Option-Implied Local Currency Credit Spreads*

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Abstract

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JEL Classification Codes: E43, E44, E52, G12, G13, G15

Keywords: Credit Risk, Corporate Debt, Derivatives, Exchange Rate, Options

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ABSTRACT

We develop an option-based framework to measure corporate credit spreads in local (LC) and foreign (FC) currencies. By construction, these measures embed identical physical default risk, so cross-currency differences isolate how default risk is priced across currencies. Using FX and equity index options from 33 markets, we construct comparable spreads not available in bond markets. LC spreads predict aggregate economic activity, including global output and US indicators, while the FC-LC spread differential forecasts exchange rate movements. Our framework links credit risk, macroeconomic activity, and exchange rate dynamics within a unified setting.

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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 embed identical physical default probabilities. Any difference between the two spreads therefore reflects how default risk is priced across currencies.

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). While they are typically measured in US dollars, corporate borrowing increasingly occurs across currencies, with non-dollar debt representing a substantial share of global credit markets (Maggiori, Neiman, and Schreger, 2020). As a result, understanding the informational content of credit spreads in both local and foreign currencies becomes important, as they may reflect distinct exposures to currency risk and global financial conditions.

Yet, comparable credit spreads across currencies are rarely available from corporate bond data. Multi-currency credit spreads or bond indices often do not exist, and, if available, differ in issuer composition, maturity, and ratings.[1] We circumvent this limitation by inferring credit spreads from option markets.

To construct these 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 are financed with local currency (LC) zero-coupon debt. Following Merton (1974), the firm's debt is equivalent to a short put option on the underlying asset, allowing us to value pseudo debt directly from traded index options. 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 construct matched credit spreads for pseudo-firms with identical physical default probabilities but debt denominated in different currencies. To obtain foreign-currency (FC)

[1] Appendix Table A.1 documents these differences.

counterparts, we use USD-denominated ETFs that track the local equity index and put options written on these ETFs. When ETF options are illiquid, we synthesize USD spreads by combining option-implied volatility on the local index with exchange rate dynamics.

Prior studies examine credit risk across currencies using either sovereign LC spreads (Du and Schreger, 2016a) or corporate currency bases, the price discrepancies 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 instead infer cross-currency credit spreads from option markets and benchmark equity indices.

Compared to existing approaches, pseudo spreads offer key advantages. By embedding identical physical default probabilities, they isolate, by construction, how default risk is priced across currencies. In contrast, corporate currency basis measures rely on matched bonds issued by the same firm and are subject to market frictions (liquidity, taxation, regulation) and segmentation (investor clienteles). Moreover, the option-based construction provides systematic measures of short-maturity credit spreads, where comparable bond-data are typically unavailable. Because pseudo spreads are derived from benchmark equity indices, they capture aggregate credit conditions instead of firm-specific risk, which is particularly relevant in bank-based financial systems (Ayala, Nedeljkovic, and Saborowski, 2017).

We construct a monthly panel of LC and FC pseudo credit spreads for 33 developed and emerging economies and the Eurozone from 1996 to 2023. The data combine options on local equity indices with options on USD-denominated ETFs tracking the same markets. The panel provides credit spreads across currencies at maturities of 3, 6, 12, and 24 months.

Pseudo credit spreads closely resemble bond-based spreads in magnitude and cyclical behavior, but exhibit systematic cross-currency differences. FC spreads are higher and more sensitive to economic downturns. For example, the average six-month LC spread for developed economies is 3.44%, about 120 basis points below the 4.64% observed for FC spreads.

Because LC and FC spreads embed identical default probabilities, these differences reflect how default risk is priced across currencies. Consistent with this interpretation, the ratio

of risk-neutral to physical default probabilities is systematically higher for FC-denominated spreads, typically ranging from 1 to 3 and occasionally exceeding 10, in line with risk premia observed in corporate bond markets (Berndt, Douglas, Duffie, and Ferguson, 2018).

To interpret these patterns, we develop a stylized model of multi-currency credit spreads. The model reproduces two central features: USD-denominated spreads are higher on average and more sensitive to downturns than their LC counterparts, reflecting the interactions between exchange rate dynamics, equity fluctuations, and risk premia. It also clarifies how credit spreads aggregate from firms to indices, showing that index spreads can be higher or lower than the average of their constituents depending on how loss given default is constant or endogenous. Intuitively, pseudo debt embeds a compound option structure, in which default risk depends on an underlying that is itself equity-like, amplifying both the level and cyclicality of credit spreads.

We next examine the determinants of LC credit spreads, addressing the literature's focus on USD-denominated measures. 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 33 basis points, while a comparable increase in the risk premium $(Q - P)$ raises spreads by roughly 52 basis points. They also rise with stock market volatility, currency depreciation, and elevated economic uncertainty, consistent with heightened perceived risk. Conversely, spreads tend to be lower in countries with stronger fundamentals, such as higher foreign exchange reserves and lower inflation.

Pseudo quanto spreads, the difference between USD and LC credit spreads, capture cross-currency differences in how default risk is priced. Consistent with the model, this reflects the covariance between default risk and the pricing kernel. Empirically, their variation reflects both default risk and risk premia: default risk and risk premia explain cross-sectional differences, whereas risk premia predominantly drive time-series dynamics. Their behavior further reflects asymmetric responses to local and USD financial conditions, as well as exposure to exchange rate volatility, interest rate differentials, and macroeconomic factors. They therefore isolate a currency-specific pricing of corporate credit risk.

In the final step of our analysis, we assess the informational content of pseudo credit spreads for forecasting aggregate real activity and exchange rate returns. We find that the aggregate LC spread is a strong predictor of global and US economic activity: a 100 basis point increase forecasts a 0.21 percentage point decline in one-quarter-ahead GDP growth (approximately 0.85 percentage points at an annualized rate), and also predicts declines in US payroll growth, industrial production, and business conditions. In contrast, the pseudo quanto component is not informative about real activity, indicating that predictive content is concentrated in the default-risk component of credit spreads.

In currency markets, pseudo credit spreads also predict exchange rate returns. Higher LC and pseudo quanto spreads predict subsequent local currency appreciation, consistent with compensation for bearing default risk and cross-currency differences in its pricing. Predictability is strongest when exchange rates co-move with local equity markets or global financial conditions, supporting the covariance-based risk-premium mechanism. The predictability holds out of sample and translates into currency portfolios: sorting on pseudo quanto spreads generates significant long-short returns that survive carry neutralization. Together, these results link currency returns to the joint pricing of default and exchange rate risk.

Finally, we use U.S. monetary policy shocks to study the cross-currency transmission of global credit conditions. Motivated by the dollar credit-supply channel of Bräuning and Ivashina (2020), we show that hawkish shocks widen USD credit spreads relative to LC spreads, particularly in emerging markets and when global financial constraints are tight. Thus, U.S. monetary policy affects not only global credit conditions, but also the currency-specific pricing of default risk.

Our analysis relates to the literature on multi-currency credit risk. Prior work studies cross-currency differences in credit risk using sovereign LC spreads constructed from bonds and interest rate swaps (Du and Schreger, 2016a) or the corporate currency basis (Caramichael, Gopinath, and Liao, 2021; Galvez, Gambacorta, Mayordomo, and Serena, 2021; Hu, Shi, Viswanath-Natraj, and Wang, 2022). We introduce a complementary approach by inferring corporate credit spreads directly from option markets. By embedding identical physical default probabilities across currencies, our framework isolates differences in how default risk

is priced, enabling consistent cross-currency comparisons within a unified setting.

Our results also relate to the literature on the informational content of credit spreads and their role in predicting economic activity and exchange rates. A large body of work shows that credit spreads forecast real activity (e.g., Gilchrist and Zakrajšek, 2012; Culp et al., 2018; Krishnamurthy and Muir, 2025; Krishnamurthy and Li, 2025; Boyarchenko and Elias, 2026; Fisher and Zhang, 2023). We contribute by constructing an aggregate cross-country measure of credit conditions from non-US markets and showing that it predicts both global and US economic activity. In currency markets, our findings connect to a growing literature on exchange rate predictability using measures of risk premia (Kremens and Martin, 2019; Della Corte et al., 2023; Kremens et al., 2025). While prior work relies on corporate equity- or sovereign credit-based quanto measures, we introduce an option-implied quanto spread that isolates cross-currency differences in the pricing of default risk and links them to expected currency returns. Our monetary policy analysis also contributes to evidence on the international transmission of U.S. monetary policy through bond markets and dollar credit supply (Albagli et al., 2019; Gilchrist et al., 2019; Bräuning and Ivashina, 2020) by showing that monetary policy differentially affects LC and USD pricing of the same default risk. Table 1 summarizes our contribution relative to these strands of the literature.

More broadly, our work connects to the literature on firms' currency choices in debt issuance. Prior work shows that firms actively choose between LC and FC borrowing in response to financing conditions and risk exposures (Maggiori, Neiman, and Schreger, 2020; Eren, Malamud, and Zhou, 2023; Bruno and Shin, 2017, 2020). Our findings highlight that currency denomination is associated with systematic differences in the pricing of credit risk, providing a new perspective on the incentives underlying firms' currency choices.

Section 2 describes the construction of pseudo credit spreads across currencies, illustrated using the U.K. Section 3 develops a stylized framework to explain differences between LC and FC spreads. Section 4 presents the international option data and examines the drivers of pseudo credit spreads. Section 5 studies their predictive content for economic activity and exchange rates. Section 6 concludes.

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.

Equation (1) highlights that pseudo debt embeds a compound option structure. In the Merton (1974) framework, equity is a call option on firm assets. In our setting, the underlying asset is the equity index, which can itself be viewed as an option-like claim on aggregate firm fundamentals, akin to the compound option structures studied by Geske (1979).

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 τ, 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 τ 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:

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

with $\widehat{r}_t(T)$ constructed using zero-coupon yields from the Federal Reserve Economic Data constant maturity Treasury rates. We construct aggregate spreads by averaging across options within rating categories and maturities. Appendix B provides implementation details.

Panel (a) in Figure 1 benchmarks our US pseudo spreads against those in Culp et al. (2018). In the only setting where direct comparison is possible, the two measures align closely. 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.

We depart from Culp et al. (2018) and infer risk-free rates directly from option prices to ensure an internally consistent option-implied framework, in which both pseudo bond yields and risk-free rates are inferred from the same set of option prices. 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.

2.3 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 FC.

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 FC 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 (LC) with that of an otherwise identical firm issuing debt in FC. 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 LC 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 FC credit spreads in the U.K. case, we rely on options on USD-denominated ETFs referencing the FTSE100. Because ETF options are American-style, Appendix D shows that the associated early-exercise premium has a negligible effect on our FC spread estimates.

The key step is to construct matched pseudo bonds with identical default probabilities across currencies. Corporations generally cannot selectively default across currencies the way sovereigns can due to cross-default and acceleration clauses. We therefore impose identical physical default probabilities for LC and FC debt.[3] Accordingly, we 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 FC.

In practice, an exact match is rarely available, so we average across options with strikes and maturities aligned with the target default probability and horizon (see Appendix B for details). We then compute FC credit spreads using risk-free rates inferred from dollar-denominated 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 as shown in Panel (b). Holding physical default risk constant,

[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.

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

cross-currency differences in spreads therefore reflect differences in risk premia. Panel (c) reports the number of options used to construct the indices, reflecting the tighter selection for FC spreads.

2.4 Synthetic Local- and Foreign-Currency Credit Spreads

When USD-denominated ETF options are unavailable, we construct synthetic FC pseudo bonds. This involves replicating FC claims using the LC index and 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 FC per unit of LC. The corresponding pseudo bond price is:

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

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 LC pseudo bond (see Appendix B.1). The option horizon τ 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 σ and σ_S denote equity and exchange rate volatilities, and ρ their correlation. We implement a conditional version using option-implied volatilities and rolling estimates of ρ (see Appendix C.2).[4]

Risk-free rates in FC are inferred from covered interest parity by combining LC box rates with the forward premium (Du and Schreger, 2016a), which provides a market-consistent funding benchmark even in the presence of CIP deviations (Appendix B.2).

[4]In implementation, we use option-implied equity volatility and at-the-money FX implied volatility, and estimate the correlation ρ 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.

Figure 3 compares empirical and synthetic spreads across currencies. Panel (a) shows LC spreads, Panel (b) FC 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.

2.5 Stylized Facts on Local- and Foreign-Currency Credit Spreads

Figure 4 documents substantial differences between LC and FC pseudo spreads. FC spreads are generally higher and more volatile (Panel a), averaging 3.90% compared with 2.90% in LC, an average wedge of about 100 basis points (Panel c).

Figure 5 relates these spreads to default risk and leverage. Risk-neutral default probabilities generally exceed physical probabilities (Panel a), with their ratio typically between 1 and 3 but exceeding 10 during periods of market stress (9/11, Global Financial Crisis, COVID pandemic), consistent with substantial time variation in default risk premia.[5] Importantly, FC volatility can be lower despite higher FC spreads (Panel b), while implied leverage ratios, defined as $L_t = A_t/K$ and $L_t^{\$} = A_t^{\$}/K^{\$}$, show stronger FC deleveraging during downturns (Panel c).

Finally, Figure 6 shows that quanto spreads are closely related to cross-currency differences in risk-neutral default probabilities. Since physical default probabilities are identical by construction, this relation points to differences in the pricing rather than the quantity of default risk.

2.6 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 correspond-

[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.

ing pseudo firm whose physical default probability matches that of the underlying firm. We then compare the credit spreads of the two.

This exercise shows that pseudo credit spreads provide an economically meaningful proxy for corporate credit risk rather than a mechanical transformation of option prices. In the simulation, pseudo-firm assets track firm equity closely, and physical default probabilities coincide by construction. Yet pseudo-firm credit spreads are larger and more volatile than the spreads of the underlying firm. This amplification is consistent with the nonlinearities arising from the compound-option interpretation of the pseudo bond (Geske, 1979), where debt is valued as a put written on an underlying that is itself an equity-like, option-based claim. Appendix E provides the full implementation.

2.7 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 (see Equation (6) in Chen et al. (2009)). 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 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 expected losses, which can outweigh the Sharpe-ratio effect and generate higher firm-level spreads. Appendix F provides a formal analysis and supporting simulation evidence.

3 A Framework for Cross-Currency Credit Premia

We develop a stylized framework to interpret differences between LC and FC pseudo credit spreads. Even with identical physical default risk, spreads differ because risk premia depend

on how default risk co-varies with currency-specific pricing kernels.

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 index 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 μ and σ denote the expected return and volatility of the equity index, and μ_S and σ_S denote the expected exchange rate return and volatility. The shocks dW_t and dW_t^S are standard Brownian motions with correlation ρ, capturing the co-movement between equity and exchange rate returns.

The index value in FC 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 LC. For any asset with return dX_t/X_t, the no-arbitrage condition implies:[6]

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

[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.

which can be rewritten as:

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

where r is the LC risk-free rate. Thus, expected excess returns are determined by the covariance of index 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 λ_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 λ_S is the currency risk premium.

These expressions show that equity and currency risk premia reflect the covariance of their payoffs with the stochastic discount factor, or 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, credit spreads reflect risk-neutral expectations of discounted payoffs. Under the physical measure, expected returns reflect compensation for risk. The mapping from physical to risk-neutral default probabilities is currency-dependent, reflecting differences in the pricing kernel 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 FC stock market risk premium. The covariance term $\rho\sigma\sigma_S$ reflects the co-movement between equity and exchange rate returns, while σ_S^2 arises from the convexity

of the exchange rate in levels.

Implications. Two implications follow. First, FC denomination introduces exchange rate exposure, affecting both asset volatility $\sigma^{\$}$ and the effective FC risk premium. Second, when FC volatility is higher, matching physical default probabilities requires lower FC leverage (i.e., a lower moneyness $K^{\$}/A^{\$}$).

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:

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

with an analogous expression in FC obtained by replacing (μ, σ) with $(\mu^{\$}, \sigma^{\$})$.

Debt D_t is valued as risk-free debt minus a put on the firm's assets, so 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, cross-currency differences in credit spreads arise from differences in risk premia embedded in $(\mu^{\$}, \sigma^{\$})$, despite identical physical default risk. Higher effective risk premia and volatility in FC raise risk-neutral default probabilities and, in turn, FC spreads relative to LC.

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). 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. The decomposition:

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

identifies the channels underlying this wedge. A higher currency risk premium λ_S raises the FC risk premium, risk-neutral default probability, and credit spread (Panels d–f). A higher equity-FX correlation similarly raises the FC risk premium and spread through $\rho\sigma\sigma_S$ (Panels g–i), despite the offsetting reduction in leverage required to hold physical default risk fixed. The convexity term σ_S^2 reinforces these effects.

Overall, the model reproduces the higher FC spreads observed empirically despite identical physical default risk. Cross-currency spread differences arise from currency risk and its interaction with equity risk, which alter the price rather than the quantity of default risk. These predictions motivate the empirical tests below.

4 Multi-Currency Credit Spreads Around The World

We study country-level pseudo credit spreads using international equity index options. After describing the data and construction of LC and FC spreads, we examine the economic content of LC and quanto spreads, the latter defined as the difference between USD and LC spreads.

4.1 International Option Data and Country Coverage

We construct an international panel of LC and USD-denominated pseudo spreads using options on local stock market indices and USD-denominated ETFs tracking the same indices. Our country coverage builds on Du and Schreger (2016a) and Kelly et al. (2016), extended to Thailand, Malaysia, India, and China as option data have become available.

We obtain index levels and end-of-day option prices from Refinitiv Datastream and OptionMetrics via Wharton Research Data Services (WRDS). Datastream provides puts and calls on local stock indices, while OptionMetrics provides options on USD-denominated index-tracking ETFs. Data cleaning and filtering are detailed in Appendix B.

Our final sample comprises 33 countries (12 emerging and 21 developed) and the Eurozone. Table 2 summarizes country and option coverage, including index identifiers, option tickers, currencies, sample periods, and average option observations. Coverage varies substantially across countries and currencies, with longer histories for LC options and more recent availability of USD-denominated ETF options. Option markets are generally more liquid in LC, although USD-denominated ETF options are more liquid for Brazil, Canada, China, Mexico,

Singapore, and Malaysia. For each country, we first construct aggregate pseudo spreads from the more liquid market using all options that pass our filters.

To ensure comparability, we restrict pseudo firms to ex-ante default probabilities below the historical Standard & Poor's CCC cumulative default rate. We aggregate option-implied yields monthly using time-to-maturity weights to construct 3-, 6-, 12-, and 24-month country-level spreads, using maturity windows of [7,182], [91,365], [182,547], and [365,1095] days, respectively. We then match LC and USD options with identical ex-ante default probabilities to construct twin pseudo bonds across currencies.

Finally, we construct risk-free benchmarks from option-implied box rates (Brenner and Galai, 1986; Van Binsbergen et al., 2022; Diamond and Van Tassel, 2021). When local box rates are unreliable due to limited liquidity, we use regional benchmarks or convert USD-implied rates into LC via covered interest parity. Appendix B provides details.

4.2 International Evidence on Multi-Currency Credit Spreads

Table 3 reports summary statistics for 6-month pseudo spreads. FC spreads generally exceed their LC counterparts. In developed economies (Panel A), average LC and FC spreads are 3.44% and 4.64%, respectively, a difference of 120 basis points (bps). LC spreads range from 157bps in the Netherlands to 780bps in New Zealand, indicating substantial cross-country variation.

Spreads are higher in emerging markets (Panel B), averaging 5.32% in LC and 5.67% in USD. While FC spreads generally exceed LC spreads, exceptions such as Denmark, Greece, New Zealand, and Taiwan indicate heterogeneity in currency risk exposure. Similar patterns hold at 3-, 12-, and 24-month maturities (Appendix Tables A.6, A.7, and A.8).

Figure 8 shows the time-series dynamics of LC and FC spreads across regions. While spreads co-move globally, their responses differ around major episodes, including the Global Financial Crisis, European sovereign debt crisis, Brexit, and COVID-19, when FC spreads typically

react more strongly. Consistent with this differential variation, LC-FC correlations range from 41% in South Korea to 97% in Greece (Table 3).

Panel A of Table 4 shows that pseudo credit spreads are downward sloping on average, but Figure 9 reveals substantial cross-country variation. Normalizing each country's term structure by its 3-month spread, some countries exhibit steeply upward-sloping profiles while others are strongly downward sloping.

Panel B reports average 6-month ex-ante default probabilities of 8.54% in developed 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 drivers of 3-month LC pseudo spreads; results are similar across maturities. Appendix Table A.11 reports summary statistics for the explanatory variables.

In column (1) of Table 5, we decompose LC spreads into physical default risk (P) and the risk premium component ($Q - P$). Both are highly significant and jointly explain 84.9% of within-country spread variation. A one percentage point increase in P raises spreads by 38bps, while the same increase in $Q - P$ raises them by 61bps, consistent with substantial time-varying risk premia in credit spreads (e.g., Gilchrist and Zakrajšek, 2012; Berndt et al., 2018; Culp et al., 2018).

Column (2) links spreads to equity market conditions. Spreads increase with stock market volatility and decrease with expected returns, consistent with structural credit risk models in which higher volatility and lower expected returns increase default risk. Column (3) shows that currency conditions also matter: a one percentage point increase in FX volatility raises spreads by about 30bps, while LC depreciation is associated with wider spreads. By contrast, local and foreign risk-free rates have little explanatory power (column 4), consistent with the short maturity of the pseudo bonds.

Columns (5)–(7) examine local and global macro-financial conditions. Locally, higher inflation is associated with wider spreads, while higher FX reserves are associated with narrower

spreads. Globally, spreads increase with macroeconomic uncertainty (Jurado et al., 2015) and US credit conditions, measured by the Gilchrist and Zakrajšek (2012) GZ spread, and decline with US real activity measured by the CFNAI. Thus, LC pseudo spreads reflect both country-specific fundamentals and global financial conditions.

4.4 Drivers of Pseudo Quanto Spreads

We next examine the drivers of pseudo quanto spreads, defined as USD minus LC pseudo spreads. Table 6 relates quanto spreads to physical default risk and cross-currency differences in risk premia. The coefficient on physical default risk is small and insignificant (0.044, column 7), while the risk-premium coefficient is large and significant (0.463, column 8). Thus, variation in pseudo quanto spreads is driven primarily by cross-currency differences in risk premia rather than physical default risk.

Table 7 examines the market and macro-financial drivers of within-country variation. Lower LC equity returns and higher volatility reduce quanto spreads by widening LC spreads (column 1), while the corresponding USD equity conditions widen quanto spreads by increasing USD spreads (column 2). These opposite effects highlight the asymmetric pricing of local and foreign risks underlying the quanto spread.

Currency and interest-rate conditions also matter. Higher FX volatility widens quanto spreads (column 3), while higher USD interest rates narrow them (column 4), indicating that cross-currency spread differences reflect both currency and interest-rate conditions.

Finally, quanto spreads decline with FX reserves (column 5), economic activity, and macroeconomic uncertainty (column 6). Together, these results show that pseudo quanto spreads capture cross-currency differences in the pricing of both country-specific and global risks.

5 Information Content of Pseudo Credit Spreads

We next study the economic content of pseudo credit spreads by examining their ability to predict aggregate real activity and exchange rate returns.

5.1 Predictability of Aggregate Economic Activity

LC pseudo spreads, constructed from equity index options, provide forward-looking measures of market-implied default risk. As in standard structural frameworks, credit spreads reflect expected losses and compensation for bearing default risk, and thus capture financial conditions relevant for investment and economic activity. If they contain forward-looking information about credit conditions, they should predict subsequent real activity.

We focus on aggregate outcomes, as pooling across countries reduces idiosyncratic variation and better captures broad economic conditions. We therefore aggregate LC spreads across countries and examine their predictive content for global and US real activity.

For each country, we average LC spreads across 3-, 6-, 12-, and 24-month maturities, capturing information across the maturity spectrum and aligning with the US pseudo spread in Culp et al. (2018). We then aggregate these country-level measures using GDP weights.

Formally, let $\mathcal{S}_t$ denote the set of non-US countries for which the LC credit spread ($\mathrm{CS}_{i,t}^{LC}$) is observed at time t. The aggregate spread is:

$$\overline{\mathrm{CS}}_t^{LC} = \sum_{i \in \mathcal{S}_t} \tilde{w}_{i,t}\, \mathrm{CS}_{i,t}^{LC}, \qquad \tilde{w}_{i,t} = Y_{i,t-4} / \sum_{j \in \mathcal{S}_t} Y_{j,t-4}, \tag{21}$$

where $Y_{i,t-4}$ denotes nominal GDP (in USD) lagged four quarters.[7] We construct the aggregate pseudo quanto spread ($\overline{\mathrm{CS}}^{\mathrm{Quanto}}$) analogously.

[7] The panel is unbalanced (1–33 countries per quarter; average 21.6). A balanced-panel benchmark based on 12 countries with at least 80% coverage is highly correlated with $\overline{\mathrm{CS}}^{LC}$ (correlation 0.94), indicating limited composition effects.

We evaluate predictive content using local projections (Jordà, 2005):

$$\sum_{k=1}^{h} \Delta Y_{t+k} = \alpha + \gamma_1 \overline{\text{CS}}_t^{LC} + \gamma_2 \overline{\text{CS}}_t^{\text{Quanto}} + \beta \Delta Y_t + \delta' z_t + \varepsilon_{t+h}, \tag{22}$$

where $h = 1, \ldots, 6$ quarters and z_t includes the term spread, real federal funds rate, and macroeconomic uncertainty index of Jurado et al. (2015). We examine GDP-weighted real GDP growth with and without the US, as well as US non-farm payroll growth, industrial production, and the ADS business conditions index (Aruoba et al., 2009). Standard errors follow Newey and West (1987) with optimal bandwidth selection.

Table 8 shows that $\overline{\text{CS}}^{LC}$ predicts real activity. At the one-quarter horizon, the coefficient is negative and significant across measures of aggregate GDP growth and for US payroll growth, industrial production, and the ADS index. For GDP-weighted growth excluding the US, a 100bps widening in $\overline{\text{CS}}^{LC}$ predicts a 0.21 percentage point decline in quarterly GDP growth, or about 0.85 percentage points annualized. In contrast, $\overline{\text{CS}}^{\text{Quanto}}$ is small and insignificant throughout. Real-activity predictability is therefore concentrated in the LC component.

We next examine whether this predictability extends beyond the one-quarter horizon. Appendix Table A.14 reports results of local projections of cumulative GDP growth through horizons of one to six quarters. For GDP-weighted growth excluding the US, the $\overline{\text{CS}}^{LC}$ coefficient increases from -0.19 at one quarter to -0.62 at six quarters and remains significant throughout. The profile is similar when US GDP is included, indicating that $\overline{\text{CS}}^{LC}$ contains persistent information about economic activity over the subsequent year to eighteen months.

Importantly, the medium-horizon result is not driven by crises. Appendix Table A.14 shows that excluding both COVID-19 and the GFC weakens the one-quarter coefficient, but the four- and six-quarter coefficients remain large and significant (-0.41, $t = -2.48$; and -0.78, $t = -2.27$). Thus, $\overline{\text{CS}}^{LC}$ contains information about economic activity over the subsequent year to eighteen months rather than solely around crisis episodes.

We next compare $\overline{\text{CS}}^{LC}$ with the US pseudo credit spread of Culp et al. (2018). Table 9 shows that the US spread predicts US activity but not aggregate international GDP growth. When

both measures enter jointly, using the component of the US spread orthogonal to $\overline{\text{CS}}^{LC}$ to mitigate collinearity, $\overline{\text{CS}}^{LC}$ remains significant across specifications while the US-specific component is insignificant. Thus, the international aggregate captures credit conditions beyond those contained in US option markets.

Appendix Table A.15 further shows that $\overline{\text{CS}}^{LC}$ predicts NBER recessions one quarter ahead (AUC= 0.88) and remains significant when controlling for the US-specific component of the US pseudo spread and standard macro predictors. Together, the evidence identifies $\overline{\text{CS}}^{LC}$ as a forward-looking measure of broad credit conditions that predicts real activity across countries and over the business cycle.

5.2 Exchange Rate Predictability

Exchange rate returns reflect compensation for cross-country differences in risk. LC pseudo spreads capture variation in country default risk and its pricing, while pseudo quanto spreads isolate cross-currency differences in how default risk is priced. Since both components contain variation in risk premia, both should contribute to predicting expected currency returns.

We test these implications using the following panel specification:

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

where $\Delta s_{i,t+4}$ denotes the 12-month-ahead exchange rate return of country i, with positive values indicating local currency appreciation against the US dollar. We use 3-month pseudo credit spreads throughout. Under a risk-based interpretation of expected currency returns, $\gamma_1, \gamma_2 > 0$: higher LC spreads compensate for country-level risk, while higher pseudo quanto spreads compensate for cross-currency differences in the pricing of default risk.

The control vector Controlsi, t includes the 3-month interest rate differential $(rUSD - r_{LC})$ to capture carry-based predictability (Fama, 1984; Bansal and Dahlquist, 2000), the real effective exchange rate (REER) (Dahlquist and Pénasse, 2022; Chernov et al., 2023), the FX

volatility risk premium (realized minus implied FX volatility), GDP growth, log FX reserves, and inflation. All specifications include country and time fixed effects, with (Driscoll and Kraay, 1998) standard errors computed with four lags.

Table 10 reports the baseline results. In Column (1), a 100bps increase in CS^{LC} predicts a 0.30% local currency appreciation over the subsequent year. Column (2) shows that CS^{Quanto} also predicts appreciation, with an effect of similar magnitude. Both coefficients remain positive when included jointly (Column 3) and with the full set of controls (Column 4). Columns (5)–(8) show that predictability holds separately across advanced and emerging economies, with stronger effects in emerging markets, and survives excluding the COVID-19 period as well as both COVID-19 and the Global Financial Crisis. Thus, LC and pseudo quanto spreads contain distinct and robust predictive information for currency returns: the former capture compensation for country-level risk, while the latter isolate cross-currency differences in the pricing of default risk.

Figure 10 plots the coefficients from (23) across horizons from 3 to 48 months. The CS^{Quanto} coefficient (Panel a) is close to zero at short horizons, rises at intermediate horizons, and peaks around 24–36 months, while the CS^{LC} coefficient (Panel b) increases more gradually. Both profiles are robust to controls (Panels c and d), consistent with persistent risk-premium variation rather than carry or real exchange rate dynamics.

Our stylized framework links this predictability to the covariance of default risk with priced states. Table 11 tests this mechanism by splitting countries according to the correlation of exchange rate returns with local equity returns, the S&P 500, and US consumption growth. Predictability is concentrated in high-correlation regimes. For the equity-FX split (columns 1–2), the high-correlation coefficients are $\hat{\gamma}_1 = 0.378$ ($t = 3.26$) and $\hat{\gamma}_2 = 0.364$ ($t = 4.79$), while both are either insignificant or only marginally significant in the low-correlation group. This asymmetry supports the covariance-based risk-premium mechanism.

We next benchmark CS^{Quanto} against two derivative-based currency risk premia. The credit-implied risk premium (CRP) of Della Corte et al. (2023) extracts a sovereign-default-related risk premium from cross-currency CDS prices, while the quanto risk premium (QRP) of

Kremens and Martin (2019) measures the risk-neutral covariance between currency and US equity returns. Appendix Table A.16 shows that CS^{Quanto}remains significant alongside the CRP, with t-statistics of 5.84 without (column 1) and 4.32 with (column 2) macro controls.

The QRP comparison is less direct because its base sample comprises six advanced currencies, whereas our pseudo quanto predictability is strongest in emerging markets. We first reproduce the strong QRP predictability of Kremens and Martin (2019) in their original specification ($t = 3.8$, column 3). Using the updated Kremens et al. (2025) series, CS^{Quanto}remains significant alongside the QRP in the emerging-market-inclusive sample in columns (5–6) ($t = 2.21$ without and 3.27 with controls), although the overlap is limited. Thus, the evidence indicates that $CS^{Quanto}$is not subsumed by either measure, rather than that one risk premium dominates the others.

Finally, Table 12 evaluates predictability out of sample against the driftless random walk. Using real-time expanding-window forecasts with a four-quarter gap to account for overlapping returns (baseline), $CS^{LC}$and CS^{Quanto}achieve out-of-sample R^2s of 2.36% and 4.52%, respectively, and 5.0% jointly. The out-of-sample R^2 compares mean squared forecast errors with those of the random walk following Campbell and Thompson (2008); the corresponding Diebold and Mariano (1995) statistics are 2.24, 3.19, and 3.63. Results are robust to rolling estimation, country demeaning, and alternative burn-in periods.

Together, these results show that LC and pseudo quanto spreads contain distinct information about expected currency returns. LC spreads capture compensation for country-level credit risk, while pseudo quanto spreads isolate a covariance-based currency risk premium that is distinct from established currency predictors and survives out of sample.

Robustness and Currency Portfolios. Figure A.7 shows that the results are not driven by individual countries: leave-one-country-out estimates remain positive and tightly clustered around the full-sample coefficients. Table A.17 shows that predictability is robust to averaging spreads across maturities. We also address concerns that predictability may arise mechanically from the construction of synthetic USD pseudo spreads. Restricting the sample

to directly observed USD spreads yields a significant CS^{Quanto}coefficient, while controlling separately for FX implied volatility, equity implied volatility, and the stock-FX correlation—the inputs to the synthetic construction—leaves the results largely unchanged. In unreported results, two-way clustering by country and quarter yields similar, albeit less precise, inference, while adding 12-month currency momentum leaves both spread coefficients unchanged.

We also assess predictability using currency portfolios. Each quarter, we sort currencies on $CS^{Quanto}$and hold a long-short portfolio of the top and bottom terciles for twelve months. Table A.18 shows that the strategy earns 2.38% annually with a Sharpe ratio of 0.57 ($t = 3.60$), which remains similar excluding either COVID-19 or the GFC. Panel B neutralizes carry through a double sort: the carry-neutral CS^{Quanto}portfolio earns 2.31% annually with a Sharpe ratio of 0.73 ($t = 4.86$), while the quanto-neutral carry portfolio earns −3.21% ($t = -2.34$). Thus, the quanto premium is distinct from carry. Figure A.8 shows that cumulative returns accrue steadily rather than around crisis episodes.

5.3 Sensitivity to Monetary Policy Surprises

We next use U.S. monetary policy shocks to examine how default risk is repriced across currencies. U.S. monetary policy affects international credit conditions through a dollar credit-supply channel: Bräuning and Ivashina (2020) show that monetary easing disproportionately increases dollar lending to emerging markets, particularly riskier borrowers, with these flows reversing upon tightening. This channel predicts stronger effects on USD than LC credit spreads, particularly in emerging markets. Consistent with this mechanism, prior work documents effects of U.S. monetary policy on international bond yields and USD sovereign credit spreads (Albagli et al., 2019; Gilchrist et al., 2019; Chari et al., 2021). Our matched pseudo bonds provide a direct cross-currency test: because physical default risk is identical across currencies, changes in the quanto spread isolate differential pricing of the same default risk.

We estimate panel regressions

$$\Delta CS^{k}_{i,t+h} = \alpha_i + \beta_h MP_t + \boldsymbol{\theta}' \mathbf{x}_{i,t} + \varepsilon_{i,t+h}, \qquad k \in \{LC, USD, Quanto\}, \tag{24}$$

where MP_t is the standardized Nakamura and Steinsson (2018) policy news shock and $CS^{Quanto} = CS^{USD} - CS^{LC}$. The controls include global and local financial and macroeconomic conditions. We focus on 3-month spreads, where monetary policy news should be reflected most directly, and report cross-maturity averages as a robustness check.[8]

Table 13 shows that a one-standard-deviation hawkish surprise widens the 3-month USD spread by 28.0bps, while the LC spread barely moves, producing a 19.8bps increase in the quanto spread. The effect is concentrated in emerging markets: the USD spread rises by 40.6bps and the quanto spread by 38.1bps, while the LC response is essentially zero. The corresponding quanto response is smaller and insignificant in advanced economies. Cross-maturity averages yield a similar pattern, with the EM quanto spread widening by 23.4bps. Appendix Table **??** reports results separately for longer maturities.

Figure 11 shows that the EM response persists beyond the initial month. The USD spread rises sharply and remains elevated, while the quanto spread remains significant through four months. As the LC spread subsequently catches up, the persistent quanto response is unlikely to reflect only differential speeds of adjustment.

The stronger EM response is consistent with greater sensitivity to global funding and intermediary constraints. We test this interpretation by conditioning on the VIX, the He et al. (2017) intermediary capital ratio, and absolute CIP deviations from Du and Schreger (2016b). Table 14 shows that hawkish shocks widen quanto spreads when the VIX is high, intermediary capital is low, or CIP deviations are wide, but not in the corresponding unconstrained states. The cross-currency repricing of default risk is therefore strongest when intermediary risk-bearing capacity is limited.

Overall, hawkish U.S. monetary policy shocks raise the price of default risk in USD relative

[8]Because pseudo spreads are measured at month-end while FOMC announcements occur within the month, the measured change may miss part of the immediate response.

to LC, particularly in emerging markets and when global financial constraints are tight.

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 spreads embed identical physical default probabilities, allowing cross-currency differences to isolate currency-specific variation in the pricing of default risk.

This structure yields a decomposition of credit spreads into components with distinct economic content. The LC component captures variation in credit conditions driven by both expected default risk and risk premia, and is informative about aggregate economic activity, including global output and key US indicators. In contrast, cross-currency differences in spreads, the pseudo quanto component, reflect how default risk is priced across currencies and predict exchange rate movements.

Our results show that currency denomination affects the pricing of credit risk, not its physical probability. Credit spreads therefore contain information beyond local credit conditions, reflecting differences in risk premia that are systematically linked to aggregate economic outcomes and currency returns.

More broadly, our framework provides a tractable way to construct comparable credit spread measures across currencies using option data, overcoming key limitations of bond markets. By separating the quantity of default risk from its price, it offers a unified approach to studying credit markets, macroeconomic activity, and exchange rates in international settings.

Table 1: **Literature on Credit Risk Pricing in International Markets.** This table summarizes the related literature on credit spreads and the pricing of credit risk across currencies. We classify each study along five dimensions: the *setting* (corporate or sovereign credit risk); whether the study exploits *Multi-currency* spreads; whether the analysis spans multiple countries; the primary *financial instrument* studied (bonds, CDS, quanto forwards, or options); and the *prediction* focus (FX risk or economic activity). The last row describes this paper.

	Setting				Financial Instrument				Prediction	
Study	Corporate	Sovereign	Multi-currency	Multi-country	Bond	CDS	Q. Forward	Options	FX	Econ. Activity
Du and Schreger (2016)		x	x	x	x					
Belz and Breckenfelder (2025)		x	x	x	x					
Buraschi, Menguturk, and Sener (2015)		x	x	x	x					
Du, Pflueger, and Schreger (2020)		x	x	x	x	x				
Augustin, Chernov, and Song (2020)		x	x	x		x				
Lando and Bang Nielsen (2018)		x	x	x		x				
Della Corte, Jeanneret, and Patelli (2023)		x	x	x		x			x	
Du and Schreger (2022)	x	x	x	x		x				
Krishnamurty and Muir (2025)	x	x		x	x					x
Caramichael, Gopinath, and Liao (2021)	x		x	x	x					x
Hu et al. (2025)	x		x	x	x				x	x
Gilchrist and Zakrajsek (2012)	x				x					x
Galai and Wiener (2012)	x		x							
Kremens and Martin (2019)	x		x				x		x	
Culp, Nozawa, and Veronesi (2018)	x							x		
This study	x		x	x				x	x	x

Table 2: 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 (2016a), 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 - 7/2023	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 - 5/2023	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
Chile	S&P/CLX IGPA	-	-	-	-	-	ECH	USD	7/2009 - 8/2023	175
China	SSE 50	SS50	CNY	4/2016 - 7/2023	50	169	FXI	USD	9/2004 - 8/2023	590
Colombia	MSCI COLCAP	-	-	-	-	-	GXG	USD	5/2020 - 8/2023	18
Denmark	OMXC 25	KC25	DKK	3/2018 - 6/2023	30	12	-	-	-	-
Europe	STOXX 50	GXE	EUR	6/2002 - 7/2023	266	2147	EZU	USD	3/2008 - 8/2023	105
France	CAC 40	PXA	EUR	12/2005 - 7/2023	261	418	EWQ	USD	9/2011 - 8/2023	78
Germany	DAX 30	DAX	EUR	7/2004 - 7/2023	224	1094	EWG	USD	12/2006 - 8/2023	197
Greece	FTSE 20	AF20	EUR	6/2016 - 6/2023	82	45	GREK	USD	5/2020 - 8/2023	78
Hong Kong	HANG SENG	HSII	HKD	6/2007 - 6/2023	252	1087	EWH	USD	4/2006 - 8/2023	152
India	NIFTY 50	INIF	INR	2/2010 - 7/2023	154	1260	EPI	USD	4/2008 - 8/2023	105
Indonesia	IDX COMPOSITE	-	-	-	-	-	EIDO	USD	8/2015 - 8/2023	54
Italy	MIB	SMIB	EUR	4/2007 - 6/2023	240	600	EWI	USD	11/2016 - 8/2023	123
Japan	NIKKEI 225	NK20	JPY	6/2007 - 7/2023	328	1494	EWJ	USD	11/2016 - 8/2023	590
Malaysia	KLCI	KLSE	MYR	5/2012 - 6/2023	61	19	EWM	USD	11/2016 - 8/2023	87
Mexico	MIECS200	MMIP	MXN	2/2016 - 7/2023	33	67	EWW	USD	12/2007 - 8/2023	351
Netherlands	AEX	EOE	EUR	10/2001 - 6/2023	190	455	EWN	USD	10/2013 - 8/2023	13
New Zealand	S&P/NZX 50	-	-	-	-	-	ENZL	USD	10/2013 - 8/2023	39
Norway	OBX	OOBX	NOK	1/2010 - 7/2023	38	176	-	-	-	-
Poland	WIG 20	WWIG	PLN	7/2013 - 7/2023	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 Africa	FTSE/JSE	-	-	-	-	-	EZA	USD	7/2008 - 8/2023	344
South Korea	KOSPI 200	K200	KRW	5/2012 - 7/2023	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 - 6/2023	8	331	EWD	USD	9/2007 - 8/2023	52
Switzerland	SMI	SMI	CHF	2/2005 - 7/2023	226	1160	EWL	USD	7/2008 - 8/2023	276.5
Taiwan	TSEC	TMTX	TWD	2/2010 - 6/2023	70	312	EWT	USD	9/2016 - 8/2023	239
Thailand	SET 50	TFXS	THB	5/2011 - 7/2023	48	90	THD	USD	3/2014 - 8/2023	70
Turkey	XU 100	XUIO	TRY	2/2019 - 6/2023	21	340	TUR	USD	6/2013 - 8/2023	-
United Kingdom	FTSE 100	ESX	GBP	6/2004 - 7/2023	1203	2075	EWU	USD	11/2016 - 8/2023	255
United States	SPY	SPX	USD	1/1996 - 8/2023	210	10751	-	-	-	-

Table 3: 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 2023 and sourced from Refinitiv Datastream and OptionMetrics via WRDS. Details on construction and filtering are provided in Appendices B and C.

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.	$\rho_{CS^{LC},CS^{\$}}$	ρ_{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 4: 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 2023 and sourced from Refinitiv Datastream and OptionMetrics via WRDS. Details are provided in Appendices B and C.

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 5: Drivers of Local-Currency Pseudo Credit Spreads (3-month)

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 (3-month)						
	Risk decomposition	Stock index moments	FX moments	Risk-free rates	Local conditions	Global conditions	
Default Probability (P)	0.283***						
	(10.14)						
Default Premium (Q - P)	0.611***						
	(11.05)						
Expected Return (LC)		-0.392**					
		(-2.54)					
Return Volatility (LC)		0.427***					
		(2.90)					
FX Return (USD per LC)			-0.074				
			(-1.53)				
FX Volatility			0.299***				
			(2.76)				
LC Risk-free Rate				0.113			
				(0.67)			
USD Risk-free Rate				-0.025			
				(-0.09)			
Term Spread				0.004			
				(1.06)			
Foreign Reserves (USD)					-0.031***		
					(-2.98)		
Local Inflation					0.176**		
					(2.12)		
CFNAI						-0.013***	
						(-2.74)	
Macro Uncertainty						0.057***	
						(3.26)	
GZ Spread							0.024***
							(4.19)
EBP							-0.006
							(-0.69)
Constant	-0.011**	0.021*	0.017	0.036***	0.393***	-0.003	-0.013
	(-2.58)	(1.82)	(1.62)	(4.41)	(3.34)	(-0.21)	(-0.97)
Observations	1,703	1,216	1,702	1,492	1,408	1,704	716
R-squared	0.849	0.373	0.471	0.435	0.457	0.508	0.620
Country FE	✓	✓	✓	✓	✓	✓	✓

Table 6: Decomposition of Pseudo Quanto Spreads (3-month)

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)	-0.001		0.098**	-0.006		0.097**	0.044*		0.093***
	(-0.01)		(2.41)	(-0.09)		(2.45)	(1.87)		(5.74)
USD Q - LC Q		0.404***	0.417***		0.400***	0.413***		0.463***	0.469***
		(16.08)	(13.06)		(17.91)	(14.00)		(16.13)	(16.07)
Constant	0.013***	0.008***	0.001	0.013***	0.008***	0.001	0.009***	0.007***	0.000
	(3.35)	(5.21)	(0.29)	(3.74)	(5.30)	(0.34)	(4.77)	(14.43)	(0.42)
Observations	1,653	1,653	1,653	1,652	1,652	1,652	1,653	1,653	1,653
R-squared	0.000	0.699	0.721	0.070	0.729	0.749	0.333	0.783	0.793
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
Country FE							✓	✓	✓
Time FE				✓	✓	✓			
Clustering by country	✓	✓	✓	✓	✓	✓			
Clustering by time	✓	✓	✓				✓	✓	✓

Table 7: 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 (3-month)						
	Stock index moments		FX moments	Risk-free rates	Local conditions	Global conditions	
Expected Return (LC)	0.364**						
	(2.54)						
Return Volatility (LC)	-0.044						
	(-0.43)						
Expected Return (USD)		-0.175***					
		(-3.73)					
Return Volatility (USD)		0.398***					
		(4.39)					
FX Return (USD per LC)			-0.037**				
			(-2.27)				
FX Volatility			0.220***				
			(3.94)				
USD - LC Risk-free Rate				-0.276***			
				(-4.22)			
Term Spread				-0.002			
				(-1.26)			
Foreign Reserves (USD)					-0.011*		
					(-1.92)		
Local Inflation					0.095		
					(1.63)		
CFNAI						-0.003*	
						(-1.72)	
Macro Uncertainty						0.012	
						(1.07)	
GZ Spread							0.004
							(1.05)
EBP							-0.002
							(-0.41)
Constant	0.001	-0.030**	-0.009	0.011***	0.136**	0.002	0.007
	(0.06)	(-2.68)	(-1.60)	(5.30)	(2.05)	(0.27)	(0.59)
Observations	1,166	1,206	1,651	1,447	1,370	1,653	713
R-squared	0.304	0.414	0.387	0.378	0.337	0.338	0.359
Country FE	✓	✓	✓	✓	✓	✓	✓

Table 8: Local-Currency Credit Spreads as Predictors of Real Economic Activity

This table reports local projection estimates (Jordà, 2005) of one-quarter-ahead real economic activity (h=1) on the aggregate local-currency pseudo credit spread ($\overline{\text{CS}}^{LC}$) and the aggregate pseudo quanto spread ($\overline{\text{CS}}^{\text{Quanto}}$):

$$\Delta Y_{t+h} = \alpha + \gamma_1 \overline{\text{CS}}_t^{LC} + \gamma_2 \overline{\text{CS}}_t^{\text{Quanto}} + \beta \Delta Y_t + \delta' z_t + \varepsilon_{t+h},$$

where $\overline{\text{CS}}^{LC}$ is the GDP-weighted average of local-currency pseudo credit spreads across countries (excluding the US), constructed from equity index options and averaged across 3-, 6-, 12-, and 24-month maturities. $\overline{\text{CS}}^{\text{Quanto}}$ is defined analogously as the GDP-weighted average of pseudo quanto spreads (USD minus local-currency spreads). The dependent variables ΔY_{t+h} are aggregate GDP growth (GDP- and equal-weighted, with and without the US; columns 1-4), US nonfarm payroll growth (column 5), industrial production growth (column 6), and the ADS business conditions index (Aruoba et al., 2009) (column 7, scaled by 1/100). All specifications include the lagged dependent variable (unreported), the term spread, the real federal funds rate, and the macroeconomic uncertainty index of Jurado et al. (2015). The sample spans 2005Q3-2023Q3. Standard errors follow Newey and West (1987) with optimal bandwidth selection. The t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Aggregate GDP growth				*US indicators*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weighting	GDP	GDP	Equal	Equal	Payrolls	Ind Prod	ADS
Sample	excl. US	incl. US	excl. US	incl. US	US	US	US
$\overline{\text{CS}}^{LC}$	−0.210**	−0.199**	−0.269***	−0.261***	−0.060**	−0.158**	−0.220**
	(−2.37)	(−2.42)	(−2.86)	(−2.83)	(−2.57)	(−2.57)	(−2.64)
$\overline{\text{CS}}^{\text{Quanto}}$	−0.026	−0.025	0.086	0.077	0.018	−0.020	−0.021
	(−0.10)	(−0.11)	(0.31)	(0.28)	(0.28)	(−0.18)	(−0.09)
Term spread	0.002	0.002	0.003	0.002	0.000	0.001	0.001
	(1.12)	(0.94)	(1.36)	(1.29)	(0.10)	(1.61)	(0.64)
Real FFR	0.000	0.000	0.001	0.001	−0.000	0.000	−0.001
	(0.37)	(0.32)	(0.81)	(0.76)	(−1.32)	(0.45)	(−0.92)
JLN uncertainty	0.003	0.002	0.006	0.006	−0.006	0.003	−0.002
	(0.11)	(0.08)	(0.20)	(0.19)	(−0.79)	(0.31)	(−0.09)
Observations	73	73	73	73	73	73	73
R^2	0.087	0.074	0.078	0.075	0.102	0.154	0.064

Table 9: Global and US Credit Spreads: Predictability of Real Activity

This table reports local projection estimates (Jordà, 2005) of one-quarter-ahead real economic activity on the aggregate local-currency pseudo credit spread ($\overline{\text{CS}}^{LC}$) and a US pseudo credit spread (CS^{USA}). The US spread is constructed following Culp et al. (2018) from S&P 500 options as the equally weighted average of high-yield and investment-grade pseudo spreads at maturities of 183, 365, and 730 days. The local-currency spread applies the same methodology to equity index options from 33 non-US countries and is aggregated as a GDP-weighted average across countries and maturities. Panel A reports baseline results using $\overline{\text{CS}}^{LC}$; Panel B uses CS^{USA} as the sole predictor; Panel C includes both $\overline{\text{CS}}^{LC}$ and the residualized US spread, $\widetilde{\text{CS}}^{USA}$, obtained by regressing CS^{USA} on $\overline{\text{CS}}^{LC}$. The dependent variables follow Table 8: aggregate GDP growth (columns 1–4, GDP- and equal-weighted, with and without the US) and US indicators (columns 5–7: nonfarm payrolls, industrial production, and the ADS index, scaled by 1/100). All specifications include the lagged dependent variable, the term spread, the real federal funds rate, and the macroeconomic uncertainty index of Jurado et al. (2015). The sample spans 2005Q3–2023Q3. Standard errors follow Newey and West (1987) with optimal bandwidth selection. The t-statistics are in parentheses. *, **, and ** denote significance at the 10%, 5%, and 1% levels.

	Aggregate GDP growth				**US indicators**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Weighting	GDP	GDP	Equal	Equal	Payrolls	Ind Prod	ADS
Sample	excl. US	incl. US	excl. US	incl. US	US	US	US
Panel A: Baseline							
$\overline{\text{CS}}^{LC}$	−0.210**	−0.199**	−0.269***	−0.261***	−0.060**	−0.158**	−0.220**
	(−2.37)	(−2.42)	(−2.86)	(−2.83)	(−2.57)	(−2.57)	(−2.64)
Observations	73	73	73	73	73	73	73
R-squared	0.087	0.074	0.078	0.075	0.102	0.154	0.064
Panel B: US spread only							
CS^{USA}	−0.486	−0.484	−0.580	−0.572	−0.142*	−0.248**	−0.296**
	(−1.64)	(−1.63)	(−1.56)	(−1.57)	(−1.80)	(−2.26)	(−2.26)
Observations	71	71	71	71	71	71	71
R-squared	0.124	0.116	0.113	0.111	0.144	0.151	0.050
Panel C: Joint specification							
$\overline{\text{CS}}^{LC}$	−0.293**	−0.285**	−0.352**	−0.345**	−0.082**	−0.184***	−0.239**
	(−2.26)	(−2.23)	(−2.29)	(−2.28)	(−2.24)	(−2.89)	(−2.44)
$\widetilde{\text{CS}}^{USA}$	−0.491	−0.511	−0.579	−0.577	−0.156	−0.134	−0.093
	(−0.90)	(−0.95)	(−0.86)	(−0.87)	(−1.18)	(−0.73)	(−0.58)
Observations	71	71	71	71	71	71	71
R-squared	0.124	0.116	0.113	0.111	0.145	0.174	0.066

Table 10: Exchange Rate Predictability

This table reports the panel OLS regression results of 12-month-ahead bilateral exchange rate returns $\Delta s_{i,t+4}$ (positive = LC appreciation against USD) on 3-month pseudo credit spreads using the following predictive regression:

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

The sample covers 33 countries over 2005-2023. CS^{LC} denotes the local-currency spread and $\mathrm{CS}^{\mathrm{Quanto}}$ the pseudo quanto spread (USD minus LC), both in decimal units (1.0 = 100 basis points). All specifications include country and time fixed effects. Columns (1)-(3) report baseline regressions without controls: CS^{LC} only, $\mathrm{CS}^{\mathrm{Quanto}}$ only, and both jointly. Column (4) adds macroeconomic controls (interest rate differential, REER, FX volatility risk premium measured as the realized minus the implied 91-day FX volatility, GDP growth, log FX reserves, and inflation; N = 1,182). Columns (5)-(8) report subsamples: advanced economies, emerging markets, the pre-Covid period, and a subsample excluding the COVID period and the Global Financial Crisis. Standard errors are Driscoll and Kraay (1998) standard errors with four lags; t-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Dependent variable: $\Delta s_{i,t+4}$							
	Without controls			With controls	AE	EM	No Covid	Ex-Covid & GFC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CS^{LC}	0.302**		0.534***	0.406***	0.312***	0.826***	0.446***	0.435***
	(2.23)		(3.75)	(4.04)	(3.84)	(3.69)	(4.35)	(4.61)
$\mathrm{CS}^{\mathrm{Quanto}}$		0.281***	0.477***	0.489***	0.392***	0.802***	0.526***	0.365***
		(2.85)	(4.30)	(4.93)	(3.88)	(4.41)	(5.28)	(4.53)
IRD				−0.317	1.221**	−1.020***	−0.383	−0.620**
				(−1.06)	(2.24)	(−2.67)	(−1.13)	(−2.21)
REER				−0.002***	−0.001	−0.003***	−0.002***	−0.002**
				(−3.41)	(−1.36)	(−2.91)	(−3.10)	(−2.64)
FX VRP				0.208	0.172	0.123	0.102	−0.348
				(0.75)	(0.40)	(0.40)	(0.32)	(−1.25)
GDP growth				0.016	−0.024	0.044	0.152	−0.052
				(0.13)	(−0.13)	(0.61)	(0.35)	(−0.14)
Log FX reserves				0.016	0.048***	0.069	0.019	0.005
				(0.90)	(3.62)	(1.04)	(1.07)	(0.27)
YoY inflation				0.621***	0.897***	0.041	0.628***	0.492**
				(2.96)	(5.14)	(0.10)	(2.74)	(2.13)
Observations	1,626	1,623	1,623	1,142	775	361	1,063	958
R-squared	0.592	0.597	0.607	0.647	0.744	0.695	0.649	0.659
Country FE	✓	✓	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 11: Exchange Rate Predictability by Correlation Regime

This table reports the panel OLS regression results of 12-month-ahead bilateral exchange rate returns $\Delta s_{i,t+4}$ (positive = LC appreciation against USD) on 3-month pseudo credit spreads using the following predictive regression:

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

Countries are split by correlation regime. The sample covers 33 countries over 2005-2023. Countries are assigned to "low" and "high" groups based on the median of each correlation measure over the full sample. All specifications include country and time fixed effects, the full control set (interest rate differential, REER, FX volatility risk premium, GDP growth, log FX reserves, and inflation), and Driscoll and Kraay (1998) standard errors with four lags. Columns (1)-(2) split by the correlation between local equity returns and exchange rate changes; columns (3)-(4) by the correlation with S&P 500 returns; and columns (5)-(6) by the correlation with US consumption growth. The t-statistics are reported in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Dependent variable: $\Delta s_{i,t+4}$					
	Corr. with LC index		**Corr. with S&P 500**		**Corr. with US cons.**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
CS^{LC}	0.162	0.378***	0.261	0.529***	0.173	0.526***
	(0.79)	(3.26)	(1.11)	(4.78)	(1.31)	(3.40)
$\mathrm{CS}^{\mathrm{Quanto}}$	0.293*	0.364***	0.495***	0.326***	0.197	0.502***
	(1.70)	(4.79)	(2.85)	(3.04)	(0.89)	(4.07)
IRD	1.440	−0.975**	−0.047	−0.826	0.387	−0.920**
	(1.59)	(−2.55)	(−0.10)	(−1.63)	(0.65)	(−2.43)
REER	−0.000	−0.002***	−0.003***	−0.003***	−0.000	−0.003***
	(−0.44)	(−2.85)	(−3.72)	(−3.77)	(−0.47)	(−3.75)
FX VRP	−1.780***	0.314	−0.849**	0.399	−0.429	0.277
	(−5.81)	(1.18)	(−2.56)	(1.59)	(−0.83)	(1.19)
GDP growth	−0.181***	0.416*	−0.148	0.518	−0.300	0.428*
	(−2.94)	(1.75)	(−1.53)	(1.61)	(−1.67)	(1.87)
Log FX reserves	0.029**	0.018	0.052***	−0.012	0.013	0.000
	(2.30)	(0.72)	(3.46)	(−0.55)	(0.47)	(0.00)
YoY inflation	0.661***	0.438	0.684**	0.085	0.895***	0.339
	(3.65)	(1.54)	(2.64)	(0.25)	(3.22)	(0.92)
Observations	495	501	564	562	565	569
R-squared	0.855	0.683	0.708	0.726	0.722	0.711
Country FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓	✓

Table 12: Out-of-Sample Predictability

This table reports out-of-sample evaluations of FX return predictability under alternative real-time designs. "Baseline" estimates predictive regressions recursively using an expanding window with a 24-quarter burn-in, a minimum of 100 training observations, and a four-quarter gap to accommodate overlapping annual returns. "Rolling 40q" estimates the regressions using the most recent 40 quarters. "Country demeaning" subtracts the training-sample country mean from returns before forecasting. "Burn-in" varies the number of initial quarters skipped. Columns report the Campbell–Thompson out-of-sample R^2 and Diebold–Mariano t-statistic relative to the driftless random walk for the local-currency spread, the quanto spread, and the two jointly. The sample is the quarterly panel of non-U.S. currencies over 2005–2023.

	CS LC			CS Quanto			Both spreads		
Design	OOS R^2	DM t	CW t	OOS R^2	DM t	CW t	OOS R^2	DM t	CW t
Baseline	2.36	2.24	6.92	4.52	3.19	8.23	5.00	3.63	9.42
Rolling 40-quarter window	2.42	1.84	7.18	5.34	3.40	8.85	5.23	3.44	9.70
Country demeaning	9.75	2.01	5.14	10.76	2.15	5.46	12.57	2.56	5.85
Burn-in 16 quarters	1.24	1.26	5.94	2.98	2.23	7.48	3.16	2.40	8.39
Burn-in 32 quarters	2.91	2.60	7.22	4.92	3.28	8.10	5.36	3.69	9.17

Table 13: U.S. Monetary Policy Shocks and Pseudo Credit Spreads by Maturity

This table reports panel regressions of the one-month change in pseudo credit spreads on the standardized Nakamura–Steinsson monetary policy shock (Acosta, 2023 update), in basis points, for $k \in \{LC, USD, Quanto\}$ with $CS^{Quanto} = CS^{USD} - CS^{LC}$. The specification is

$$\Delta CS^{k}_{i,t+1} = \alpha_i + \beta\, MP_t + \boldsymbol{\theta}'\mathbf{x}_{i,t} + \varepsilon_{i,t+1},$$

estimated separately at each maturity, and each coefficient is β, the response to a one-standard-deviation hawkish surprise. "All" is the unconditional coefficient. "EM" and "AE" come from a single regression that adds the interaction $MP_t \times EM_i$. Emerging markets: Brazil, Chile, China, Colombia, India, Indonesia, Malaysia, Mexico, Poland, South Africa, Thailand, Turkey. All specifications include US and local controls, country fixed effects, and two-way (country, month) clustered standard errors. t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Panel A: 3-month (91d)			**Panel B: 6-month (182d)**		
	ΔCS^{LC}	ΔCS^{USD}	ΔCS^{Quanto}	ΔCS^{LC}	ΔCS^{USD}	ΔCS^{Quanto}
All	6.70	28.0*	19.8***	13.6**	24.3***	6.90
	(0.52)	(1.67)	(2.83)	(2.04)	(4.60)	(1.16)
EM	1.90	40.6***	38.1***	30.3**	43.4***	12.8
	(0.09)	(3.08)	(3.34)	(2.37)	(8.09)	(0.81)
AE	8.40	23.5**	13.2	6.30	16.0***	4.20
	(0.62)	(2.50)	(1.61)	(0.76)	(2.59)	(0.64)
N	3,892; 28 countries			3,180; 27 countries		

	Panel C: 12-month (365d)			**Panel D: 24-month (730d)**		
	ΔCS^{LC}	ΔCS^{USD}	ΔCS^{Quanto}	ΔCS^{LC}	ΔCS^{USD}	ΔCS^{Quanto}
All	14.2*	20.8**	3.50	23.5**	22.0	−2.00
	(1.80)	(2.38)	(0.44)	(2.22)	(1.23)	(−0.10)
EM	17.2**	23.4**	6.00	11.9	33.9*	22.0**
	(2.30)	(2.17)	(0.46)	(1.00)	(1.71)	(2.12)
AE	12.7	19.5*	2.30	30.4**	14.9	−16.4
	(1.13)	(1.68)	(0.22)	(2.00)	(0.56)	(−0.57)
N	2,209; 25 countries			1,671; 17 countries		

	Panel E: Cross-maturity average		
	ΔCS^{LC}	ΔCS^{USD}	ΔCS^{Quanto}
All	13.0	22.9*	9.10*
	(1.53)	(1.90)	(1.65)
EM	15.4	38.9***	23.4**
	(1.14)	(3.36)	(2.51)
AE	12.1	17.2	4.10
	(1.44)	(1.31)	(0.68)
N	3,957; 28 countries		

Table 14: Monetary Policy Repricing and Financial Conditions (3-month, $h = 1$)

This table interacts the standardized Nakamura–Steinsson monetary policy shock (Acosta, 2023 update) with an indicator for the conditioning variable lying above ("high/wide") or below ("low/narrow") its median. Coefficients are in basis points, with $CS^{Quanto} = CS^{USD} - CS^{LC}$. The specification is

$$\Delta CS^{k}_{i,t+1} = \alpha_i + \beta_H \left(MP_t \times D_t\right) + \beta_L \left(MP_t \times (1 - D_t)\right) + \boldsymbol{\theta}' \mathbf{x}_{i,t} + \varepsilon_{i,t+1},$$

where $D_t = 1$ when the conditioning variable is above its median. The reported rows are β_H (high/wide) and β_L (low/narrow). Panel A splits on the VIX; Panel B on the He–Kelly–Manela (2017) intermediary capital ratio, where low capital signals binding constraints; Panel C on the country-specific absolute CIP deviation from Du and Schreger (2016), where wide deviations signal frictions in currency markets (data end March 2021). All specifications include US and local controls, country fixed effects, and two-way clustered standard errors. $N = 3{,}892$ (28 countries) in Panels A and B and 2,797 (23 countries) in Panel C. t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	ΔCS^{LC}	ΔCS^{USD}	ΔCS^{Quanto}
Panel A: VIX			
$MP\times$ High VIX	3.30	33.3	28.4***
	(0.17)	(1.34)	(2.68)
$MP\times$ Low VIX	12.0	19.6	6.20
	(1.15)	(1.11)	(0.58)
Panel B: Intermediary capital ratio			
$MP\times$ Low capital	6.50	29.2	21.1***
	(0.48)	(1.64)	(2.97)
$MP\times$ High capital	9.40	6.30	−4.30
	(0.54)	(0.25)	(−0.26)
Panel C: |CIP deviation|			
$MP\times$ Wide |CIP|	13.4	36.8	18.6*
	(0.52)	(1.20)	(1.88)
$MP\times$ Narrow |CIP|	14.3	13.7	2.00
	(0.84)	(0.55)	(0.10)

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 B 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.

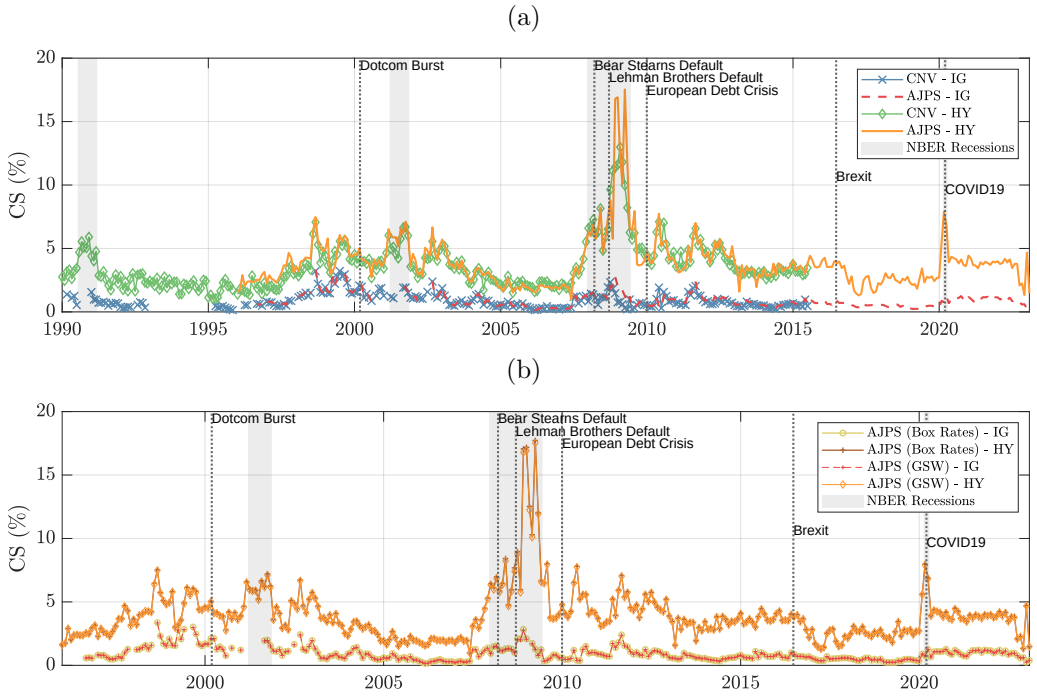


Figure 2: Empirical Credit Spreads of Six-Month ESX Pseudo Bonds (United Kingdom)

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 B). 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 2023. Shaded areas denote recessions.

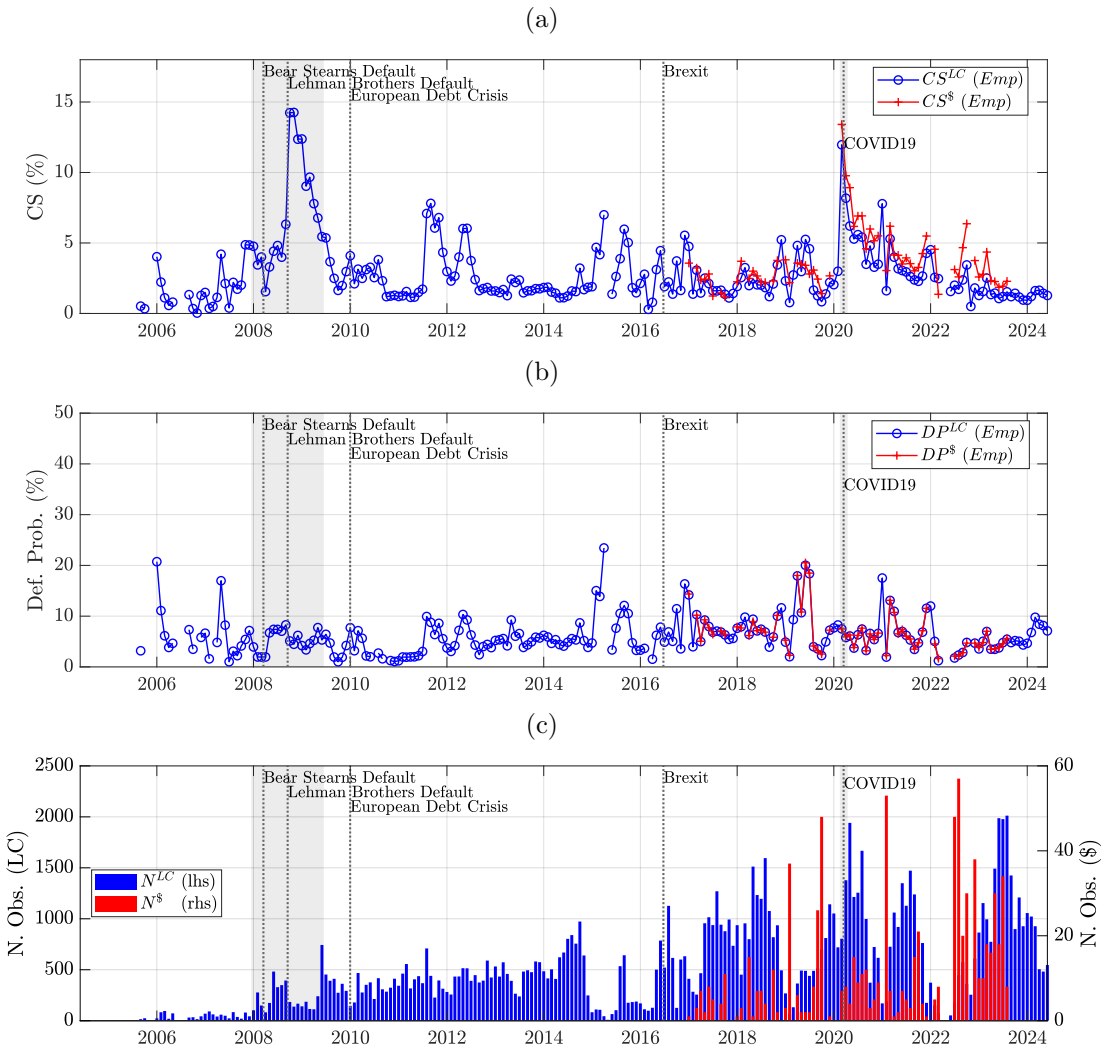


Figure 3: Synthetic Credit Spreads of Six-Month ESX Pseudo Bonds (United Kingdom)

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 B and C). 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 2023. Shaded areas denote recessions.

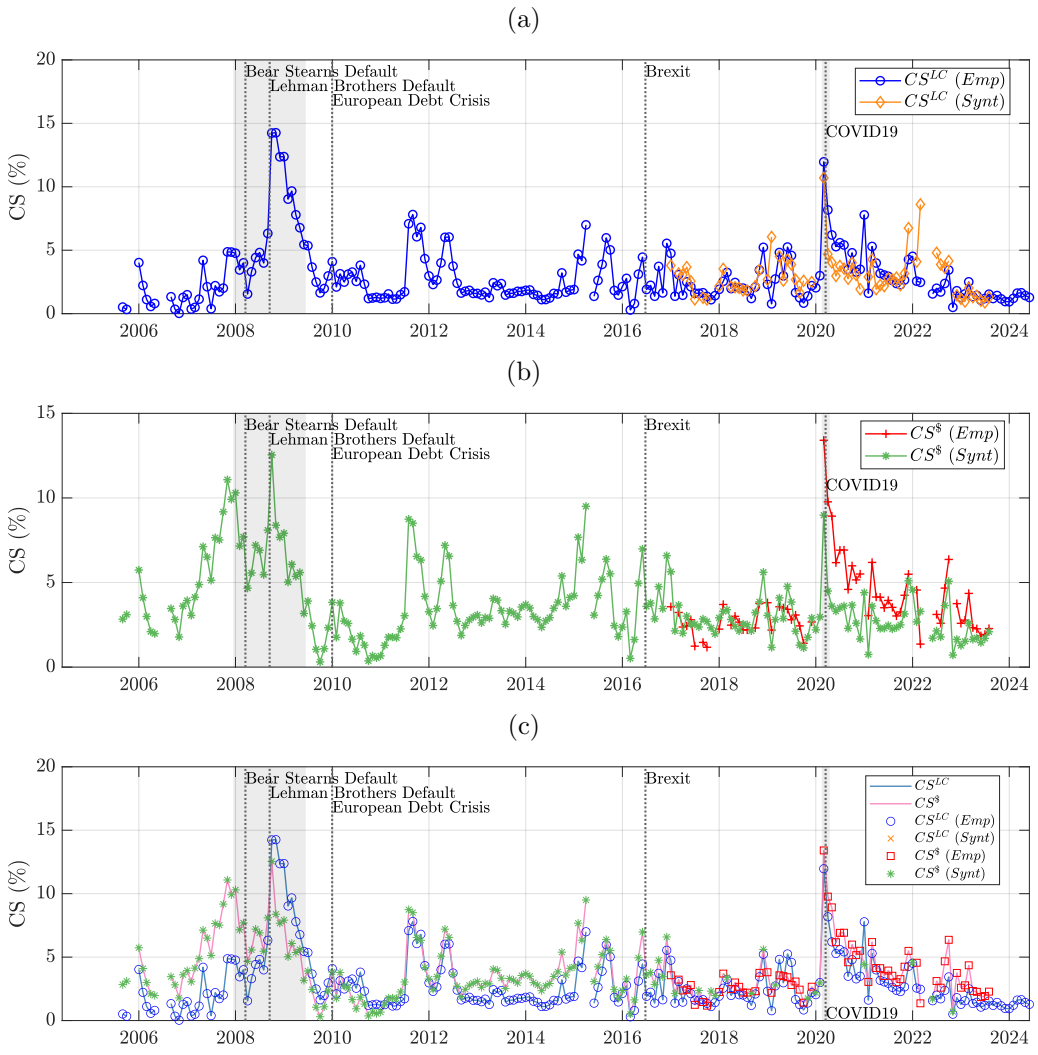


Figure 4: Credit Spreads of Six-Month ESX Pseudo Bonds - By Currency

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 B and C). 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 2023. Shaded areas denote recessions.

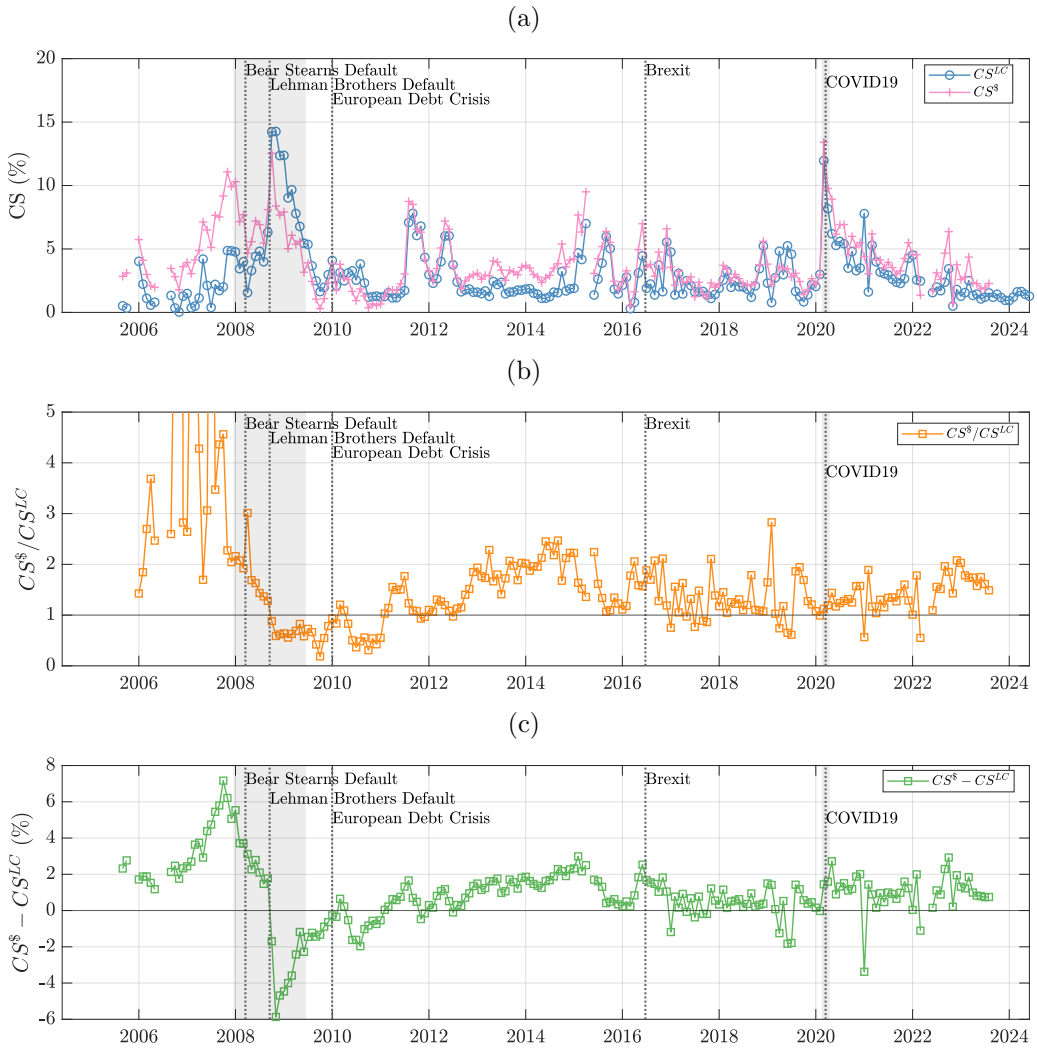


Figure 5: Default probabilities, volatility, and leverage: United Kingdom.

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 B and C). 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 2023. Shaded areas denote recessions.

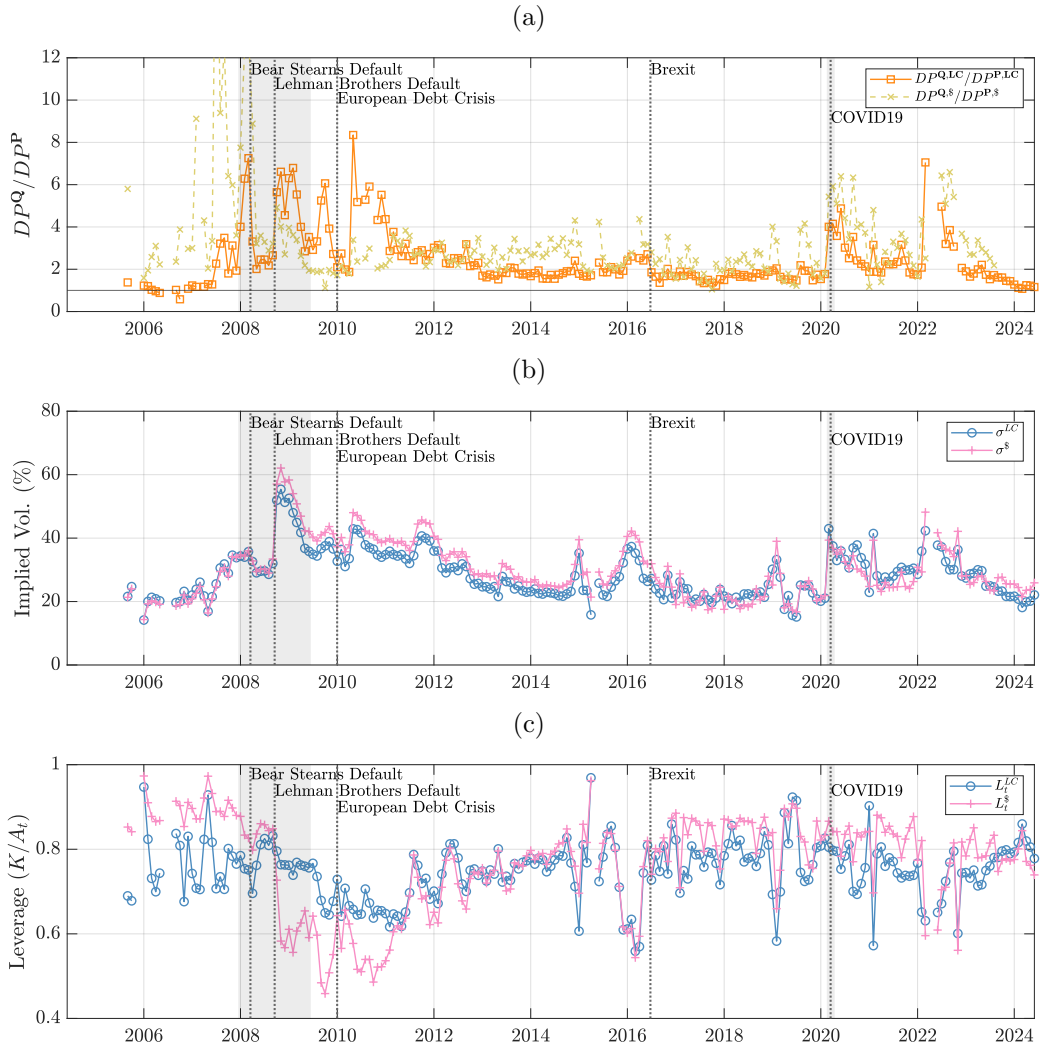


Figure 6: Quanto Spreads and Risk Premia (United Kingdom)

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 B and C). The data are monthly from 2003 to 2023.

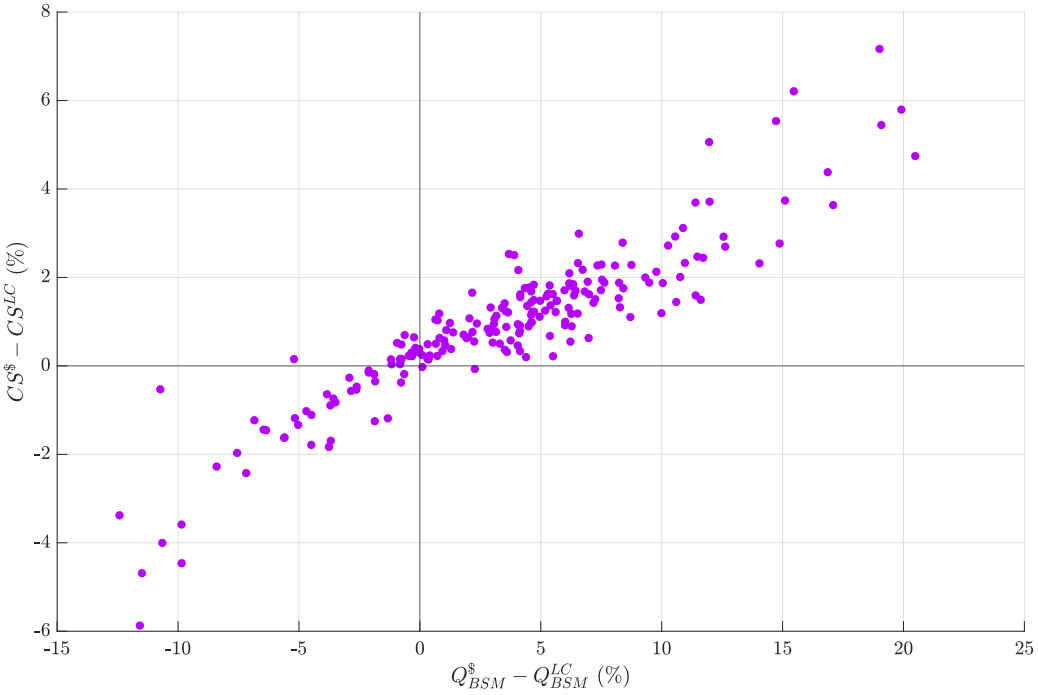


Figure 7: Cross-Currency Credit Spreads: Model-Implied Levels and Drivers

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.

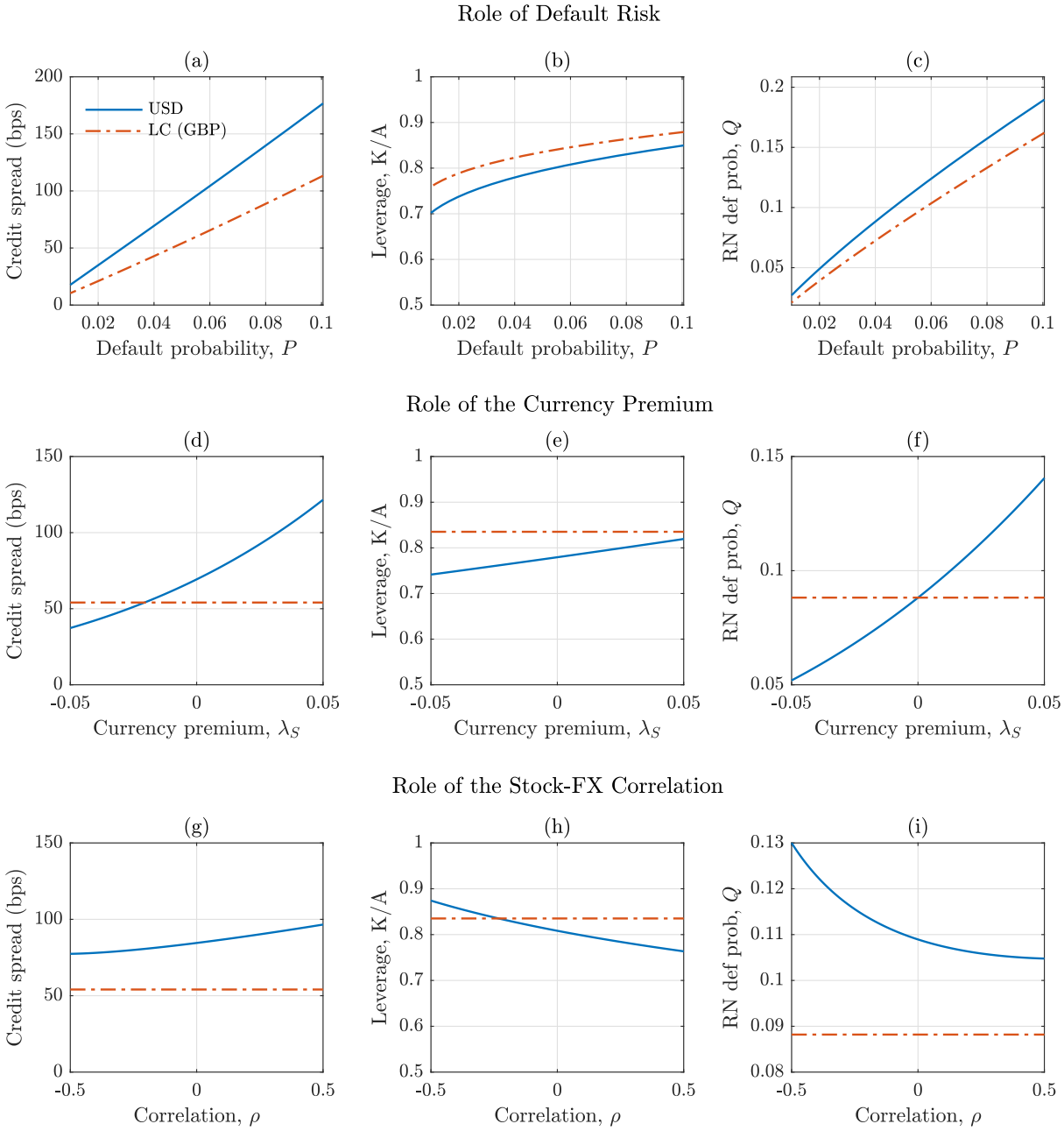


Figure 8: Regional Dynamics of Local- and Foreign-Currency Pseudo Credit Spreads (6-Month)

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 2023 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, Spain, Sweden, Switzerland United Kingdom 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 B and C.

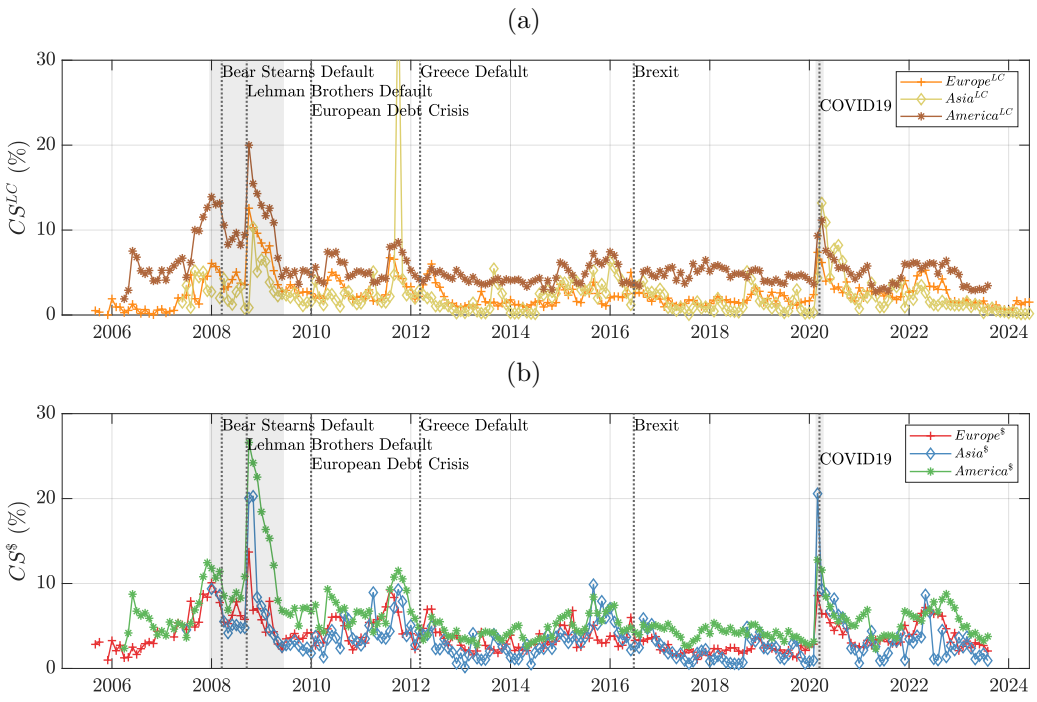


Figure 9: Cross-Country Term Structures of Pseudo Credit Spreads

This figure plots term structures of pseudo credit spreads across five country groups: Europe Advanced, Pacific Advanced, Other Advanced, Asia Emerging, and Other Emerging. Panel (a) shows LC spreads and Panel (b) USD-denominated spreads, normalized by subtracting the corresponding 3-month spread so that all curves start at zero. Panel (c) reports pseudo quanto spreads (USD minus LC), likewise normalized relative to the 3-month spread. The regional grouping highlights differences in the slope of the term structure across advanced and emerging markets. LC pseudo bonds are constructed from options on domestic stock market indices, while USD-denominated pseudo bonds use options on ETFs tracking the same indices. Option maturities are restricted to 7–182, 91–365, 182–547, and 365–1095 days for the 3-, 6-, 12-, and 24-month horizons, respectively. Data are monthly from 2003 to 2023 and sourced from Refinitiv Datastream and OptionMetrics via WRDS. Details on country composition and construction are provided in Appendices B and C.

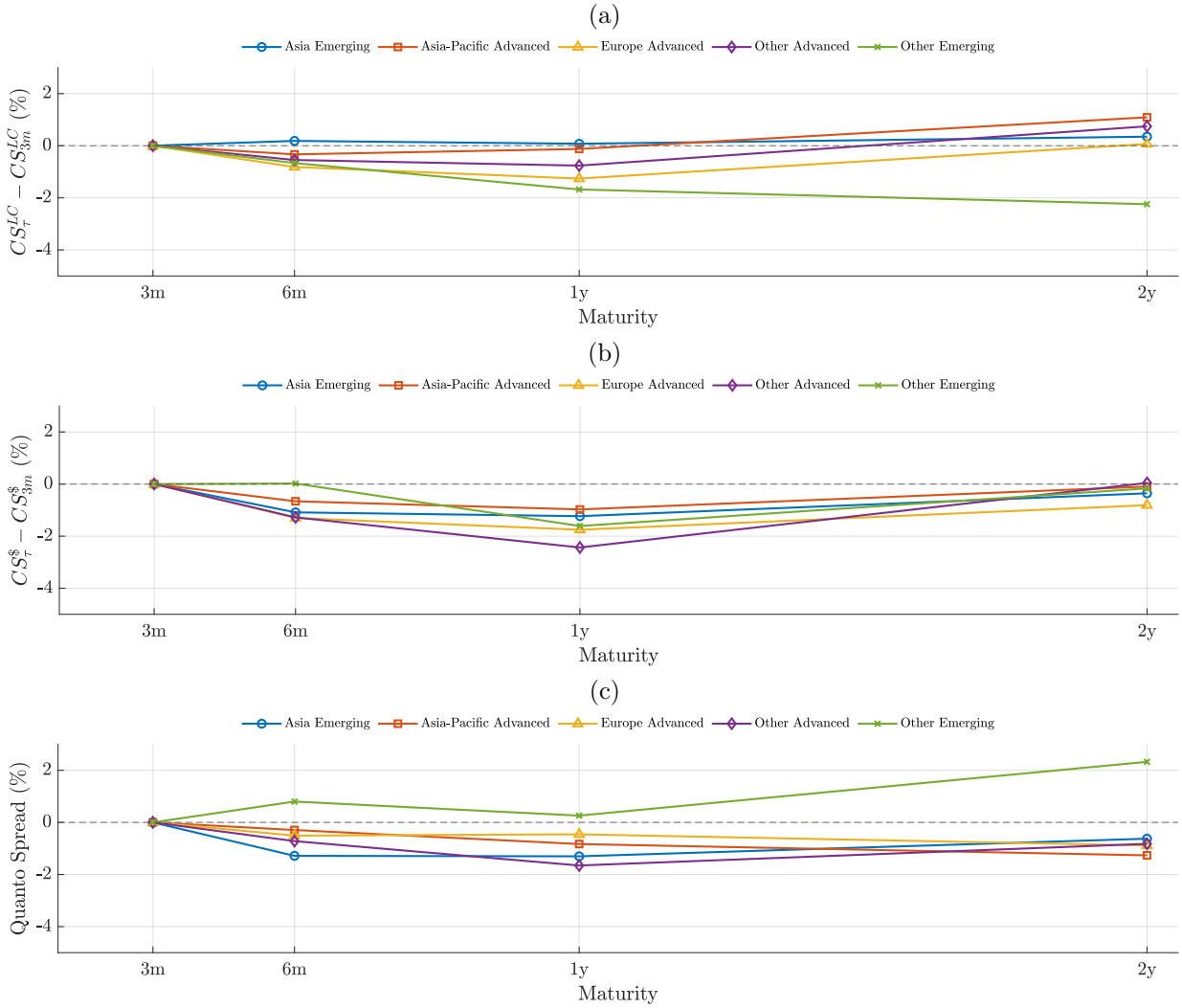


Figure 10: Horizon Dependence of Exchange Rate Predictability

This figure plots slope coefficients from the panel specification (23) with country and time fixed effects as a function of the prediction horizon h (3-48 months), and using Driscoll and Kraay (1998) standard errors. Panels (a) and (b) report results of the empirical model without macroeconomic controls (interest rate differential, REER, GDP growth, log FX reserves, and inflation) while panels (c) and (d) report results including controls. Panels (a) and (c) report the coefficients for the pseudo quanto spread ($\text{CS}^{\text{Quanto}}$), and panels (b) and (d) those on the local-currency pseudo credit spread (CS^{LC}). The solid blue line relies on 3-month spreads. Shaded bands denote 90% confidence intervals, and the vertical dotted line marks the 12-month baseline horizon. Panels (a) and (b) exclude macroeconomic controls; Panels (c) and (d) include the full control set (interest rate differential, REER, GDP growth, log FX reserves, and inflation). Standard errors are clustered by quarter. The sample size decreases with h due to right-censoring.

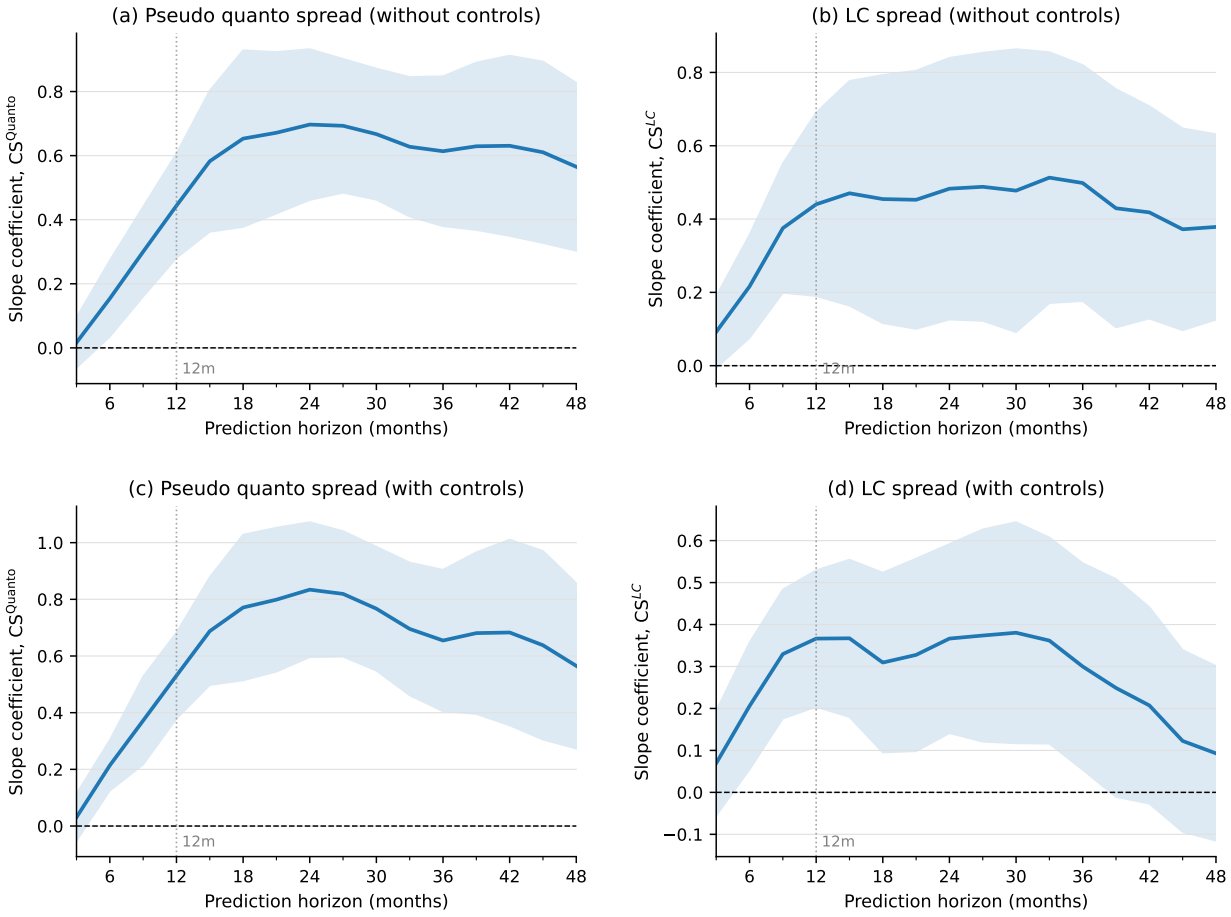
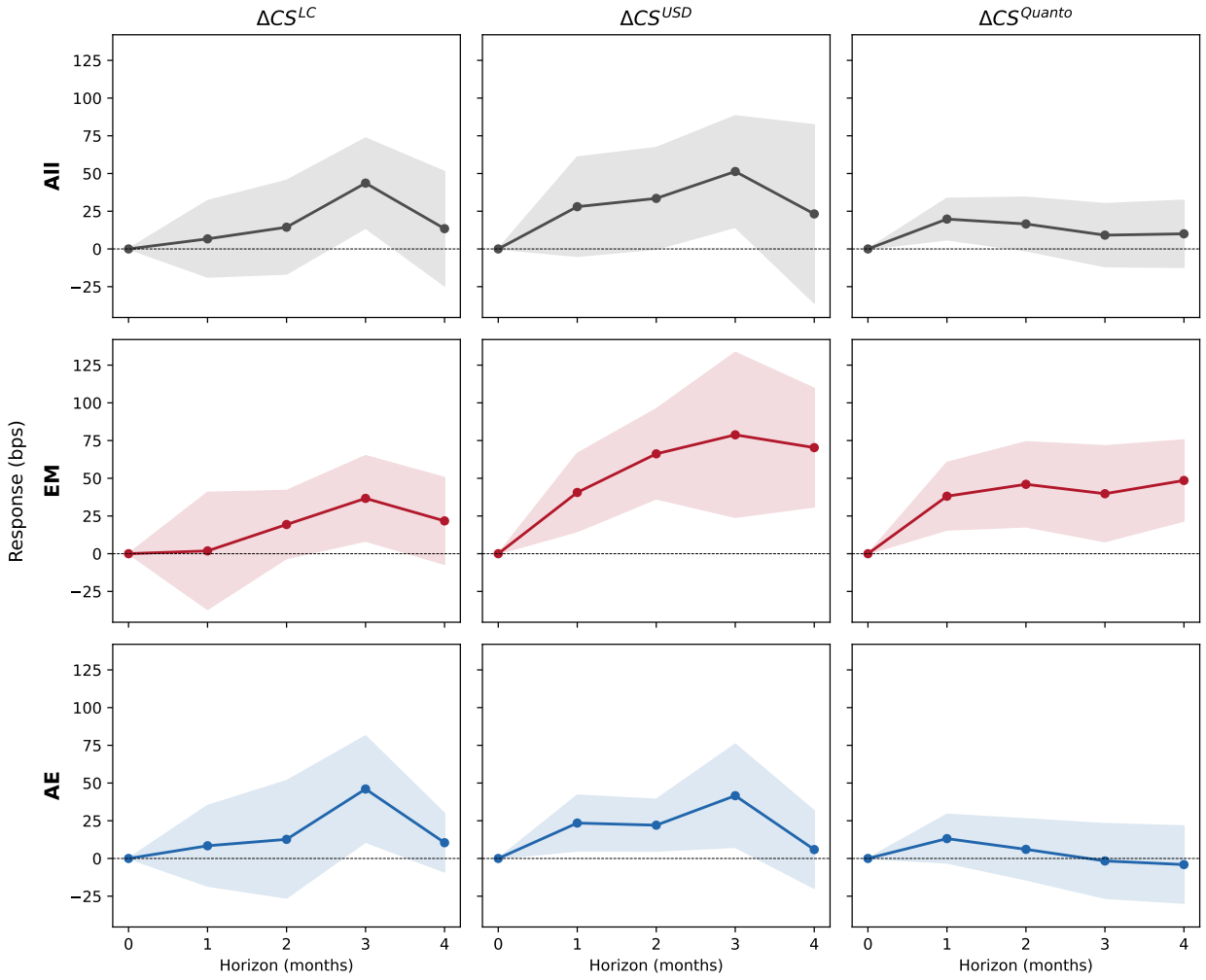


Figure 11: Impulse Response Functions to US Monetary Policy Shocks

This figure plots the response of three-month pseudo credit spreads to a one-standard-deviation Nakamura–Steinsson (Acosta, 2023 update) monetary policy shock at horizons $h = 0, \ldots, 4$ months. The grid has rows for the All, EM, and AE subsamples and columns for the LC spread, the USD spread, and the pseudo quanto spread $CS^{Quanto} = CS^{USD} - CS^{LC}$. Each cell traces β_h from the panel regression $\Delta CS^{k}_{i,t+h} = \alpha_i + \beta_h \, MP_t + \boldsymbol{\theta}' \mathbf{x}_{i,t} + \varepsilon_{i,t+h}$ over $h = 0, \ldots, 4$, on a common scale, in basis points. Shaded areas are 95% confidence intervals from two-way clustered standard errors.



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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 Data Appendix

We construct an international panel of local currency and USD-denominated pseudo spreads using several data sources. Our working data set contains an unbalanced sample of 33 countries (12 emerging and 21 developed) as well as the Eurozone from October 2001 to June 2023, except for options on the S&P500 that are available since 1996. Table 2 summarizes the coverage, including index identifiers, option tickers, currency denominations, sample periods, and the average number of option observations.

Local currency Price Index Series and USD ETFs. We download historical data on local-currency stock indices, corresponding dividend yields, and USD-denominated ETFs from Refinitiv Datastream (via Refinitiv Eikon). When dividend data are unavailable, we infer them using both the total return price and ex-dividend return series. Columns (4), (5), and (6) in Table A.2 present data availability for the local-currency stock market indices, while column (7) indicates data availability for the corresponding USD ETFs. The starting date of each local currency index time series varies greatly across countries. Data on the US stock market date back to 1871, but for most countries, the data start in the early 1980s. ETFs were not traded before the mid-to-late 1990s and are, therefore, only available much later. These data are used to estimate the ex-ante probability of default of pseudo debt as described in Section B.1, and to estimate Black-Scholes-Merton implied volatilities.

Options on Local Currency Indices and USD ETFs. We obtain end-of-day put and call option data from two sources: Datastream (formerly Thomson Reuters, now LSEG), accessed through Workspace, for options on international stock indices in local currency; and OptionMetrics, via Wharton Research Data Services (WRDS), for options on USD-denominated index-tracking ETFs. Our sample construction begins with the set of emerging and developed markets identified in Du and Schreger (2016a) and Kelly et al. (2016). Table 2 lists the countries, the underlying index of the option, and the currency in which the option is priced. 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. Our unbalanced sample spans from October 2001 to June 2023, except for options on the S&P500, which start in 1996.

Options on local-currency indices are standard European-style contracts. 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 whose implied volatility lies more than one standard deviation from the mean of their moneyness peer group (0.05-width bins); (vi) options for which put-call parity implies an interest rate 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.

Options on USD-denominated ETFs are American-style. For these options, we follow Culp et al. (2018) and retain those 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.

Spot exchange rates. We obtain the spot exchange rates from Bloomberg. The local currency time series ticker is expressed in units of USD with mnemonic "USDCCY Curncy". Our spot exchange rate data span twenty-six currency pairs at a daily frequency. We use the last value of the day. Table A.2 lists the various exchange rates used in our analysis; note that we use the CNH (offshore market Chinese Yuan) instead of the CNY to represent the Renminbi value because of trading restrictions on the latter.

Forward exchange rates. Forward points and days-to-maturity are downloaded from Bloomberg. These data span twenty-six currency pairs at a daily frequency, for contract maturities of 1, 3, 6, 12, 18, 24, and 36 months. In Table A.2, columns (2) and (3) present information on data availability. Forward points fp can be positive or negative. They serve as inputs to compute the forward exchange rate F using the 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 risk-free rates implied by covered interest rate parity as in Du et al. (2018), as described in Section B.2. The dating convention of forward contracts varies by currency, since the year is assumed to have either 360 or 365 days, depending on the country. For example, the forward basis for a contract with 27 days-to-maturity is computed as $\rho = (360/27)(\ln(F) - \ln(S))$ when the daycount convention indicates 360 days in a year. The last row of Table A.2 describes the Bloomberg and Datastream ticker formats used to download each time series.

Options on exchange rates. Put options on the exchange rates are available from Bloomberg, FX options are quoted in terms of implied volatility. We download the daily implied volatilities for various maturities of at-the-money options. Data availability is described in Table A.2, column (1). 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 described in Section C.2.

Macroeconomic and financial data. Nominal GDP (in USD), consumer price inflation, and foreign exchange reserves are from the IMF International Financial Statistics (IFS). Real effective exchange rates (REER) are from the Bank for International Settlements (BIS). The interest rate differential ($r_{USD} - r_{LC}$) is constructed from the box rates described in Section B.2. The Chicago Fed National Activity Index (CFNAI) is from the Federal Reserve Bank of Chicago. The Aruoba-Diebold-Scotti (ADS) business conditions index is from the Federal Reserve Bank of Philadelphia (Aruoba et al., 2009). Non-farm payroll employment and industrial production are from the Federal Reserve Economic Data (FRED). The GZ credit spread is from Gilchrist and Zakrajšek (2012), obtained from the Federal Reserve Board. Macroeconomic uncertainty is from Jurado et al. (2015), obtained from Sydney Ludvigson's website. US zero-coupon Treasury yields are from Gürkaynak et al. (2007), obtained through FRED. S&P 500 prices and dividend distributions (1946–2023) are from CRSP. Moody's historical default frequencies are from Moody's (2022). NBER recession dates are used for shading in figures and are from the National Bureau of Economic Research.

B Computing Pseudo Credit Spreads

We describe our procedure for constructing the empirical pseudo credit spreads. This involves the estimation of physical default probabilities (Section B.1), the estimation of riskless rates (Section B.2), the aggregation of credit spreads into country-level indices (Section B.3), and the matching of pseudo bonds across currencies (Section B.4). Data sources and availability are described in Appendix A.

B.1 Estimating Physical 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 allow us to match pseudo-debt contracts on the same index across currencies by default risk. To that end, we proceed to describe how we estimate the expected return and expected volatility of returns under the physical measure and then describe how we assign the physical default probability.

Forecasting Expected Returns. We estimate the time-t expected return parameter $\mu_{t,\tau}$ for some forecast horizon τ 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:

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

where ε_t represents the residuals. The parameters of the AR(1) model, β_0 and β_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 recursively forecast the expected return and accumulate returns over the desired τ-month horizon. The predicted expected return is then given by:

$$\widehat{\mu}_{t,\tau} = \sum_{s=1}^{\tau} \widehat{\mu}_{t,s} = \sum_{s=1}^{\tau} \left[\widehat{\beta}_0 + \widehat{\beta}_1 \ln(A_{t+s}/A_{t+s-1}) \right]. \tag{B.2}$$

In the particular case of the US, we follow Culp et al. (2018) and estimate $\mu_{t,\tau}$ using 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:

$$\ln(A_{t+\tau}/A_t) = a_{t,\tau} + b_{t,\tau} D_t/P_t + u_{t,\tau}, \qquad t = 0, 1, 2, \ldots T - \tau, \tag{B.3}$$

where D_t/P_t is proxied as the difference between one-year cumulative value-weighted total and capital returns, minus one.[9] The predicted expected return is then given by $\widehat{\mu}_{t,\tau} = \widehat{a}_{t,\tau} + \widehat{b}_{t,\tau} D_t/P_t$.

Volatility Estimation. We estimate the time-t expected return volatility $\sigma_{t,\tau}$ for some forecast horizon τ 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:

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

where η_t represents the return residuals. The parameters of the GARCH(1,1) model, α, β, and ω 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 τ-month horizon based on the following equation:

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

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

$$\ln(A_{t+\tau}/A_t) = \mu_{t,\tau} + \sigma_{t,\tau} \varepsilon_{t+\tau}, \tag{B.6}$$

where $\mu_{t,\tau}$ is the time-t expected log return on the local market index over horizon τ and $\varepsilon_{t+\tau}$ is a standardized shock scaled by asset return volatility $\sigma_{t,\tau}$. For each pseudo-firm i, identified by strike price K_i, the time-t ex-ante default probability over horizon τ is defined as:

$$p_{i,t}(\tau) = \mathbb{P} \left[A_{t,\tau} < K_i \mid \mathcal{F}_t \right], \tag{B.7}$$

[9] That is, $D_t/P_t \approx (TR_t/TR_{t-252})/(P_t/P_{t-252}) - 1$, where TR_t and P_t denote the total-return and price indices, respectively.

where $A_{t,\tau}$ denotes predicted asset growth over forecast horizon τ, 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 τ, we first construct the empirical distribution of historical shocks, defined as $\widehat{\varepsilon}_{t,\tau} = \left(\ln\left(A_{t+\tau}/A_t\right) - \widehat{\mu}_{t,\tau}\right)/\widehat{\sigma}_{t,\tau}$, where $\widehat{\mu}_{t,\tau}$ and $\widehat{\sigma}_{t,\tau}$ are estimated based on Equations (B.2) and (B.5), 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., $\widehat{\varepsilon}_{s,\tau} < \widehat{X}_{i,t}$.

For the theoretical case of zero leverage ($K = 0$), the default probability is zero by construction. For strike prices between zero and the smallest observed strike $\underline{K}$, we assign default probabilities by linear interpolation between this zero-leverage anchor and the first empirical observation.

B.2 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.

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:

$$p_t(K,T) - c_t(K,T) = e^{-r(T-t)}K - i_t, \tag{B.8}$$

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 (B.8), 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, $i = 1, \ldots, K$:

$$p_{i,t}(T) - c_{i,t}(T) = \alpha_t(T) + \beta_t(T)K_i + u_{i,t}(T), \tag{B.9}$$

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 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 (B.9) is estimated using options with more than seven days 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 box rates. To construct a daily term structure of box rates we linearly interpolate estimated box rates using 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.

For Euro area members, we replace the country-specific box rate denominated in EUR with a regional box rate index, computed as the simple average of the box rates for time t and maturity τ for Belgium, Spain, France, Germany, Italy, the Netherlands, and the STOXX index.

For non-Euro European countries, we construct a European regional box rate index as follows. We first 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 (2016a),[10]

$$\widehat{r}^{\$}_{t,T} = \widehat{r}^{LC}_{t,T} - \rho_{t,T}, \tag{B.10}$$

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 into the appropriate currency using the CIP condition, or obtained from applying the CIP condition to the US box rates.

[10]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).

B.3 Aggregation of Credit Spreads

We construct aggregate pseudo credit spreads representing the credit risk of the basket 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, using the physical default probabilities estimated in Section B.1.

For each country, we build pseudo credit spreads with maturities of 3 months, 6 months, 1 year, and 2 years. For 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.

To construct a country-level credit spread at the monthly frequency, we first estimate the pseudo credit spread at the pseudo-firm level (for each date-maturity-strike) as the difference between the pseudo yields and maturity-matched riskless rate obtained from box rates as described in Section B.2. Then, we aggregate the pseudo credit spreads within a given month using 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.

$$\tilde{\omega}_{i,T,\bar{T}} = \phi\left(\frac{T-\bar{T}}{30Days}\right), \tag{B.11}$$

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

$$\omega_{i,T,\bar{T}} = \frac{\tilde{\omega}_{i,T,\bar{T}}}{\sum_i^n \tilde{\omega}_{i,T,\bar{T}}}. \tag{B.12}$$

US Credit Spreads and Aggregation to IG and HY Indices. For the U.S., we construct investment-grade (IG) and high-yield (HY) indices of pseudo-bond yields. We assign a pseudo credit rating to each pseudo-bond by matching its default probability, computed as in Section B.1, to the average cumulative default rates by letter rating from Moody's 2022 Annual Default Study Report (Moody's, 2022). Since pseudo bonds are predominantly short-maturity, we rely on the 1-year and 2-year cumulative default probabilities (reported in Table A.4 for convenience). Pseudo bonds rated Baa or above are classified as IG; the remainder as HY. For each category, we construct monthly US pseudo yields by applying the maturity windows and weighting scheme of Section B.3 to all end-of-month observations.

B.4 Matching Pseudo Bonds Across Currencies

When we observe both local-currency options on the stock index and USD options on the corresponding ETF, we could in principle directly compare pseudo credit spread estimates across currencies. However, the physical default probabilities implied by each set of options do not necessarily coincide. We therefore refine the selection of pseudo bonds that enter the monthly aggregation step. We start by selecting a currency benchmark for each country based on the highest number of observations for the pseudo credit spread index time series. Table A.13 presents the selection of the currency benchmark for each country and maturity.

We then retain only those pseudo bonds denominated in the other currency whose physical default probabilities and maturities lie within 50 bps and 91 days, respectively, of their benchmark counterparts. The matched subset is then aggregated into monthly indices using the maturity-weighted scheme of Section B.3.

C Estimation of Synthetic Credit Spreads

When option data in one of the currencies is insufficiently liquid, we generate synthetic put option prices in the missing currency using the Black-Scholes formula, with inputs described in Sections C.1 and C.2. The resulting synthetic options are aggregated into country-level credit spreads following Section B.3.

C.1 Synthetic Strikes, Riskless Rates, and Dividend Yields

To illustrate our framework, let's assume that options data for the ETF denominated in USD (the foreign currency) are not readily available, whereas those for the main stock market index denominated in the local currency are. We generate the synthetic FC-denominated credit spreads using pseudo bond prices $\widehat{B}_t^{\$}(K^{FC}, T)$, computed as:

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

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

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

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. The time to maturity τ and the dividend yield are fixed to be identical to those of the available twin LC option. We compute the riskless rate in FC by applying the covered interest rate parity condition to the riskless rate denominated in LC. 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:

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

The ex-ante default probability in FC is computed following the description in Section B.1, but applied to the stock index in FC. We describe how we construct the implied volatility in FC in the next section.

C.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:

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

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

$$\mathrm{d}A_t^{\$} \;\; = A_t^{\$} \left[\left(\mu^S + \mu + \rho\sigma\sigma^S \right) \mathrm{d}t + \sigma^{\$} \mathrm{d}W_t^{\$} \right],$$

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

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

with

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

which we can compute using implied volatilities of foreign exchange and stock index options. We measure use σ_S using at-the-money implied volatilities of exchange rate options from Bloomberg. To estimate σ, we use local-currency options of similar moneyness, avoiding biases from differences in the implied volatility smile. Where necessary, we also match the maturity of the exchange-rate options by interpolation. The correlation ρ between exchange rate returns and asset returns is obtained using a 5-year rolling window. Our results are similar when we use dynamic conditional correlations (Engle, 2002).

D American Option Bias in Pseudo Credit Spreads

The local-currency spread uses European options on local equity indices, while the foreign-currency spread uses American options on USD-denominated ETFs. Because American options embed an early-exercise premium absent from our European-option mapping, this difference may bias the foreign-currency spread.

We show that this bias is small because the options are short-dated and out of the money, limiting the value of early exercise. Treating an American put as European overstates the foreign-currency spread and therefore the difference between FC and LC spreads. We quantify this bias theoretically and then assess it empirically using the United Kingdom as a case study.

D.1 Model-Implied Early-Exercise Premium

The early-exercise premium is the value of exercising before maturity, $\text{EEP} = P_{\text{American}} - P_{\text{European}} \geq 0$. Since American puts have no closed-form price, we value them in a Black-Scholes setting with continuous dividend yield q using a 2,000-step Cox-Ross-Rubinstein tree. We compute the EEP as the difference between American and European prices on the same tree.

The foreign-currency pseudo bond and its implied spread are $\widehat{B}_t^{\$}(K^{\$}, T) = K^{\$}\widehat{Z}_t^{\$}(T) - \widehat{P}_t^{\$}(K^{\$}, T)$; $\widehat{cs}_t^{\$} = -(T-t)^{-1}\ln(\widehat{B}_t^{\$}/K^{\$}) - \widehat{r}_t^{\$}(T)$. Treating an American put as European understates the pseudo-bond value and therefore overstates the foreign-currency spread by:

$$\text{bias}_{cs} \;=\; (T-t)^{-1}\,\ln\!\left(\widehat{B}_t^{\$,\text{E}}/\widehat{B}_t^{\$,\text{A}}\right) \;\geq\; 0, \tag{D.1}$$

where $\widehat{B}_t^{\$,\text{E}}$ and $\widehat{B}_t^{\$,\text{A}}$ use European and American put prices, respectively. The foreign-currency spread, and thus the quanto spread $CS^{Quanto} = CS^{\$} - CS^{LC}$, is overstated by this amount.

We calibrate the model and compute the bias across moneyness and interest rates. Figure A.1 reports the bias relative to the spread level for three- and six-month options. In the out-of-the-money region used for construction, where implied leverage $K/A < 1$, the bias is negligible: for $K/S \leq 0.8$, it never exceeds 2.1 basis points, or 1.3% of the spread, even at $r = 5\%$. This reflects the limited value of early exercise for out-of-the-money puts. Even at

the money and $r = 5\%$, the bias reaches only 32 basis points against a spread of roughly 1,300 basis points, or 2.4%. This case is rare, as USD rates reached 5% only in 2022–2023 and at-the-money strikes correspond to the riskiest pseudo firms. The bias increases with interest rates and maturity and decreases with dividend yields and distance from the money.

D.2 Empirical Assessment

We assess the bias empirically using the United Kingdom, where the local-currency spread uses European FTSE 100 options and the foreign-currency spread uses American options on a USD-denominated ETF tracking the same index. To isolate early exercise, we reprice the USD options as European using Black-Scholes-Merton and compare the resulting foreign-currency spread with that based on observed American prices.

Figure A.2 compares the six-month UK foreign-currency spreads under our baseline methodology with those obtained by repricing the observed American puts as European using Black-Scholes-Merton. The two series exhibit nearly identical levels and dynamics, except around the COVID-19 pandemic.

As explained in Appendix C, missing option data in one currency are replaced with synthetic options constructed from the other currency. For the United Kingdom, GBP-denominated FTSE 100 options generate synthetic USD options, which are already priced as European using Black-Scholes-Merton. Hence, Figure A.2 differs only when observed American ETF puts are available, primarily after 2017.

E 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.

E.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,

   $$dA_t/A_t = \mu_A\, dt + \sigma_A\, dW_t. \tag{D.2}$$

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

   $$A_{t+\Delta} = A_t \exp\Big[(\mu_A - \tfrac{1}{2}\sigma_A^2)\Delta + \sigma_A\sqrt{\Delta}\,\varepsilon_t\Big], \tag{D.3}$$

   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:

   $$K_t = K_0 e^{\mu_A t}. \tag{D.4}$$

3. *Equity and debt valuation.*

Under the risk-neutral measure Q, define

$$d_1 = \frac{\ln(A_t/K_t) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}, \qquad d_2 = d_1 - \sigma_A\sqrt{T}. \tag{D.5}$$

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

$$E_t = A_t\,\Phi(d_1) - K_t\,e^{-rT}\,\Phi(d_2), \tag{D.6}$$

$$B_t = K_t e^{-rT} - \big[K_t\,\Phi(-d_2) - A_t\,\Phi(-d_1)\big]. \tag{D.7}$$

The continuously compounded yield and credit spread are given by

$$y_t = -\frac{1}{T}\ln\left(\frac{B_t}{K_t}\right), \qquad s_t = y_t - r. \tag{D.8}$$

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

   The physical default probability at horizon T is

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

   and the corresponding risk-neutral probability is

$$\mathrm{PD}_t^{(Q)} = \Phi\left(\frac{\ln(K_t/A_t) - (r - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right). \tag{D.10}$$

5. *Construct the pseudo firm.*

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

$$A_t^{(\mathrm{ps})} = E_t. \tag{D.11}$$

   (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

$$\eta_t = \frac{A_t}{E_t}\Phi(d_1), \tag{D.12}$$

the pseudo asset's drift and volatility under P are

$$\mu_{A,t}^{(\mathrm{ps})} = r + \eta_t(\mu_A - r), \qquad \sigma_{A,t}^{(\mathrm{ps})} = \eta_t \sigma_A, \tag{D.13}$$

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:

$$\Phi\left(\frac{\ln(K_t^{(\mathrm{ps})}/A_t^{(\mathrm{ps})}) - (\mu_{A,t}^{(\mathrm{ps})} - \frac{1}{2}(\sigma_{A,t}^{(\mathrm{ps})})^2)T}{\sigma_{A,t}^{(\mathrm{ps})}\sqrt{T}}\right) = \Phi\left(\frac{\ln(K_t/A_t) - (\mu_A - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right). \tag{D.14}$$

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

$$d_1^{(\mathrm{ps})} = \frac{\ln(A_t^{(\mathrm{ps})}/K_t^{(\mathrm{ps})}) + (r + \frac{1}{2}(\sigma_t^{(Q)})^2)T}{\sigma_t^{(Q)}\sqrt{T}}, \qquad d_2^{(\mathrm{ps})} = d_1^{(\mathrm{ps})} - \sigma_t^{(Q)}\sqrt{T}. \tag{D.15}$$

The pseudo firm's debt value is then

$$B_t^{(\mathrm{ps})} = K_t^{(\mathrm{ps})}e^{-rT} - \Big[K_t^{(\mathrm{ps})}\Phi(-d_2^{(\mathrm{ps})}) - A_t^{(\mathrm{ps})}\Phi(-d_1^{(\mathrm{ps})})\Big]. \tag{D.16}$$

Its yield and credit spread are

$$y_t^{(\mathrm{ps})} = -\frac{1}{T}\ln\left(\frac{B_t^{(\mathrm{ps})}}{K_t^{(\mathrm{ps})}}\right), \qquad s_t^{(\mathrm{ps})} = y_t^{(\mathrm{ps})} - r. \tag{D.17}$$

The corresponding physical and risk-neutral default probabilities are

$$\mathrm{PD}_t^{(P,\mathrm{ps})} = \Phi\left(\frac{\ln(K_t^{(\mathrm{ps})}/A_t^{(\mathrm{ps})}) - (\mu_{A,t}^{(\mathrm{ps})} - \frac{1}{2}(\sigma_{A,t}^{(\mathrm{ps})})^2)T}{\sigma_{A,t}^{(\mathrm{ps})}\sqrt{T}}\right), \tag{D.18}$$

$$\mathrm{PD}_t^{(Q,\mathrm{ps})} = \Phi\left(\frac{\ln(K_t^{(\mathrm{ps})}/A_t^{(\mathrm{ps})}) - (r - \frac{1}{2}(\sigma_t^{(Q)})^2)T}{\sigma_t^{(Q)}\sqrt{T}}\right). \tag{D.19}$$

We then compute

$$\left(\frac{Q}{P}\right)_{\text{firm}} = \frac{\text{PD}_t^{(Q)}}{\text{PD}_t^{(P)}}, \qquad \left(\frac{Q}{P}\right)_{\text{pseudo}} = \frac{\text{PD}_t^{(Q,\text{ps})}}{\text{PD}_t^{(P,\text{ps})}}. \tag{D.20}$$

E.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.3 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. Although pseudo-firm assets closely track firm equity, pseudo-firm credit spreads are larger and more volatile than those of the underlying firm. This difference reflects the nonlinear mapping from firm assets into equity and then into pseudo debt, which gives the pseudo spread a compound option structure (Geske, 1979).

Figure A.4 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 remain strongly related to those of the underlying firm, but pseudo-firm spreads are systematically higher in magnitude. This gap arises because the pseudo bond is written on firm equity rather than directly on firm assets, so the compound option structure amplifies the nonlinear response of spreads to changes in underlying risk. Thus, the pseudo spread preserves the underlying credit-risk signal while embedding stronger option-induced curvature.

E.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 $\sigma_t^{(Q)} = 1.5\,\sigma_{A,t}^{(\text{ps})}$.[11]

[11] 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 $\sqrt{33.23/14.93} \approx 1.5$.

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.

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.

F 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.

F.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 μ 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.

F.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

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

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.

F.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 (F.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 σ 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.5 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 Culp et al. (2018). The results, reported in Figure A.6, show that the model generates lower index spreads than firm-level spreads across all rating categories, consistent with the data.

G Derivations of the Model of Local and Foreign Currency Credit Spreads

G.1 Fundamental Equation of Asset Pricing in Continuous Time

We here verify that

$$\mathbb{E}_t\left[\frac{d(M_tX_t)}{M_tX_t}\right] = 0 \tag{G.1}$$

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

$$\frac{dB_t}{B_t} = rdt, \tag{G.2}$$

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

We indeed have

$$\mathbb{E}_t\left[\frac{d(M_tB_t)}{M_tB_t}\right] = \underbrace{\mathbb{E}\left[\frac{dM_t}{M_t}\right]}_{-rdt} + \underbrace{\mathbb{E}\left[\frac{dB_t}{B_t}\right]}_{rdt} + \underbrace{\mathbb{E}\left[\frac{dM_t}{M_t}\frac{dB_t}{B_t}\right]}_{0} = 0, \tag{G.3}$$

which verifies that Equation (G.1) holds.

G.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):

$$\begin{aligned} df(M,S,B^\$) = {} & \frac{B^\$}{S}\,dM - \frac{MB^\$}{S^2}\,dS + \frac{M}{S}\,dB^\$ \\ & + \frac{1}{2}\left(2M\frac{B^\$}{S^3}(dS)^2 + 0(dM)^2 + 0(dB^\$)^2\right) \\ & - \frac{1}{S^2}B^\$dMdS + \frac{1}{S}dMdB^\$ - M\frac{1}{S^2}dSdB^\$. \end{aligned} \tag{G.4}$$

After taking expectations, we obtain

$$\begin{aligned}\mathbb{E}_t\left[df(M,S,B^{\$})\right] = \mathbb{E}_t\left[\frac{B^{\$}}{S}\,dM\right] - \mathbb{E}_t\left[\frac{MB^{\$}}{S^2}\,dS\right] + \mathbb{E}_t\left[\frac{M}{S}\,dB^{\$}\right] \\ + \underbrace{\mathbb{E}_t\left[M\frac{B^{\$}}{S^3}(dS)^2\right]}_{M\frac{B^{\$}}{S}\sigma_S^2 dt} - \mathbb{E}_t\left[\frac{1}{S^2}B^{\$}dMdS\right] \\ + \underbrace{\mathbb{E}_t\left[\frac{1}{S}dMdB^{\$}\right]}_{0} - \underbrace{\mathbb{E}_t\left[M\frac{1}{S^2}dSdB^{\$}\right]}_{0}.\end{aligned} \tag{G.5}$$

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

$$\mathbb{E}_t\left[\frac{df(M,S,B^{\$})}{M(1/S)B^{\$}}\right] = \underbrace{\mathbb{E}_t\left[\frac{dM}{M}\right]}_{-rdt} - \mathbb{E}_t\left[\frac{dS}{S}\right] + \underbrace{\mathbb{E}_t\left[\frac{dB^{\$}}{B^{\$}}\right]}_{r^{\$}dt} + \sigma_S^2 dt - \mathbb{E}_t\left[\frac{dM}{M}\frac{dS}{S}\right]. \tag{G.6}$$

Finally, after re-arranging, we obtain

$$\mathbb{E}_t\left[\frac{dS}{S}\right] = (r^{\$} - r + \sigma_S^2)dt - \mathbb{E}_t\left[\frac{dM}{M}\frac{dS}{S}\right]. \tag{G.7}$$

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 Sources

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 in the last row of the table.

						Local CCY Index - LC			Foreign CCY Index - USD ETF
		(1)	(2)	(3)		(4)	(5)	(6)	(7)
Country	Exchange rate	IV ATM	Forward	Forward DTM	Index Name	Price index	Total Return	Dividend	Price index
Australia	AUD/USD	✓	✓	✓	S&P/ASX 200	✓	✓	-	✓
Belgium	EUR/USD	✓	✓	✓	Belgium 20	✓	✓	-	✓
Brazil	BRL/USD	✓	✓	✓	BOVESPA	-	✓	✓	✓
Canada	CAD/USD	✓	✓	✓	S&P/TSX 60 INDEX	✓	✓	✓	✓
Chile	CLP/USD	✓	✓	✓	S&P/CLX IGPA	✓	-	-	✓
China	CNH/USD	✓	✓	✓	CHINAAMC CHINA 50 ETF	✓	-	✓	✓
Colombia	COP/USD	✓	✓	✓	MSCI COLCAP INDEX	✓	-	-	✓
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)	✓	✓	-	✓
Indonesia	IDN/USD	✓	✓	✓	IDX COMPOSITE INDEX	✓	-	-	✓
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	✓	-	✓	✓
Netherlands	EUR/USD	✓	✓	✓	AEX INDEX	✓	✓	✓	✓
New Zealand	NZD/USD	✓	✓	✓	S&P/NZX 50	✓	-	-	✓
Norway	NOK/USD	✓	✓	✓	OSLO SE OBX	✓	✓	-	✓
Poland	PLN/USD	✓	✓	✓	WARSAW GENERAL INDEX 20	✓	✓	-	✓
Singapore	SGD/USD	-	-	-	MSCI SINGAPORE	-	-	-	-
South Africa	ZAR/USD	✓	✓	✓	FTSE/JSE	✓	✓	✓	✓
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	✓	✓	✓	✓
United States	-	-	-	-	S&P 500	✓	-	✓	-
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	
		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 B.2. 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
Denmark	SPX box rate + CIP	332	0.018	0.020	0.020	-0.006	0.049
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
New Zealand	SPX box rate + CIP	332	0.006	0.003	0.030	-0.031	0.060
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
Chile	SPX box rate + CIP	311	0.048	0.043	0.035	0.001	0.108
China	Asian index	96	0.026	0.027	0.017	0.003	0.052
Colombia	SPX box rate + CIP	295	0.067	0.059	0.044	0.018	0.142
India	Asian index	169	0.065	0.064	0.017	0.039	0.097
Indonesia	SPX box rate + CIP	235	0.077	0.067	0.047	0.034	0.145
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
South Africa	SPX box rate + CIP	332	0.090	0.077	0.035	0.054	0.162
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	λ_S	0.02
Exchange rate return volatility	σ_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	μ	0.06
Stock market risk premium	λ_A	0.041
Correlation between LC stock index and exchange rate	ρ	0.13
Stock index return volatility	σ	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 B and C 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 2023.

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.	$\rho_{CS^{LC},CS^{\$}}$	ρ_{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
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	3,333	3.84	2.68	3.57	0.43	10.57	3,225	5.70	4.48	4.40	1.29	14.37	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 B and C 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 2023.

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.	$\rho_{CS^{LC},CS^{\$}}$	ρ_{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 B and C 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 2023.

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 B and C 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 2023.

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)	1704	0.046	0.038	0.000	0.293	0.010	0.093
CS Diff (USD-LC,3m)	1653	0.013	0.031	-0.155	0.236	-0.021	0.047
Default Prob (3m)	1703	0.069	0.051	0.000	0.329	0.013	0.140
Q - P (LC,3m)	1703	0.060	0.056	-0.239	0.288	0.006	0.141
Q Diff (USD-LC,3m)	1653	0.012	0.065	-0.201	0.302	-0.076	0.084

Local Determinants

	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
Exp Return (LC)	1218	0.066	0.040	-0.105	0.227	0.014	0.120
Return Vol (LC)	1217	0.090	0.025	0.033	0.208	0.061	0.121
Exp Return (USD)	1206	0.069	0.048	-0.058	0.270	0.016	0.131
Return Vol (USD)	1206	0.121	0.032	0.048	0.320	0.086	0.173
FX Return (USD/LC)	1703	-0.006	0.044	-0.349	0.210	-0.055	0.042
FX Volatility	1702	0.096	0.046	0.004	0.411	0.053	0.150
LC Risk-free Rate	1492	0.025	0.034	-0.062	0.430	-0.004	0.070
FX Reserves (USD)	1428	11.253	1.321	7.813	14.814	9.860	12.892
Local Inflation	1414	0.028	0.025	-0.026	0.164	0.002	0.061

Global Determinants

	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
USD Risk-free Rate	1704	0.012	0.016	0.000	0.053	0.000	0.046
Term Spread	1704	1.325	1.226	-1.720	3.570	-0.450	2.777
CFNAI	1704	-0.125	0.577	-2.393	1.433	-0.353	0.303
Macro Uncertainty	1704	0.826	0.135	0.668	1.277	0.707	0.995
GZ Spread	716	2.570	1.148	1.580	7.565	1.727	3.602
EBP	716	0.031	0.646	-0.580	2.555	-0.345	0.787

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)	1731	0.006	0.016	-0.068	0.081	0.003	0.010
Agg growth (NoUS,EW,3m)	1715	0.006	0.019	-0.109	0.087	0.001	0.012
Agg growth (VW,3m)	1731	0.006	0.016	-0.072	0.080	0.002	0.009
Agg growth (EW,3m)	1715	0.006	0.019	-0.107	0.086	0.002	0.012
Agg growth (NoUS,VW,12m)	1731	0.024	0.027	-0.103	0.124	-0.009	0.038
Agg growth (VW,12m)	1731	0.023	0.026	-0.096	0.121	-0.009	0.035
Agg growth (NoUS,EW,12m)	1655	0.023	0.030	-0.124	0.130	-0.007	0.044
Agg growth (EW,12m)	1655	0.023	0.029	-0.120	0.129	-0.006	0.042
Country growth (12m)	1653	0.020	0.039	-0.248	0.228	-0.017	0.059
FX Return (USD/LC,12m)	1655	-0.025	0.102	-0.756	0.316	-0.152	0.081

Credit Spreads and Risk Decomposition

	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
CS LC (AVG)	1731	0.042	0.031	0.000	0.336	0.010	0.080
CS Diff (USD-LC,AVG)	1674	0.011	0.026	-0.144	0.236	-0.015	0.042
Default Probability (P)	1703	0.069	0.051	0.000	0.329	0.013	0.140
Default Prob (avg)	1730	0.100	0.061	0.000	0.348	0.017	0.180
Default Premium (Q - P)	1703	0.060	0.056	-0.239	0.288	0.006	0.141
Q - P (LC,avg)	1730	0.084	0.064	-0.153	0.301	0.014	0.174

Controls

	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
CS US (orth,3m)	1596	-0.000	0.985	-2.560	7.037	-0.875	0.934
CS US (orth,avg)	1616	-0.000	1.008	-2.664	6.514	-0.887	0.969
Term Spread	1731	1.321	1.223	-1.720	3.570	-0.427	2.730
Macro Uncertainty	1731	0.826	0.134	0.668	1.277	0.707	0.995
FFR	1731	1.248	1.654	0.060	5.330	0.083	4.517
GZ Spread (orth,3m)	713	-0.000	0.410	-1.223	1.506	-0.372	0.337
GZ Spread (orth,avg)	719	0.000	0.409	-1.197	1.481	-0.377	0.379
Country growth	1728	0.005	0.025	-0.259	0.204	-0.006	0.018

Measures of FX Cyclicality

	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
Corr (LC Index,FX)	1572	0.200	0.266	-0.597	0.759	-0.182	0.532
Corr (SPX,FX)	1711	0.393	0.237	-0.445	0.848	0.060	0.680
Corr (US Cons,FX)	1711	0.079	0.131	-0.335	0.529	-0.068	0.253

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 ΔY_{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 (ε_{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	-5.279***	-7.355***	-5.236***	-7.350***	-6.965***	-8.824***	-6.819***	-8.707***
	(-7.17)	(-5.24)	(-7.38)	(-5.58)	(-8.12)	(-6.12)	(-8.11)	(-6.16)
Default Premium (Q - P)	-1.832***	-0.418	-1.911***	-0.634	-2.547***	-0.896	-2.505***	-0.912
	(-2.74)	(-0.30)	(-2.99)	(-0.48)	(-3.33)	(-0.62)	(-3.34)	(-0.65)
Term Spread	0.327***	0.824***	0.304***	0.723***	0.454***	0.987***	0.438***	0.946***
	(8.86)	(9.26)	(8.60)	(8.66)	(10.76)	(10.86)	(10.58)	(10.62)
Macro Uncertainty	3.780***	8.734***	3.926***	8.894***	5.431***	11.723***	5.328***	11.503***
	(10.20)	(10.28)	(11.06)	(11.25)	(12.81)	(13.83)	(12.82)	(13.85)
CS US	-0.791***	-0.775***	-0.806***	-0.812***	-1.053***	-0.893***	-1.035***	-0.893***
	(-15.77)	(-7.73)	(-16.46)	(-8.60)	(-17.51)	(-8.58)	(-17.54)	(-8.76)
Constant	-2.389***	-5.162***	-2.531***	-5.251***	-3.899***	-7.885***	-3.808***	-7.669***
	(-7.35)	(-6.90)	(-8.14)	(-7.55)	(-10.55)	(-10.61)	(-10.51)	(-10.53)
Observations	1,596	1,616	1,596	1,616	1,596	1,616	1,596	1,616
R-squared	0.183	0.168	0.174	0.166	0.165	0.213	0.165	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.4, 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
Poland	LC	LC	LC	-
South Africa	FC	FC	FC	-
Thailand	LC	FC	FC	-
Turkey	FC	FC	FC	FC

Table A.14: Real-Activity Predictability: Crisis Robustness of the Local-Currency Spread

This table reports the coefficient on the GDP-weighted local-currency spread $\overline{\text{CS}}^{LC}$ from local projections of cumulative GDP-weighted real GDP growth (in percent) over the next h quarters, from Eq. (22). Panel A uses the ex-U.S. growth measure and Panel B includes the United States. Each panel reports the coefficient on the full sample, after dropping the 2020–2021 Covid recession (Ex-Covid), and after dropping the 2020–2021 and 2008–2009 crises jointly (Ex-Covid & GFC). All specifications include the term spread, the real federal funds rate, and the macro-uncertainty index. The data are quarterly over 2005–2023, with Newey-West t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: Without U.S.

Horizon	Full	Ex-Covid	Ex-Covid & GFC
$h = 1$	-0.190	-0.111	-0.049
	$(-2.15)^{**}$	$(-2.59)^{***}$	(-1.18)
$h = 2$	-0.223	-0.113	-0.122
	$(-2.26)^{**}$	(-1.28)	(-1.00)
$h = 4$	-0.457	-0.364	-0.413
	$(-2.35)^{**}$	$(-2.23)^{**}$	$(-2.48)^{**}$
$h = 6$	-0.618	-0.553	-0.772
	$(-1.99)^{**}$	$(-1.84)^{*}$	$(-2.27)^{**}$

Panel B: With U.S.

Horizon	Full	Ex-Covid	Ex-Covid & GFC
$h = 1$	-0.181	-0.104	-0.057
	$(-2.23)^{**}$	$(-2.51)^{**}$	$(-1.66)^{*}$
$h = 2$	-0.225	-0.118	-0.128
	$(-2.31)^{**}$	(-1.29)	(-1.15)
$h = 4$	-0.456	-0.369	-0.429
	$(-2.56)^{**}$	$(-2.41)^{**}$	$(-2.86)^{***}$
$h = 6$	-0.593	-0.539	-0.756
	$(-2.06)^{**}$	$(-1.92)^{*}$	$(-2.38)^{**}$

Table A.15: Recession Classification and the US Pseudo Credit Spread

This table reports probit models for a U.S. NBER recession indicator one quarter ahead. The regressors are the aggregate local-currency spread $\overline{\text{CS}}^{LC}$ and the U.S. pseudo credit spread CS^{USA} of Culp et al. (2018), the equally-weighted average of the 6-month, 1-year, and 2-year U.S. high-yield and investment-grade pseudo spreads. Column 3 combines $\overline{\text{CS}}^{LC}$ with the orthogonalized spread $\widetilde{\text{CS}}^{USA}$, the residual from projecting CS^{USA} on $\overline{\text{CS}}^{LC}$, so that its two coefficients isolate the shared and the U.S.-specific components. Panel A includes no controls; Panel B adds the term spread, the real federal funds rate, and the macro-uncertainty index. Coefficients are expressed per 100 basis points, and AUC is the area under the ROC curve. The data are quarterly over 2005–2023, with z-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

Panel A: No Controls

	(1) $\overline{\text{CS}}^{LC}$	(2) CS^{USA}	(3) $\overline{\text{CS}}^{LC}+\widetilde{\text{CS}}^{USA}$
$\overline{\text{CS}}^{LC}$	0.540		0.563
	$(3.34)^{***}$		$(3.01)^{***}$
CS^{USA}		0.749	
		$(3.40)^{***}$	
$\widetilde{\text{CS}}^{USA}$			0.542
			$(1.75)^{*}$
Pseudo-R^2	0.33	0.36	0.38
AUC	0.88	0.88	0.88
Observations	76	73	73

Panel B: With Controls

	(1) $\overline{\text{CS}}^{LC}$	(2) CS^{USA}	(3) $\overline{\text{CS}}^{LC}+\widetilde{\text{CS}}^{USA}$
$\overline{\text{CS}}^{LC}$	0.645		0.952
	$(2.99)^{***}$		$(2.87)^{***}$
CS^{USA}		1.338	
		$(2.81)^{***}$	
$\widetilde{\text{CS}}^{USA}$			0.996
			$(1.77)^{*}$
Pseudo-R^2	0.47	0.50	0.53
AUC	0.94	0.94	0.94
Observations	74	71	71

Table A.16: Exchange Rate Predictability Robust to Credit and Quanto Risk Premia

This table reports panel regressions of exchange rate returns on pseudo credit spreads together with the credit risk premium (CRP) of Della Corte et al. (2023) or the quanto risk premium (QRP) of Kremens and Martin (2019). CS^{LC} denotes the local-currency pseudo credit spread and CS^{Quanto} the pseudo quanto spread (USD minus LC). Columns (1)-(2) use the set of currencies of Della Corte et al. (2023) (Euro, Mexico, South Africa, and Turkey in the column without macroeconomic controls), with the 12-month FX return as the dependent variable. Column (3) reproduces Kremens and Martin (2019) Table 5 on their sample period: the dependent variable is instead the 24-month currency appreciation, estimated with currency fixed effects and no time effects over 2009-2015. Columns (4)-(6) use the updated Kremens et al. (2025) QRP series over 2009-2019, with the 12-month FX return as the dependent variable. "With/without controls" refers to the six macro controls (interest rate differential, REER, FX volatility risk premium, GDP growth, log FX reserves, and inflation; coefficients unreported). All specifications except column (3) include country and time fixed effects and Driscoll and Kraay (1998) standard errors, with t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Credit RP (CRP)		**Quanto RP (QRP)**			
	(1) Without controls	(2) With controls	(3) KM (2019) 2009-2015	(4) Full sample 2009-2019	(5) Without controls	(6) With controls
CS^{LC}	0.220	1.402**			0.284*	0.062
	(0.39)	(2.27)			(1.81)	(0.48)
CS^{Quanto}	2.339***	2.021***			0.308**	0.312***
	(5.84)	(4.32)			(2.21)	(3.27)
CRP	1.269**	0.758				
	(2.13)	(0.75)				
QRP			3.269***	1.026	0.911	−0.345
			(3.77)	(0.83)	(0.75)	(−0.29)
Macro controls	—	✓	—	—	—	✓
Country FE	✓	✓	✓	✓	✓	✓
Time FE	✓	✓	—	✓	✓	✓
Observations	126	102	468	534	534	426

Table A.17: Exchange Rate Predictability: Robustness

This table reports robustness results for the baseline panel regression of 12-month-ahead bilateral exchange rate returns $\Delta s_{i,t+4}$ (positive = LC appreciation against USD) on pseudo credit spreads. The sample covers 33 countries over 2005-2023. CS^{LC} denotes the local-currency pseudo credit spread and $\text{CS}^{\text{Quanto}}$ the pseudo quanto spread (USD minus LC), both in decimal units. All specifications include country and time fixed effects, as well as baseline controls (interest rate differential, REER, FX VRP, GDP growth, FX Reserves, Inflation). Column (1) uses cross-maturity average spreads (3, 6, 12, and 24 months) in the full sample. Columns (2)-(5) use 3-month spreads and progressively control for inputs to the synthetic USD spread construction (Equation 10): Column (2) restricts to directly observed USD spreads; Column (3) adds FX implied volatility (σ_{FX}); Column (4) adds local equity implied volatility (σ^{Stock}); and Column (5) adds the stock-FX correlation (ρ). Standard errors are Driscoll and Kraay (1998) standard errors with four lags, with t-statistics in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	Dependent variable: $\Delta s_{i,t+4}$				
	(1)	(2)	(3)	(4)	(5)
	Avg spread	Emp. FC only	$+\sigma_{FX}$	$+\sigma^{Stock}$	$+\rho$
CS^{LC} (avg)	0.296**				
	(2.18)				
$\text{CS}^{\text{Quanto}}$ (avg)	0.480***				
	(3.40)				
CS^{LC}		0.487***	0.391***	0.388***	0.336***
		(3.27)	(4.03)	(4.06)	(3.29)
$\text{CS}^{\text{Quanto}}$		0.401*	0.448***	0.493***	0.412***
		(1.95)	(4.28)	(4.89)	(3.67)
FX implied vol. (σ_{FX})			0.382		
			(1.50)		
Stock implied vol. (σ^{Stock})				0.039	
				(0.96)	
Stock-FX corr. (ρ)					−0.011
					(−0.26)
IRD	−0.304	−0.405	−0.193	−0.313	−0.361
	(−1.03)	(−1.47)	(−0.56)	(−1.07)	(−0.95)
REER	−0.002***	−0.003***	−0.002***	−0.002***	−0.002***
	(−3.39)	(−5.30)	(−2.92)	(−3.39)	(−3.26)
FX VRP	0.261	0.243	0.165	0.210	0.071
	(0.85)	(0.77)	(0.60)	(0.75)	(0.19)
GDP growth	0.013	−0.009	0.031	0.028	0.069
	(0.11)	(−0.08)	(0.24)	(0.22)	(0.52)
Log FX reserves	0.016	0.005	0.015	0.017	0.012
	(0.84)	(0.29)	(0.84)	(0.97)	(0.65)
YoY inflation	0.620***	0.927***	0.587***	0.615***	0.582**
	(2.99)	(3.37)	(2.91)	(2.93)	(2.43)
Observations	1,142	863	1,142	1,142	1,012
R-squared	0.642	0.667	0.650	0.647	0.646
Country FE	✓	✓	✓	✓	✓
Time FE	✓	✓	✓	✓	✓

Table A.18: Currency Portfolios Sorted on the Pseudo Quanto Spread

This table reports long-short currency portfolios, rebalanced quarterly and held for twelve months. Panel A sorts non-U.S. currencies into terciles on each signal (the pseudo quanto spread $\text{CS}^{\text{Quanto}}$, the local-currency spread CS^{LC}, and the carry) and reports the top-minus-bottom return. Panel B double-sorts on the quanto spread and carry: the carry-neutral quanto portfolio sorts currencies into carry terciles, forms the quanto top-minus-bottom within each carry tercile, and averages across the three; the quanto-neutral carry portfolio does the reverse, and both require at least twelve currencies each quarter to support the three-by-three grid. Panel C reports robustness of the $\text{CS}^{\text{Quanto}}$ tercile portfolio to excluding each crisis window and to a quintile long-short. Returns and the Sharpe ratio are annualized and in percent. The data are quarterly over 2005–2023, with Newey-West t-statistics (four lags) in parentheses.

Panel A: Sort Signal (Tercile Long-Short)

	Return (%/yr)	Sharpe	t-stat	Quarters
$\text{CS}^{\text{Quanto}}$	2.38	0.57	3.60	69
CS^{LC}	−1.27	−0.21	−1.15	69
Carry (−IRD)	−2.75	−0.37	−2.04	69

Panel B: Double Sort on $\text{CS}^{\text{Quanto}}$ and Carry

	Return (%/yr)	Sharpe	t-stat	Quarters
$\text{CS}^{\text{Quanto}}$ long-short, carry-neutral	2.31	0.73	4.86	64
Carry long-short, quanto-neutral	−3.21	−0.44	−2.34	64

Panel C: $\text{CS}^{\text{Quanto}}$ Portfolio Robustness

	Return (%/yr)	Sharpe	t-stat	Quarters
Excluding 2020–2021	2.67	0.62	4.05	61
Excluding 2008–2009	2.04	0.61	3.81	61
Quintile long-short (Q5−Q1)	2.45	0.44	2.57	69

Figure A.1: Early-Exercise Bias from Treating American ETF Puts as European.

This figure plots the overstatement of the foreign-currency pseudo spread as a percentage of the spread level across moneyness K/S, assuming $\sigma = 25\%$ and dividend yield $q = 2\%$. Solid and dashed lines correspond to six- and three-month options, respectively, for risk-free rates $r \in 1\%, 3\%, 5\%$, spanning USD rates over 1996–2023. The shaded area denotes the out-of-the-money strike region used in pseudo-bond construction. Results are similar at other volatilities.

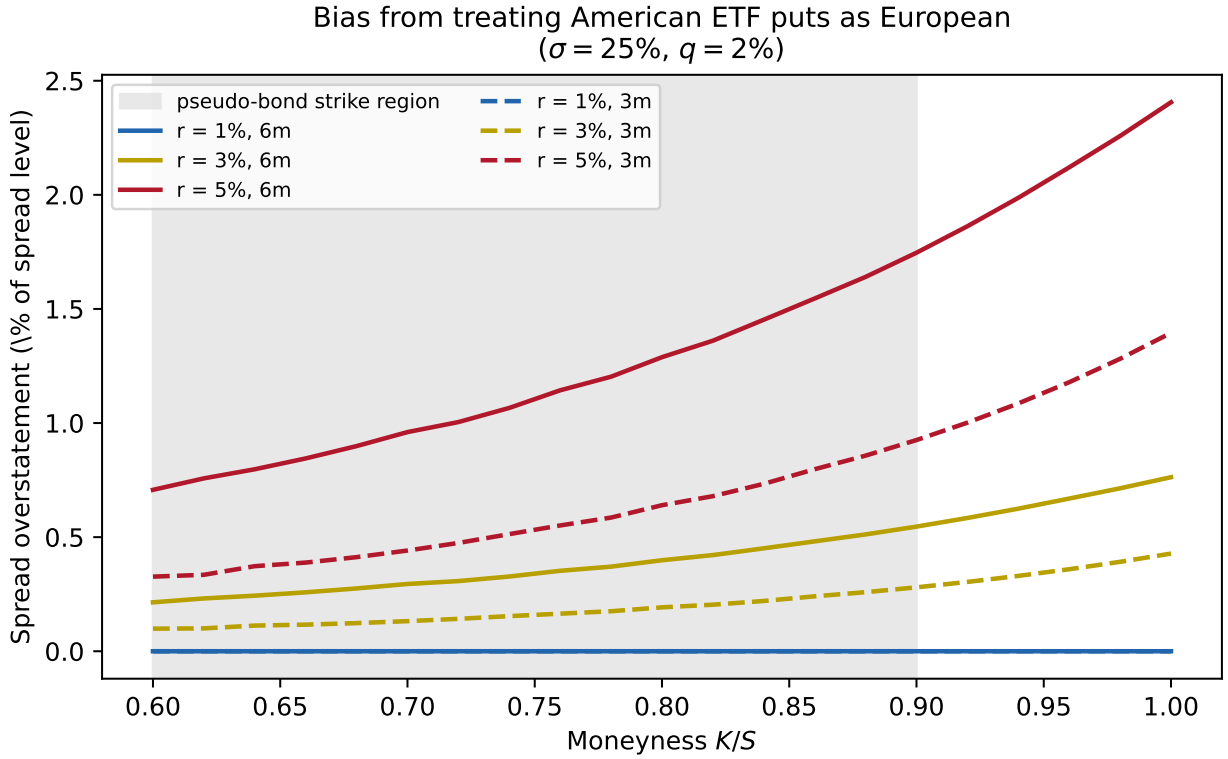


Figure A.2: American versus European Treatment of UK Foreign-Currency Spreads.

This figure plots the six-month UK foreign-currency pseudo spread under two treatments of the ETF put options. The baseline uses observed American option prices, while the alternative reprices the same options as European using Black–Scholes–Merton. Before 2017, both series use synthetic USD options constructed from GBP-denominated FTSE 100 options and therefore coincide.

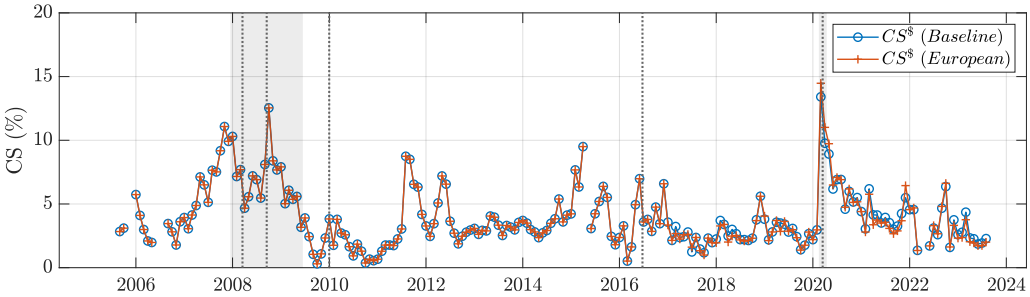


Figure A.3: Dynamics of Firm and Pseudo-Firm Credit Risk: Single Simulation.

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 $r = 3\%$.

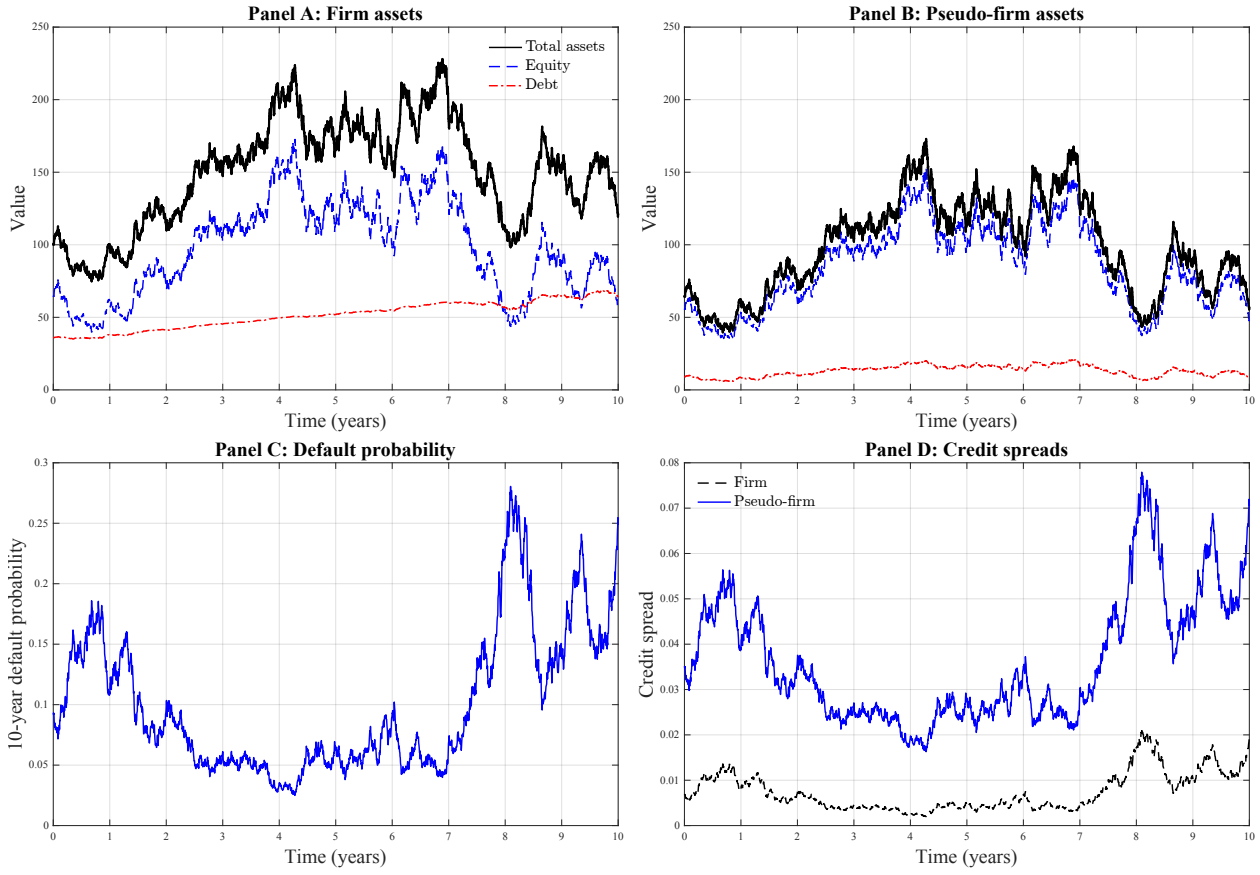


Figure A.4: Linking Pseudo and Firm Credit Spreads: Simulation Evidence.

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.

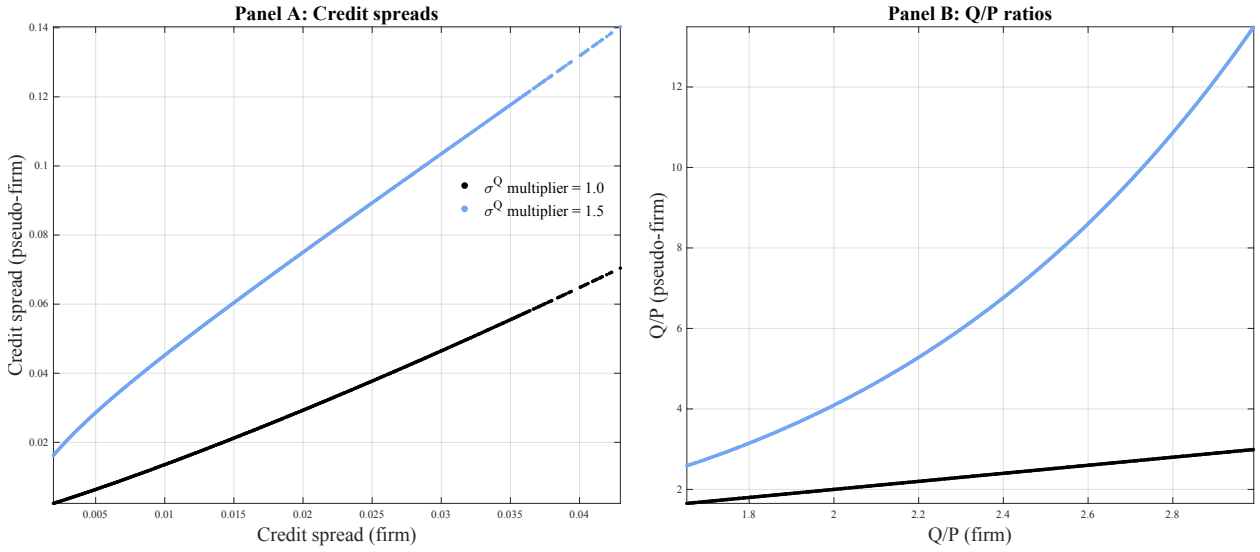


Figure A.5: Decomposition of credit spreads as a function of asset volatility.

The figure illustrates how asset volatility σ 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 $r = 3\%$.

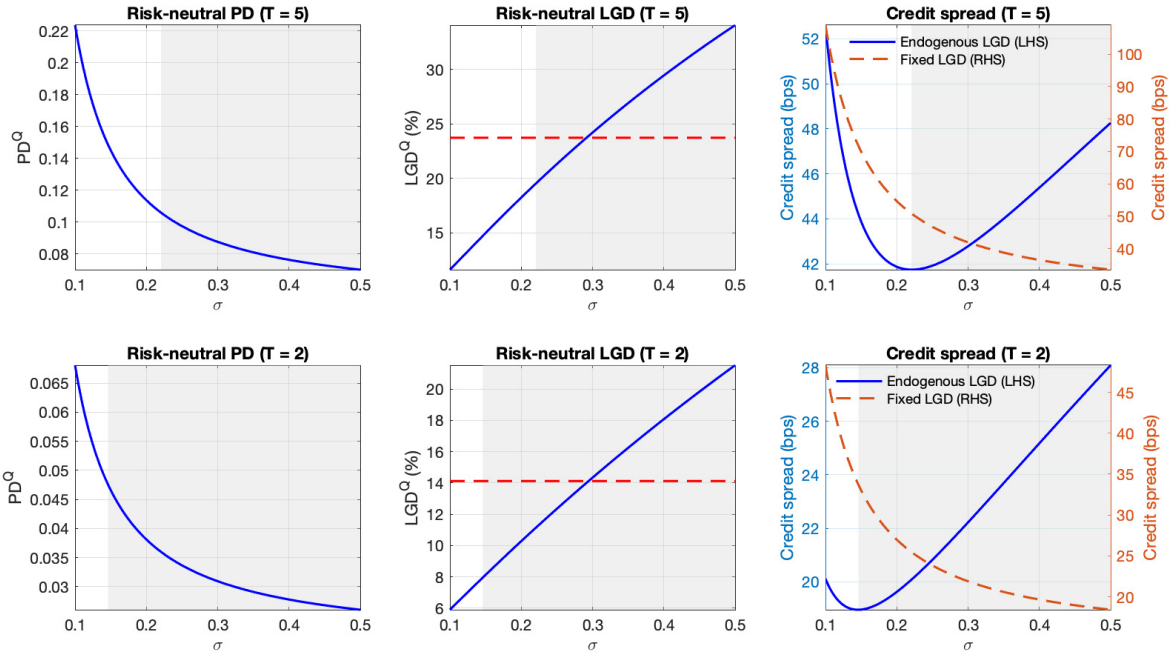


Figure A.6: Firm-level vs. index credit spreads.

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.

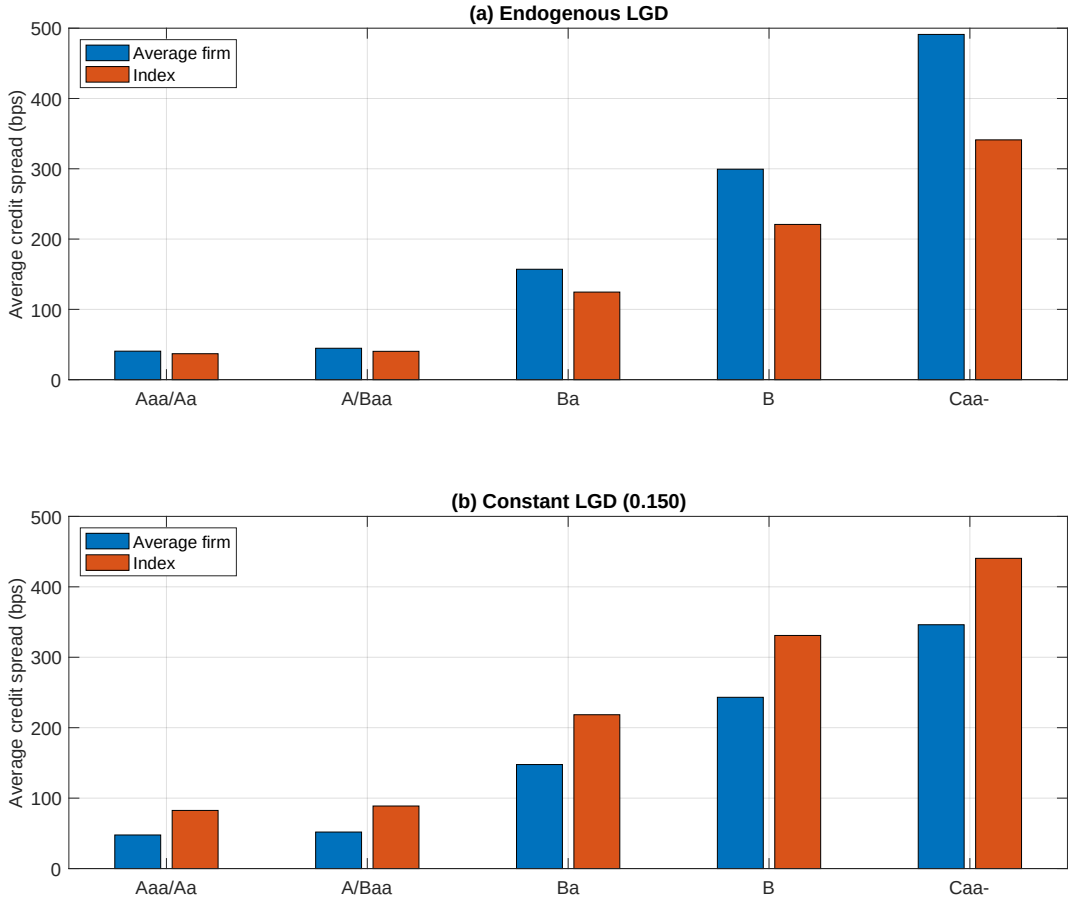


Figure A.7: Leave-One-Country-Out Jackknife.

This figure reports coefficient estimates from the baseline panel specification (23) using Driscoll and Kraay (1998) standard errors (four lags) and the full set of macroeconomic control variables (interest rate differential, REER, FX volatility risk premium, GDP growth, log FX reserves, and inflation), where each marker sequentially re-estimates the baseline exchange-rate panel (Table 10, column 4), dropping one country at a time. The left panel shows estimates of $\hat{\gamma}_1$ (LC pseudo spread), and the right panel estimates of $\hat{\gamma}_2$ (pseudo quanto spread). Blue (red) markers denote advanced (emerging market) economies. The shaded green band indicates the full-sample 90% confidence interval, and the dashed vertical line the full-sample estimate using 90% Driscoll–Kraay confidence intervals. All estimates use 3-month pseudo spreads with standard errors clustered by quarter.

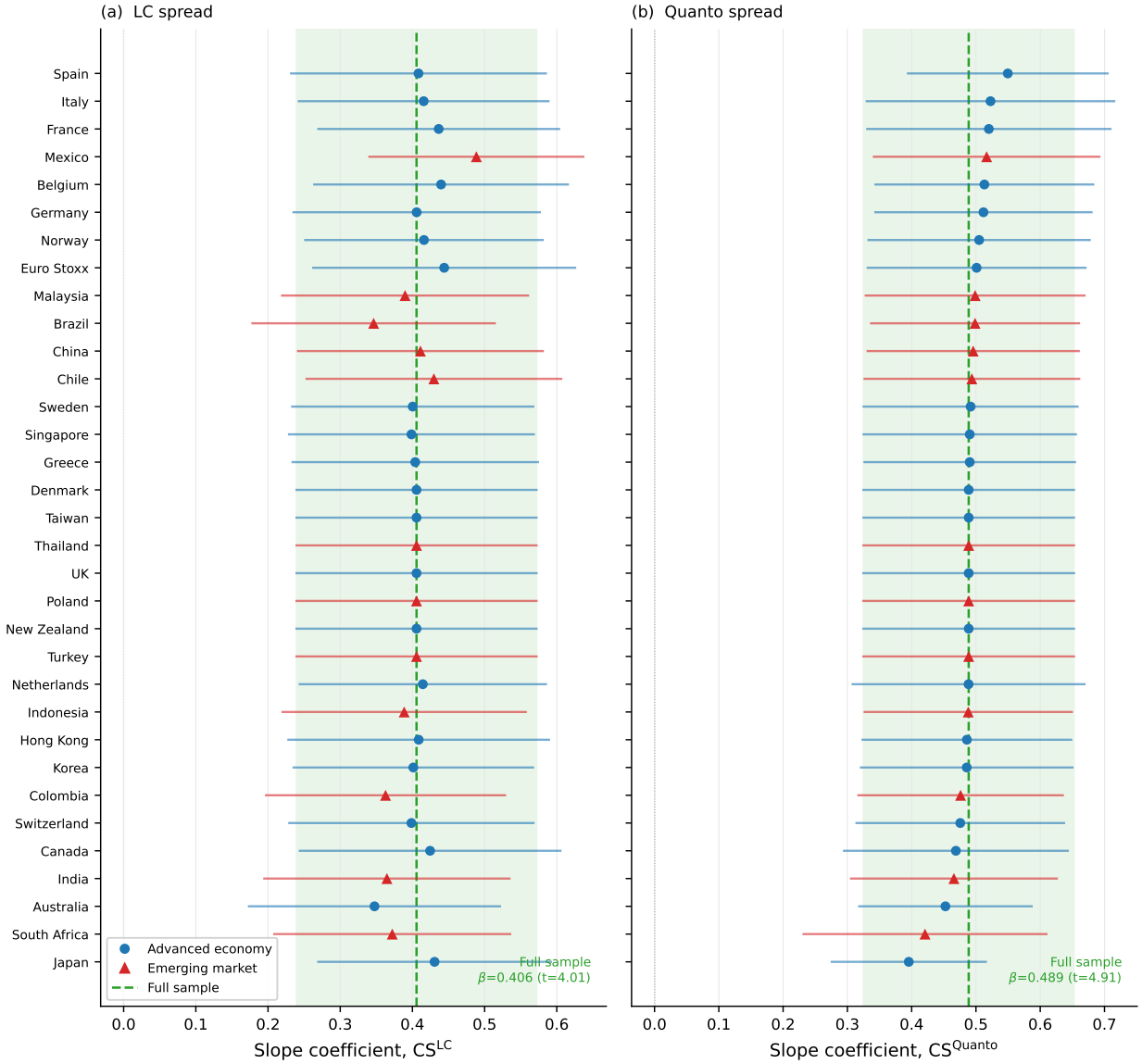


Figure A.8: Cumulative Performance of the Quanto-Sorted Currency Portfolio

This figure plots the cumulative arithmetic return (in percent) of the pseudo quanto spread (CS^{Quanto}) tercile long-short currency portfolio and of the equal-weighted average non-U.S. currency return against the U.S. dollar. Each quarter, the long-short portfolio is long the top tercile and short the bottom tercile sorted on the 3-month quanto spread, held for twelve months and implemented as four overlapping quarterly tranches. A positive value denotes local-currency appreciation. Shaded areas denote U.S. NBER recessions (2007:Q4–2009:Q2 and 2020:Q1–2020:Q2). The data are quarterly over 2005–2023.

