.40 | 45 | 4.75 | 3.81 | 2.99 | 1.54 | 10.63 | 0.76 | 0.55 |
| South Africa | 93 | 7.46 | 7.13 | 3.16 | 3.14 | 13.56 | 93 | 8.21 | 7.51 | 3.92 | 3.70 | 18.13 | 0.83 | - |
| Thailand | 24 | 6.18 | 6.00 | 2.75 | 2.00 | 10.66 | 31 | 5.29 | 4.85 | 2.66 | 1.46 | 9.32 | 0.86 | 0.48 |
| Turkey | 94 | 4.57 | 4.48 | 2.70 | 1.06 | 8.43 | 94 | 5.52 | 5.07 | 2.09 | 2.98 | 10.27 | 0.35 | 0.28 |
| All | 1,019 | 4.49 | 3.93 | 3.08 | 0.68 | 10.19 | 1,014 | 4.80 | 4.16 | 2.91 | 1.38 | 10.33 | 0.76 | - |

## Table A.8: Local and Foreign Currency Pseudo Credit Spreads – 24-Month Horizon

This table presents summary statistics of the 24-month pseudo credit spreads by country in local and foreign currency. Pseudo bonds in local currency (LC) are constructed from put options on the corresponding domestic stock market index, while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks each of them. When an observation is missing, it is replaced by the synthetic counterpart of the empirical time series. For two-year bonds, we restrict the option maturity to be within [365,1095] days. See Appendices A and B for details. The units are in percentage terms: for example, the average LC credit spread for all developed countries is 4.26%. The last two columns report the correlation between the LC and USD credit spreads, and the correlation between the LC stock index and USD/LC exchange rate returns. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

**Panel A: Developed Countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{A,S}$ |
| Australia | 83 | 2.86 | 2.75 | 1.52 | 0.53 | 5.88 | 83 | 5.88 | 3.62 | 0.96 | 5.86 | 11.51 | 0.64 | 0.47 |
| Canada | 79 | 3.65 | 3.70 | 1.10 | 2.00 | 5.74 | 79 | 3.56 | 1.41 | 1.61 | 3.36 | 6.36 | 0.77 | 0.56 |
| Euro Area | 128 | 2.94 | 2.59 | 2.76 | 0.02 | 7.94 | 119 | 6.30 | 5.70 | 1.43 | 4.13 | 18.34 | 0.76 | 0.27 |
| France | 82 | 3.46 | 2.93 | 2.50 | 0.51 | 8.52 | 82 | 6.14 | 4.51 | 0.84 | 4.93 | 14.93 | 0.91 | 0.24 |
| Germany | 126 | 3.44 | 3.47 | 1.33 | 1.41 | 5.97 | 126 | 3.50 | 1.63 | 2.07 | 3.10 | 7.42 | 0.68 | 0.23 |
| Hong Kong | 115 | 5.57 | 4.44 | 5.20 | 1.70 | 12.56 | 115 | 3.63 | 1.16 | 2.17 | 3.33 | 5.96 | 0.25 | 0.17 |
| Italy | 110 | 1.68 | 1.22 | 1.34 | 0.35 | 4.80 | 102 | 1.41 | 1.28 | 0.21 | 1.13 | 3.89 | 0.90 | 0.30 |
| Japan | 95 | 2.94 | 2.80 | 1.62 | 0.59 | 6.05 | 84 | 2.26 | 1.53 | 0.17 | 1.91 | 5.09 | 0.77 | -0.44 |
| Netherlands | 90 | 3.05 | 2.63 | 2.46 | 0.07 | 8.75 | 82 | 4.55 | 3.13 | 0.66 | 3.44 | 10.16 | 0.76 | 0.18 |
| South Korea | 182 | 8.24 | 6.14 | 11.38 | 1.61 | 17.20 | 182 | 6.25 | 3.09 | 2.69 | 5.55 | 13.23 | 0.20 | 0.46 |
| Spain | 2 | 1.46 | 1.46 | 0.13 | 1.36 | 1.55 | 2 | 2.19 | 0.03 | 2.17 | 2.19 | 2.21 | 1.00 | 0.35 |
| Sweden | 61 | 7.18 | 6.57 | 2.82 | 3.60 | 12.23 | 61 | 12.50 | 6.58 | 1.86 | 14.16 | 22.44 | 0.70 | 0.26 |
| Switzerland | 110 | 4.01 | 4.30 | 1.75 | 0.19 | 7.12 | 106 | 5.38 | 2.39 | 1.77 | 5.23 | 9.21 | 0.77 | -0.08 |
| Taiwan | 36 | 4.14 | 3.50 | 3.00 | 0.09 | 8.88 | 36 | 3.73 | 1.48 | 2.13 | 3.18 | 6.72 | 0.53 | 0.53 |
| United Kingdom | 162 | 4.27 | 3.98 | 2.94 | 0.55 | 9.31 | 144 | 4.73 | 3.32 | 0.34 | 4.15 | 10.38 | 0.79 | 0.21 |
| All | 1,461 | 4.26 | 3.65 | 5.05 | 0.32 | 9.50 | 1,403 | 4.90 | 3.94 | 0.66 | 3.86 | 13.55 | 0.37 | - |

**Panel B: Emerging Countries**

| | Local Currency CS | | | | | | Foreign Currency CS | | | | | | Correlations | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{CS^{LC},CS^{\$}}$ | $\rho_{A,S}$ |
| Brazil | 189 | 4.55 | 3.60 | 3.61 | 1.51 | 13.15 | 189 | 6.93 | 4.59 | 3.07 | 5.56 | 16.42 | 0.89 | 0.64 |
| China | 143 | 3.92 | 2.90 | 3.30 | 1.49 | 9.84 | 143 | 4.04 | 1.17 | 2.75 | 3.76 | 6.12 | 0.53 | 0.32 |
| India | 162 | 2.44 | 1.86 | 2.41 | 0.22 | 6.59 | 153 | 4.06 | 3.32 | 0.81 | 3.18 | 10.32 | 0.71 | 0.56 |
| Mexico | 174 | 4.43 | 3.83 | 2.81 | 1.10 | 10.14 | 174 | 5.05 | 2.64 | 1.88 | 4.68 | 10.13 | 0.73 | 0.54 |
| Turkey | 57 | 5.19 | 5.24 | 2.77 | 0.45 | 9.77 | 57 | 5.59 | 1.23 | 3.72 | 5.50 | 7.90 | 0.04 | 0.28 |
| All | 725 | 3.98 | 3.17 | 3.17 | 0.55 | 10.20 | 716 | 5.18 | 3.36 | 1.52 | 4.49 | 10.58 | 0.70 | - |

Table A.9: Local and Foreign Currency Ex-ante Default Probabilities – 6-Month Horizon

This table presents summary statistics of the 6-month ex-ante default probabilities by country in local and foreign currency. Pseudo bonds in local currency (LC) are constructed from put options on the corresponding domestic stock market index, while those in foreign currency (labeled with $) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks each of them. The empirical default probability for each pseudo bond under the physical measure $P$ is based on the historical default frequency. When an observation is missing, it is replaced by the synthetic counterpart of the empirical time series. For six-month bonds, we restrict the option maturity to be within [91,365] days. See Appendices A and B for details. The units are in percentage terms: For example, the average LC ex-ante default probability for all developed countries is 8.54%. The last two columns report the correlation between the LC and USD ex-ante default probabilities. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

**Panel A: Developed Countries**

| | Local Currency | | | | | | Foreign Currency | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{DP^{LC},DP^{\$}}$ |
| Australia | 193 | 9.13 | 8.94 | 2.90 | 4.65 | 14.30 | 193 | 9.13 | 8.90 | 2.90 | 4.65 | 14.44 | 0.9987 |
| Belgium | 8 | 18.35 | 19.08 | 4.48 | 11.99 | 25.79 | 8 | 18.35 | 19.08 | 4.48 | 11.99 | 25.79 | 1.0000 |
| Canada | 208 | 13.91 | 13.60 | 3.82 | 7.63 | 19.83 | 208 | 13.90 | 13.60 | 3.82 | 7.63 | 19.83 | 1.0000 |
| Denmark | 1 | 18.43 | 18.43 | 0.00 | 18.43 | 18.43 | 1 | 18.43 | 18.43 | 0.00 | 18.43 | 18.43 | - |
| Euro Area | 182 | 9.20 | 8.00 | 5.97 | 1.13 | 20.18 | 182 | 9.18 | 7.98 | 5.98 | 0.95 | 20.18 | 0.9998 |
| France | 132 | 3.61 | 1.13 | 4.83 | 0.18 | 14.02 | 132 | 3.63 | 1.14 | 4.82 | 0.19 | 14.02 | 0.9998 |
| Germany | 194 | 4.56 | 2.59 | 4.69 | 0.30 | 13.48 | 194 | 4.57 | 2.60 | 4.69 | 0.30 | 13.36 | 0.9994 |
| Greece | 40 | 15.12 | 15.29 | 3.73 | 9.06 | 21.05 | 40 | 15.12 | 15.29 | 3.73 | 9.06 | 21.05 | 1.0000 |
| Hong Kong | 173 | 6.14 | 4.44 | 4.81 | 0.77 | 14.96 | 173 | 6.13 | 4.46 | 4.81 | 0.61 | 14.86 | 0.9992 |
| Italy | 150 | 2.74 | 2.23 | 2.60 | 0.46 | 6.94 | 150 | 2.73 | 2.23 | 2.59 | 0.45 | 6.52 | 0.9991 |
| Japan | 195 | 5.98 | 4.29 | 5.05 | 0.79 | 16.74 | 196 | 6.03 | 4.30 | 5.08 | 0.72 | 16.76 | 0.9997 |
| Netherlands | 194 | 3.55 | 2.21 | 3.58 | 0.26 | 10.28 | 194 | 3.55 | 2.21 | 3.58 | 0.26 | 10.28 | 1.0000 |
| New Zealand | 28 | 14.57 | 15.70 | 6.55 | 4.14 | 24.16 | 28 | 14.57 | 15.70 | 6.55 | 4.14 | 24.16 | 1.0000 |
| Norway | 89 | 12.39 | 11.96 | 3.92 | 6.61 | 19.11 | 89 | 12.39 | 11.96 | 3.92 | 6.61 | 19.11 | 1.0000 |
| Singapore | 77 | 15.89 | 15.29 | 5.51 | 8.27 | 24.73 | 77 | 15.89 | 15.29 | 5.51 | 8.27 | 24.73 | 1.0000 |
| South Korea | 192 | 11.55 | 10.93 | 4.82 | 3.89 | 20.20 | 192 | 11.55 | 10.93 | 4.83 | 3.85 | 20.27 | 0.9997 |
| Spain | 160 | 11.48 | 11.26 | 4.72 | 3.98 | 20.23 | 160 | 11.49 | 11.26 | 4.72 | 3.98 | 20.23 | 1.0000 |
| Sweden | 117 | 17.20 | 17.95 | 4.70 | 6.34 | 23.70 | 117 | 17.21 | 17.84 | 4.69 | 6.34 | 23.65 | 0.9998 |
| Switzerland | 157 | 5.86 | 4.16 | 5.46 | 0.25 | 16.69 | 157 | 5.87 | 4.26 | 5.46 | 0.25 | 16.69 | 0.9999 |
| Taiwan | 81 | 12.41 | 11.95 | 3.97 | 5.58 | 19.08 | 81 | 12.41 | 11.95 | 3.97 | 5.58 | 19.08 | 1.0000 |
| United Kingdom | 218 | 5.97 | 5.31 | 3.82 | 1.12 | 13.57 | 218 | 5.97 | 5.32 | 3.83 | 1.12 | 13.58 | 0.9995 |
| All | 2,789 | 8.54 | 7.83 | 6.14 | 0.51 | 19.76 | 2,790 | 8.54 | 7.86 | 6.14 | 0.49 | 19.76 | 0.9998 |

**Panel B: Emerging Countries**

| | Local Currency | | | | | | Foreign Currency | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Country** | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | N | Mean | Median | SD | $5^{th}$ prc. | $95^{th}$ prc. | $\rho_{DP^{LC},DP^{\$}}$ |
| Brazil | 207 | 13.51 | 13.62 | 2.60 | 9.17 | 17.29 | 207 | 13.51 | 13.62 | 2.60 | 9.17 | 17.29 | 0.9999 |
| Chile | 78 | 13.77 | 13.74 | 5.22 | 6.63 | 22.75 | 78 | 13.77 | 13.74 | 5.22 | 6.63 | 22.75 | 1.0000 |
| China | 161 | 10.66 | 10.94 | 2.77 | 5.79 | 14.51 | 161 | 10.66 | 10.94 | 2.77 | 5.79 | 14.51 | 1.0000 |
| Colombia | 7 | 13.14 | 12.33 | 6.33 | 5.28 | 22.21 | 7 | 13.14 | 12.33 | 6.33 | 5.28 | 22.21 | 1.0000 |
| India | 156 | 8.31 | 7.90 | 4.78 | 1.79 | 19.04 | 156 | 8.33 | 7.91 | 4.76 | 1.79 | 18.93 | 0.9995 |
| Indonesia | 49 | 13.65 | 14.04 | 5.82 | 2.53 | 22.76 | 49 | 13.65 | 14.04 | 5.82 | 2.53 | 22.76 | 1.0000 |
| Malaysia | 71 | 17.02 | 16.86 | 5.84 | 8.33 | 25.56 | 71 | 17.02 | 16.86 | 5.84 | 8.33 | 25.56 | 1.0000 |
| Mexico | 188 | 10.39 | 10.42 | 4.34 | 2.83 | 17.33 | 188 | 10.40 | 10.31 | 4.35 | 2.83 | 17.33 | 0.9998 |
| Poland | 91 | 10.16 | 9.72 | 4.27 | 4.50 | 17.58 | 91 | 10.16 | 9.72 | 4.27 | 4.50 | 17.58 | 1.0000 |
| South Africa | 170 | 10.15 | 9.94 | 2.94 | 6.34 | 15.30 | 170 | 10.15 | 9.94 | 2.94 | 6.34 | 15.30 | 1.0000 |
| Thailand | 83 | 15.10 | 15.63 | 4.98 | 5.49 | 22.04 | 83 | 15.10 | 15.63 | 4.98 | 5.49 | 22.03 | 0.9999 |
| Turkey | 115 | 10.07 | 9.61 | 5.65 | 2.74 | 21.05 | 115 | 10.07 | 9.61 | 5.65 | 2.74 | 21.05 | 1.0000 |
| All | 1,376 | 11.53 | 11.31 | 4.84 | 3.66 | 20.41 | 1,376 | 11.54 | 11.31 | 4.83 | 3.66 | 20.41 | 0.9999 |

Table A.10: Descriptive Statistics – Analysis of the Drivers

This table presents descriptive statistics of the variables used in the analysis of the drivers of the local currency (LC) pseudo credit spreads and the credit spread quanto (Section 4). The credit spread quanto is defined as the difference between USD and LC credit spreads. The physical default probability is denoted by $P$, while the risk-neutral counterpart is denoted by $Q$. All credit spreads and default probabilities are for pseudo bonds with 3-month maturity. The frequency of the data is quarterly, computed as the average monthly observations within a quarter. Section 2 provides details on the computation of the local variables. The global determinants are detailed in Section 4.

**Credit Spreads and Risk Decomposition**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| CS LC (3m) | 1743 | 0.0454 | 0.0378 | 0.0001 | 0.293 | 0.0096 | 0.0926 |
| CS Diff (USD-LC,3m) | 1692 | 0.0212 | 0.068 | -0.1549 | 0.5263 | -0.0207 | 0.0543 |
| Default Prob (3m) | 1743 | 0.0828 | 0.1055 | 0 | 0.9065 | 0.0134 | 0.1518 |
| Q - P (LC,3m) | 1743 | 0.0464 | 0.1101 | -0.8255 | 0.2883 | 0.0027 | 0.1403 |
| Q Diff (USD-LC,3m) | 1692 | 0.0115 | 0.0646 | -0.2008 | 0.3021 | -0.0754 | 0.084 |

**Local Determinants**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| Exp Return (LC) | 1257 | 0.0657 | 0.0398 | -0.1049 | 0.2274 | 0.0145 | 0.1196 |
| Return Vol (LC) | 1257 | 0.0897 | 0.0246 | 0.0326 | 0.2084 | 0.0604 | 0.1206 |
| Exp Return (USD) | 1206 | 0.0691 | 0.0477 | -0.0584 | 0.27 | 0.016 | 0.1306 |
| Return Vol (USD) | 1206 | 0.1206 | 0.0323 | 0.048 | 0.3198 | 0.086 | 0.1726 |
| FX Return (USD/LC) | 1620 | -0.0054 | 0.0423 | -0.3491 | 0.2096 | -0.0548 | 0.041 |
| FX Volatility | 1615 | 0.0938 | 0.0435 | 0.0036 | 0.4114 | 0.0538 | 0.1452 |
| LC Risk-free Rate | 1531 | 0.0242 | 0.0341 | -0.0623 | 0.4295 | -0.0045 | 0.069 |
| FX Reserves (USD) | 1344 | 11.0723 | 1.1454 | 7.8135 | 13.7856 | 9.7687 | 12.6251 |
| Local Inflation | 1330 | 0.0262 | 0.025 | -0.026 | 0.164 | 0.0008 | 0.059 |

**Global Determinants**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| USD Risk-free Rate | 1743 | 0.0118 | 0.0162 | 0.0001 | 0.0529 | 0.0003 | 0.0463 |
| Term Spread | 1743 | 1.3215 | 1.2218 | -1.72 | 3.57 | -0.45 | 2.73 |
| CFNAI | 1743 | -0.1234 | 0.5763 | -2.3933 | 1.4333 | -0.3533 | 0.3033 |
| Macro Uncertainty | 1743 | 0.8264 | 0.1353 | 0.6679 | 1.2772 | 0.7067 | 0.9953 |
| GZ Spread | 723 | 2.5636 | 1.1436 | 1.5795 | 7.5648 | 1.7265 | 3.6023 |
| EBP | 723 | 0.0297 | 0.6428 | -0.5799 | 2.5549 | -0.345 | 0.7866 |

## Table A.11: Descriptive Statistics – Predictability Analysis

This table presents descriptive statistics of the variables used in the predictability analysis of economic activity and exchange rates (Section 5). Aggregate and country-level economic growth are computed one-quarter-ahead (denoted by '3m') or one-year-ahead (denoted by '12m'). Aggregate economic growth is the equally-weighted ('W') or GDP-weighted ('VW') average of real GDP growth across all countries or excluding the US ('NoUS'). The physical default probability is denoted by $P$, while the risk-neutral counterpart is denoted by $Q$. Credit spreads and default probabilities are for pseudo bonds with either 3-month maturity ('3m') or computed as their equally weighted average at 3-month, 6-month, 1-year, and 2-year horizons ('avg'), following the methodology of Culp et al. (2018). The variable CS US is our updated option-implied credit spread for the US, following Culp et al. (2018), which is orthogonalized to local currency (LC) and USD pseudo credit spreads. The GZ Spread of Gilchrist and Zakrajšek (2012) is additionally orthogonalized to CS US. The frequency of the data is quarterly, computed as the average monthly observations within a quarter. Section 5 provides details on the variables.

**Dependent Variables**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| Agg growth (NoUS,VW,3m) | 1770 | 0.006 | 0.0158 | -0.0677 | 0.0815 | 0.0034 | 0.01 |
| Agg growth (NoUS,EW,3m) | 1754 | 0.0059 | 0.0194 | -0.108 | 0.0874 | 0.0019 | 0.0124 |
| Agg growth (VW,3m) | 1770 | 0.0058 | 0.0156 | -0.0721 | 0.0796 | 0.0024 | 0.0095 |
| Agg growth (EW,3m) | 1754 | 0.0059 | 0.0191 | -0.106 | 0.0864 | 0.0024 | 0.0123 |
| Agg growth (NoUS,VW,12m) | 1770 | 0.0237 | 0.0271 | -0.1032 | 0.124 | -0.0089 | 0.0383 |
| Agg growth (VW,12m) | 1770 | 0.0229 | 0.0256 | -0.0956 | 0.1215 | -0.0093 | 0.0346 |
| Agg growth (NoUS,EW,12m) | 1696 | 0.0233 | 0.03 | -0.1225 | 0.131 | -0.0069 | 0.0448 |
| Agg growth (EW,12m) | 1696 | 0.0231 | 0.0294 | -0.119 | 0.1297 | -0.0054 | 0.0432 |
| Country growth (12m) | 1572 | 0.0197 | 0.039 | -0.2483 | 0.2283 | -0.0165 | 0.0547 |
| FX Return (USD/LC,12m) | 1572 | -0.0238 | 0.0985 | -0.7557 | 0.3162 | -0.1465 | 0.0806 |

**Credit Spreads and Risk Decomposition**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| CS LC (AVG) | 1770 | 0.0474 | 0.0338 | 0.0001 | 0.3767 | 0.014 | 0.0892 |
| CS Diff (USD-LC,AVG) | 1718 | 0.0146 | 0.0633 | -0.144 | 0.5257 | -0.0067 | 0.026 |
| Default Prob (3m) | 1743 | 0.0828 | 0.1055 | 0 | 0.9065 | 0.0134 | 0.1518 |
| Default Prob (avg) | 1763 | 0.1121 | 0.1065 | 0 | 0.9065 | 0.0181 | 0.1894 |
| Q - P (LC,3m) | 1743 | 0.0464 | 0.1101 | -0.8255 | 0.2883 | 0.0027 | 0.1403 |
| Q - P (LC,avg) | 1743 | 0.0464 | 0.1101 | -0.8255 | 0.2883 | 0.0027 | 0.1403 |

**Controls**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| CS US (orth,3m) | 1634 | 0 | 1.0167 | -3.3566 | 7.097 | -0.9255 | 0.976 |
| CS US (orth,avg) | 1659 | 0 | 0.9952 | -2.9106 | 6.5631 | -0.8701 | 0.9573 |
| Term Spread | 1770 | 1.3121 | 1.2194 | -1.72 | 3.57 | -0.4383 | 2.73 |
| Macro Uncertainty | 1770 | 0.8256 | 0.1346 | 0.6679 | 1.2772 | 0.7067 | 0.9953 |
| FFR | 1770 | 1.2457 | 1.6541 | 0.06 | 5.33 | 0.0833 | 4.5167 |
| GZ Spread (orth,3m) | 720 | 0 | 0.4083 | -1.1977 | 1.5105 | -0.3737 | 0.3331 |
| GZ Spread (orth,avg) | 730 | 0 | 0.4062 | -1.2199 | 1.5004 | -0.3754 | 0.3597 |
| Country growth | 1646 | 0.005 | 0.0249 | -0.2585 | 0.2035 | -0.0056 | 0.0177 |

**Measures of FX Cyclicality**

| | N | Mean | SD | Minimum | Maximum | 10% Pct. | 90% Pct. |
|---|---|---|---|---|---|---|---|
| Corr (LC Index,FX) | 1609 | 0.1994 | 0.2626 | -0.5971 | 0.7594 | -0.1776 | 0.5301 |
| Corr (SPX,FX) | 1646 | 0.3961 | 0.2394 | -0.4449 | 0.8484 | 0.0597 | 0.6825 |
| Corr (US Cons,FX) | 1646 | 0.0742 | 0.1292 | -0.335 | 0.5291 | -0.0702 | 0.2362 |

Table A.12: Predictability of aggregate GDP growth – Robustness

This table reports the results of different versions of the following predictive regression:

$$\Delta Y_{t+h} = \alpha + \beta \Delta Y_{t-1} + \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_t + \varepsilon_{t+h},$$

where $\Delta Y_{t+h}$ reflects the one-quarter-ahead ($h = 1$) or one-year-ahead ($h = 4$) real GDP growth averaged across countries (including or excluding USA). Panel A uses weights given by the mean GDP over the sample period, while Panel B uses equal weights. The variables of interest are the default probability ($P$) and the default risk premium, measured as the difference between the physical ($P$) and risk-neutral ($Q$) default probabilities. These measures are centered around the 3(12)-month maturity in the case of the 3(12) month forecast horizon. The controls include the term spread, the Macroeconomic Uncertainty Index of Jurado et al. (2015), and the (updated, LC) quarterly SPX pseudo spread of Culp et al. (2018), denoted by 'CS USA'. We adjust the standard errors using the Newey and West (1987) kernel, where the bandwidth is selected optimally to account for potential serial correlation across residuals ($\varepsilon_{t+1}$), and further control for the lag of aggregate economic growth. The tables report the regression coefficients, which are multiplied by 100, as well as the $t$-stats in parenthesis.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | GDP-weighted | | | | Equal-weighted | | | |
| | Without USA | | With USA | | Without USA | | With USA | |
| | 3m | 12m | 3m | 12m | 3m | 12m | 3m | 12m |
| Default Probability | -3.543*** | -5.217*** | -3.570*** | -5.309*** | -4.798*** | -6.280*** | -4.704*** | -6.221*** |
| | (-7.27) | (-4.89) | (-7.66) | (-5.31) | (-8.62) | (-5.78) | (-8.62) | (-5.84) |
| Default Premium (Q - P) | -3.410*** | -4.934*** | -3.450*** | -5.049*** | -4.540*** | -5.669*** | -4.459*** | -5.643*** |
| | (-7.20) | (-4.65) | (-7.63) | (-5.08) | (-8.41) | (-5.25) | (-8.43) | (-5.33) |
| Term Spread | 0.323*** | 0.822*** | 0.300*** | 0.722*** | 0.446*** | 0.997*** | 0.430*** | 0.956*** |
| | (8.81) | (9.35) | (8.55) | (8.76) | (10.68) | (11.14) | (10.51) | (10.90) |
| Macro Uncertainty | 3.810*** | 9.099*** | 3.959*** | 9.273*** | 5.477*** | 12.157*** | 5.377*** | 11.942*** |
| | (10.39) | (10.79) | (11.29) | (11.83) | (13.12) | (14.52) | (13.12) | (14.55) |
| CS US | -0.776*** | -0.765*** | -0.794*** | -0.808*** | -1.035*** | -0.878*** | -1.019*** | -0.880*** |
| | (-15.48) | (-7.72) | (-16.23) | (-8.66) | (-17.28) | (-8.57) | (-17.31) | (-8.76) |
| Constant | -2.424*** | -5.388*** | -2.565*** | -5.492*** | -3.929*** | -8.185*** | -3.842*** | -7.974*** |
| | (-7.57) | (-7.32) | (-8.38) | (-8.02) | (-10.84) | (-11.25) | (-10.80) | (-11.17) |
| Observations | 1,634 | 1,634 | 1,634 | 1,634 | 1,634 | 1,634 | 1,634 | 1,634 |
| R-squared | 0.175 | 0.165 | 0.167 | 0.164 | 0.158 | 0.213 | 0.157 | 0.210 |

Table A.13: Benchmark Currency Choices for Matching Procedure.

This table presents our benchmark currency choices, local (LC) or foreign (FC). As detailed in Section B.3, our methodology allows us to match ex-ante default probabilities to then estimate comparable credit spread indices across currencies. Benchmark currency choices are based on sample length; estimations based on local currency are preferred when samples in both currencies are similar.

**Panel A: Developed Countries**

| | Maturity | | | |
|---|---|---|---|---|
| **Country** | 3m | 6m | 1y | 2y |
| Australia | FC | FC | FC | LC |
| Belgium | LC | FC | FC | - |
| Canada | FC | FC | FC | FC |
| Denmark | LC | LC | - | - |
| Euro Area | LC | LC | LC | LC |
| France | LC | LC | LC | LC |
| Germany | LC | LC | LC | FC |
| Greece | FC | FC | - | - |
| Hong Kong | LC | LC | FC | FC |
| Italy | LC | LC | LC | LC |
| Japan | LC | LC | LC | LC |
| Netherlands | LC | LC | LC | LC |
| New Zealand | FC | FC | FC | FC |
| Norway | LC | LC | LC | LC |
| Singapore | FC | FC | FC | - |
| South Korea | FC | FC | FC | FC |
| Spain | FC | FC | FC | LC |
| Sweden | LC | LC | LC | LC |
| Switzerland | LC | LC | LC | LC |
| Taiwan | LC | FC | FC | FC |
| United Kingdom | LC | LC | LC | LC |

**Panel B: Emerging Countries**

| | Maturity | | | |
|---|---|---|---|---|
| **Country** | 3m | 6m | 1y | 2y |
| Brazil | FC | FC | FC | FC |
| Chile | FC | FC | FC | - |
| China | FC | FC | FC | FC |
| Colombia | FC | FC | FC | - |
| India | LC | LC | LC | LC |
| Indonesia | FC | FC | FC | - |
| Malaysia | FC | FC | FC | - |
| Mexico | FC | FC | FC | FC |
| Philippines | FC | FC | FC | FC |
| Poland | LC | LC | LC | - |
| South Africa | FC | FC | FC | - |
| Thailand | LC | FC | FC | - |
| Turkey | FC | FC | FC | FC |

Figure A.1: Dynamics of Firm and Pseudo-Firm Credit Risk: Single Simulation.

This figure illustrates a simulated path for a firm and its pseudo counterpart. Panel A shows the firm's asset, equity, and debt values under the Merton model, while Panel B reports the corresponding quantities for the pseudo firm, whose asset equals the firm's equity. Panel C plots physical default probabilities, which coincide by construction, and Panel D reports credit spreads. The baseline parameters are $A_0 = 100$, drift $\mu_A = 7\%$, volatility $\sigma_A = 25\%$, and risk-free rate $r = 3\%$.

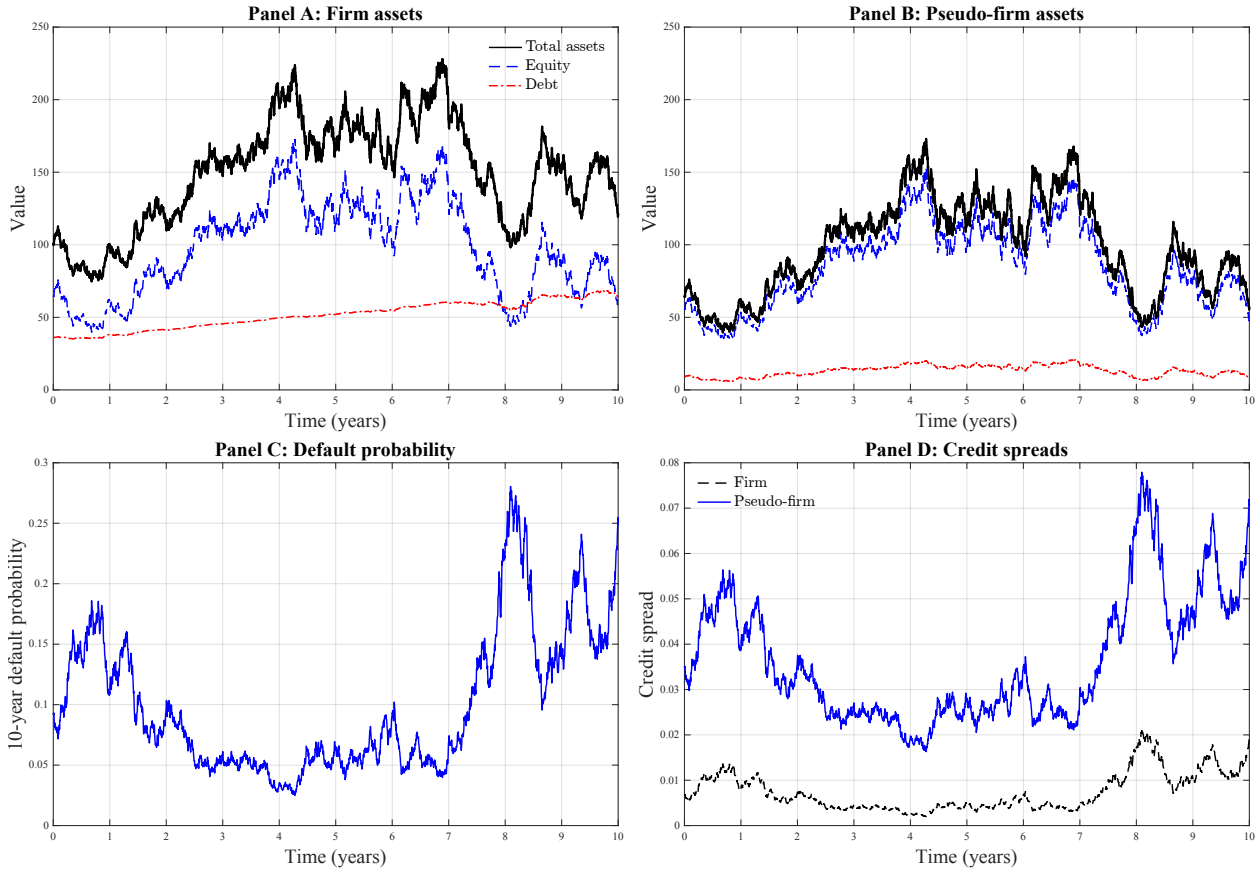


Figure A.2: Linking Pseudo and Firm Credit Spreads: Simulation Evidence.

Panels A and C plot firm and pseudo-firm credit spreads, while Panels B and D report $Q/P$ ratios. The figure is based on Monte Carlo simulations with fixed model parameters. The top row sets the pseudo-firm risk-neutral volatility multiplier to 1.0, and the bottom row to 1.5. Colors indicate the firm's annualized physical default probability.

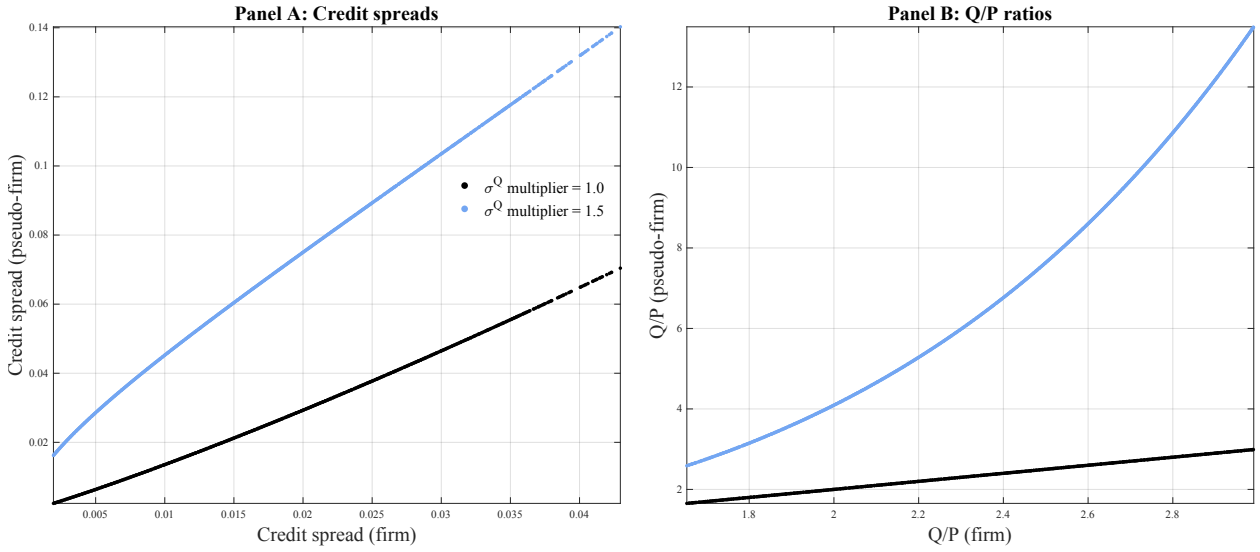


Figure A.3: Decomposition of credit spreads as a function of asset volatility.

The figure illustrates how asset volatility $\sigma$ affects the components of credit spreads in the Merton model. The left panels plot the risk-neutral default probability $\text{PD}^{(Q)}$, the middle panels plot the risk-neutral loss given default $\text{LGD}^{(Q)}$, and the right panels plot the resulting credit spread $s$. The top row corresponds to a maturity of $T = 5$ years, while the bottom row corresponds to $T = 2$ years. For each maturity, the face value of debt is chosen so that the physical default probability $\text{PD}^{(P)}$ is held fixed at 1% per year as volatility varies. As volatility increases, $\text{PD}^{(Q)}$ declines due to a lower asset Sharpe ratio, while $\text{LGD}^{(Q)}$ rises as default outcomes occur further in the left tail of the asset distribution. The interaction of these forces generates a non-monotonic relationship between volatility and credit spreads, which is more pronounced at shorter maturities. Dashed red lines in the middle and right panels show a counterfactual in which $\text{LGD}^{(Q)}$ is held fixed at its panel-specific average level. The model calibration assumes a physical asset drift set to $\mu = 7\%$ and a risk-free rate to $r = 3\%$.

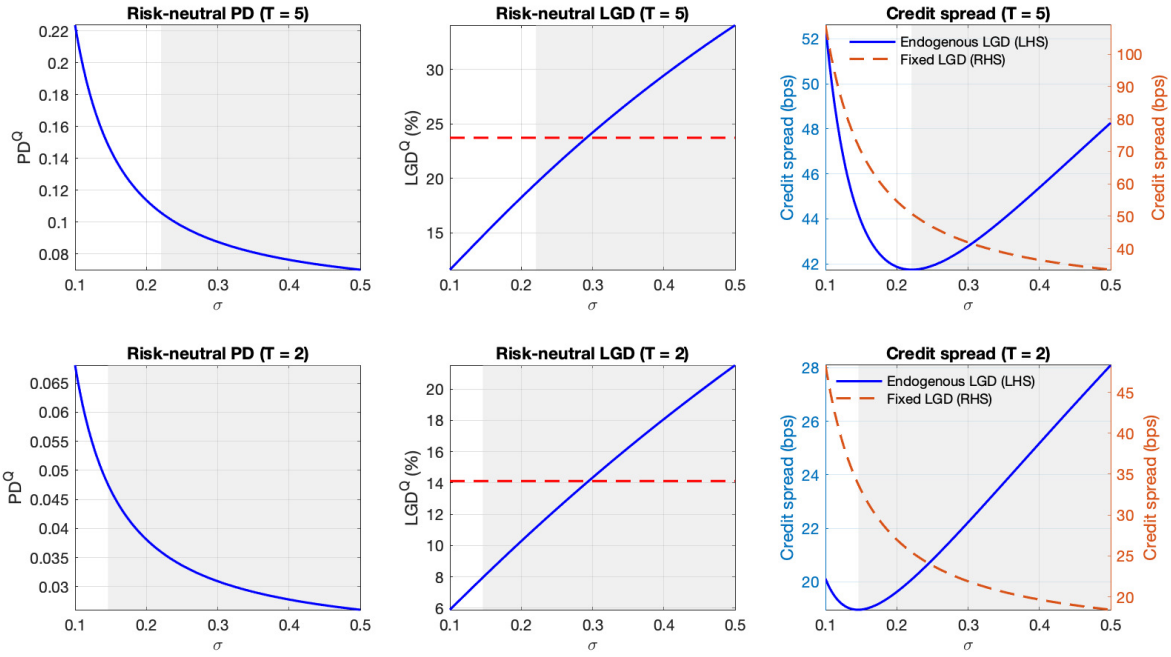


Figure A.4: Firm-level vs. index credit spreads.

The figure reports model-implied credit spreads for individual firms and for the aggregate market index. For each default-risk bucket, the left bar shows the cross-sectional average credit spread across firms, while the right bar shows the credit spread computed from the aggregate index. Default-risk buckets are defined by annual physical default probabilities calibrated to the ex post default frequencies in reported in Table A4 of Culp et al.: Aaa/Aa (1.94%), A/Baa (2.13%), Ba (6.98%), B (12.6%), and Caa− (19.6%). Panel (a) considers the Merton model with endogenous loss given default (LGD), while Panel (b) uses a constant value (set to 15%). Credit spreads are averaged over a simulated daily path covering $T = 2$ years. Asset dynamics are simulated under the physical measure using the following parameter values: drift $\mu = 7\%$, risk-free rate $r = 3\%$, maturity $T = 2$, systematic volatility $\sigma_M = 10\%$, idiosyncratic volatility $\sigma_\varepsilon = 20\%$, and $N = 3{,}000$ firms.

