

Option-Implied Local Currency Credit Spreads

ABSTRACT

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

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1 Introduction

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

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

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

We then construct matched credit spreads for pseudo-firms with identical default probabilities but debt denominated in different currencies. To obtain the foreign-currency (FC) counterpart, we use USD-denominated ETFs that track the local stock market index and the put options written on these ETFs. When options on the USD ETFs lack sufficient liquidity,

we synthesize USD credit spreads by combining option-implied volatility on the local index and the exchange rate.

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

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

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

We first document several empirical properties of pseudo credit spreads. Pseudo spreads closely resemble credit spreads inferred from corporate bonds in both magnitude and cyclical behavior. For example, the average six-month local-currency (LC) pseudo spread for

developed economies is approximately 3.44%, about 120 basis points lower than the 4.64% observed for the foreign-currency (FC) counterpart. FC spreads are generally higher and more sensitive to economic downturns.

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

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

We next examine the determinants of LC credit spreads, addressing the literature’s predominant focus on USD-denominated spreads. LC spreads respond strongly to both default risk and risk premia: a 1 percentage point increase in the physical default probability P raises spreads by about 35 basis points, while a 1 percentage point increase in the risk premium ($Q - P$), where Q denotes the risk-neutral default probability, raises spreads by roughly 55 basis points. LC spreads also increase with higher stock market volatility, currency depreciation, and elevated economic uncertainty, consistent with heightened perceived risk. Conversely, spreads tend to be lower in countries with larger foreign exchange reserves and lower domestic inflation, suggesting that stronger monetary policy credibility helps anchor

local-currency credit conditions.

Turning to pseudo quanto spreads – the difference between USD and LC credit spreads, we find that they primarily capture cross-currency variation in risk premia. In line with our model, pseudo quanto spreads arise from the covariance between default risk and the pricing kernel, rather than from differences in default probabilities. Their dynamics are driven by exchange rate volatility, relative equity market performance, and interest rate differentials, while global factors play a more limited role. These findings establish the pseudo quanto spread as a measure of currency-specific pricing of credit risk.

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

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

Our empirical findings are consistent with evidence of exchange rate predictability with mea-

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

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

More broadly, our work connects to the literature on firms’ currency choices in debt issuance. [Maggiori, Neiman, and Schreger \(2020\)](#) document that larger firms are more likely to issue debt in foreign currency, while smaller firms predominantly borrow in local currency. Similarly, [Eren, Malamud, and Zhou \(2023\)](#) show that firms in emerging markets often favor foreign currency debt, even when local currency borrowing would provide a better hedge during economic downturns. Using firm-level bond data, [Bruno and Shin \(2017, 2020\)](#) find that emerging market firms frequently pursue a carry trade strategy by issuing

dollar-denominated debt to finance investments in domestic currency assets.

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

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

2 Methodology

We introduce a novel measure of multi-currency credit risk derived from option markets. Building on Culp et al. (2018), who infer credit spreads for synthetic, or “pseudo,” firms from traded put options, we revisit the construction of pseudo bonds to ensure alignment with their methodology. We then extend the framework to quantify country-level corporate credit risk in both local and foreign currencies.

2.1 Pseudo Bonds

Pseudo firms are hypothetical entities with fully transparent balance sheets. As an illustration, consider a pseudo-firm entirely invested in the S&P500 Index, so that its assets are

given by $A_t = SPX_t$. The asset value of such a firm reflects aggregate U.S. equity market risk – specifically, the risk of the firms comprising the S&P500 basket.

The pseudo firm finances its investment through the issuance of equity and zero-coupon debt with face value K and maturity T . Because the firm may default, its debt is risky. At maturity, bondholders receive the full face value K if the firm is solvent, or the firm’s assets A_T if it defaults. The bondholder’s payoff is therefore $\min(K, A_T) = K - \max(K - A_T, 0)$. Following [Merton \(1974\)](#), the value of the pseudo bond at any time $t < T$ equals K times the value of a risk-free discount bond with face value 1, denoted $\widehat{Z}_t(T)$, minus the value of a European put option with strike K written on the firm’s assets, denoted $\widehat{P}_t^{SPX}(K, T)$. We use the notation $\widehat{(\cdot)}$ to indicate traded or observable market instruments. The no-arbitrage price of the pseudo bond is therefore:

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

with the implied leverage ratio determined by K/A_t for any choice of strike K .

2.2 Empirical Default Probabilities and Credit Spreads

We replicate and extend the results of [Culp et al. \(2018\)](#) to benchmark our methodology. The main steps are summarized below and detailed in [Appendix A](#).

First, we compute expected (ex-ante) default probabilities to map pseudo bonds to pseudo rating categories based on Moody’s historical default rates. For each pseudo-firm i , defined by a strike K_i and horizon τ , the ex-ante default probability is given by:

$$p_{i,t}(\tau) = \mathbb{P}[A_{i,t+\tau} < K_i \mid \mathcal{F}_t], \quad (2)$$

where $\mathcal{F}_t$ defines all information available at time t . We hereafter drop subscript i to simplify notation. Asset growth over a forecast horizon τ is assumed to have an expected component

$\mu_{t,\tau}$ and an unexpected component, such that:

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

where the standardized shocks $\varepsilon_{t+\tau}$ are scaled using the asset volatility parameter $\sigma_{t,\tau}$.

To estimate $\mu_{t,\tau}$, we use post-war data on the S&P500 index and dividends from the Center for Research in Security Prices (CRSP), covering 1946-2023. Based on end-of-month observations, we estimate expected asset growth via an expanding-window forecasting regression using the dividend-price ratio D_t/P_t :

$$\ln(A_{t+\tau}/A_t) = a_{t,\tau} + b_{t,\tau}D_t/P_t + u_{t+\tau}, \quad t = 0, 1, 2, \dots, T - \tau, \quad (4)$$

where D_t/P_t is the ratio of one-year cumulative value-weighted returns, computed with and without dividends, minus one. The expected return is then predicted as $\hat{\mu}_{t,\tau} = \hat{a}_{t,\tau} + \hat{b}_{t,\tau}D_t/P_t$.

We estimate $\sigma_{t,\tau}$ by fitting a GARCH(1,1) model to the demeaned monthly log returns of the S&P500 index, using data up to and including time t to avoid look-ahead bias. Based on the fitted values $\hat{\sigma}_t$, we compute $\hat{\sigma}_{t,\tau}$ following [Campbell et al. \(1996\)](#).

Next, we compute the historical distribution of shocks, defined as $\hat{\varepsilon}_{t+\tau} = (\ln(A_{t+\tau}/A_t) - \hat{\mu}_{t,\tau})/\hat{\sigma}_{t,\tau}$. Unlike the log-normal asset return assumption in [Merton \(1974\)](#), the distribution of $\hat{\varepsilon}_{t+\tau}$ is left unspecified.

Using the historical shock distribution, we estimate default probabilities as $\hat{p}_t(\tau) = \mathbb{P}[A_{t+\tau} < K \mid \mathcal{F}_t] = \mathbb{P}[\hat{\varepsilon}_{t+\tau} < X_t \mid \mathcal{F}_t]$, where $X_t = (\ln(K/A_t) - \hat{\mu}_{t,\tau})/\hat{\sigma}_{t,\tau}$. This is computed as the in-sample frequency of shocks falling below the threshold X_t , i.e., $\hat{p}_t(\tau) = n(\hat{\varepsilon}_{t+\tau} < X_t)/n(\hat{\varepsilon}_{t+\tau})$, where $n(\cdot)$ indicates the number of events.

Second, following [Culp et al. \(2018\)](#), we assign each pseudo-firm i at time t to a pseudo rating category by comparing its estimated ex-ante default probability $\hat{p}_t(\tau)$ with Moody's historical U.S. default frequencies by credit rating, based on data from 1970 to 2022.¹

¹[Culp et al. \(2018\)](#) rely on Moody's *Corporate Defaults and Recovery Rates* covering 1970-2013 ([Moody's, 2014](#)). We use updated tables spanning 1970-2022, which accounts for minor discrepancies ([Moody's, 2022](#)).

Third, we compute empirical credit spreads for each pseudo rating category. For each strike K and maturity T , we use Equation (1) to compute the pseudo bond price based on the corresponding SPX put option. This yields the pseudo yield $\hat{y}_t(K, T) = -(T - t)^{-1} \ln \left(\hat{B}_t(K, T)/K \right)$. SPX option data are obtained from OptionMetrics for the period 1996-2023. For risk-free discount rates $\hat{r}_t(T)$, we follow Culp et al. (2018) and construct zero-coupon yields from constant maturity Treasury rates obtained from the Federal Reserve Economic Data (FRED) database. These inputs allow us to compute empirical credit spreads as:

$$\hat{cs}_t(K, T) = \hat{y}_t(K, T) - \hat{r}_t(T). \quad (5)$$

As in Culp et al. (2018), we construct 2-year empirical pseudo spreads at a monthly frequency across rating categories. We restrict the sample to options with more than 365 days to maturity. Each month, we compute an equally weighted average yield within each rating bucket, adjusting for maturity differences by weighting pseudo yields according to their normalized distance from the 2-year target (e.g., 730 days). For investment-grade (high-yield) pseudo bonds, we average across those rated Baa or higher (Ba or lower). See Appendix A for further details.

Panel (a) of Figure 1 plots the time series of investment-grade and high-yield pseudo spreads from the publicly available data of Culp et al. (2018) alongside our replicated series. Our data begin in 1996 – when OptionMetrics coverage starts – and extend the sample through 2023. The two series are closely aligned across both rating categories. A regression of the Culp et al. (2018) 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) bonds.

FIGURE 1 ABOUT HERE

2.3 Option-Implied Risk Free Rates

We depart from [Culp et al. \(2018\)](#) along one dimension to ensure internal consistency with our construction of option-implied credit spreads. Specifically, we compute risk-free rates implied from option markets, following the methodology of [Van Binsbergen et al. \(2022\)](#).

[Brenner and Galai \(1986\)](#) and [Van Binsbergen et al. \(2022\)](#) show that option strategies – specifically box trades – can be used to construct synthetic risk-free loans. We follow this approach by applying the put-call parity relation to European-style options on the S&P500 index to extract interest rates from option prices. These so-called box rates are considered free from credit risk and convenience yields.

Panel (b) of Figure 1 compares our replicated time series of investment-grade (IG) and high-yield (HY) pseudo credit spreads constructed using the risk-free rates of [Gürkaynak et al. \(2007\)](#) with those based on box rates. The series lie nearly on top of each other, with Pearson correlation coefficients exceeding 0.98 in both cases. This indicates that the two measures track each other closely across both IG and HY segments.

2.4 Empirical Local and Foreign Currency Pseudo Credit Spreads

We extend the above methodology to compute pseudo credit spreads in both local and foreign currencies for a broad cross-section of countries. This requires sufficient option data on the domestic stock index (in local currency) and on exchange-traded funds (ETFs) tracking that index in foreign currency. For the United States, such option data on the S&P500 in foreign currency are not available, which prevents the construction of pseudo spreads from a foreign investor’s perspective. We therefore illustrate our approach using the United Kingdom’s FTSE100 index, for which we observe options in both GBP (local currency) and USD (foreign currency).² Moreover, given greater liquidity in shorter-maturity options, we focus on pseudo spreads with a six-month horizon.

²For consistency, USD denotes the foreign currency throughout the paper and is referenced using the \$ symbol.

Conceptually, we analyze the credit spread of a pseudo U.K. firm and its matched foreign-currency (FC) counterpart. Specifically, we consider an identical pseudo firm that issues debt in USD to finance the purchase of the FTSE100 index. This setup allows us to construct comparable credit spreads in local and foreign currencies, abstracting from differences in liquidity, covenants, or legal structures.

Panel (a) of Figure 2 plots the time series of the aggregate 6-month U.K. pseudo credit spread denominated in local currency, constructed from FTSE100 Index (ESX) options using the methodology and filters described in Sections 2.2 and 2.3. We construct one representative country index and restrict ex-ante default probabilities to remain below the CCC Global Corporate Average Cumulative Default Rate reported by S&P for the period 1981-2023.³ We use only options with maturities between 91 and 365 days. The local currency credit spread exhibits considerable volatility, with pronounced spikes around major macroeconomic events such as the Global Financial Crisis, Brexit, and the COVID-19 pandemic.

FIGURE 2 ABOUT HERE

To compute U.K. pseudo credit spreads denominated in foreign currency, we rely on a new dataset of ETF options that track national stock market indices in USD. In our example, we use USD-denominated ETF options referencing the FTSE100 index. A key challenge in constructing pseudo twins is identifying the strike price that equates the implied default probabilities of the LC and FC pseudo bonds. This condition is economically motivated: unlike sovereigns, corporations cannot selectively default by currency. Hence, the default probabilities must be identical across both bonds.⁴ This requires finding a strike $K^\$$ on the FC-denominated options such that:

$$\hat{p}_t(\tau) = \mathbb{P}[A_{t+\tau} < K \mid \mathcal{F}_t] \equiv \hat{p}_t^\$(\tau) = \mathbb{P}[A_{t+\tau}^\$ < K^\$ \mid \mathcal{F}_t], \quad (6)$$

³Specifically, the upper cut for maturities equal or lower than 12 months is 25.98%, while that for the 24-month maturity is 35.95% for the two-year horizon.

⁴While the physical default probability is the same across both pseudo bonds, the risk-adjusted (i.e., risk-neutral) default probabilities may differ due to variation in investor pricing of credit and currency risk.

where $A_{t+\tau}^{\$}$ denotes the value of the FTSE100 index measured in foreign currency (USD). Since a unique strike $K^{\$}$ that exactly matches the default probability of the LC pseudo bond is rarely available, we average over a set of ETF options with strike-maturity pairs $(K^{\$}, T^{\$})$ that closely align with the LC bond’s default probability and target maturity. Details are provided in Appendix A. To compute FC pseudo credit spreads, we use the risk-free benchmark implied by box rates extracted from ETF options on the FC-denominated market index.

Panel (a) of Figure 2 overlays the time series of the U.K.’s 6-month pseudo credit spread denominated in foreign currency (USD). Due to limited data availability, this series begins in 2016. The FC-denominated spreads exhibit dynamics similar to their LC (GBP) counterparts, but are generally larger and more volatile, though the ranking occasionally reverses. Importantly, while USD-denominated bonds are influenced by USD-GBP exchange rate movements, they continue to reflect the credit risk of the underlying U.K. ESX pseudo bond.

Panel (b) of Figure 2 plots the time series of ex-ante default probabilities for both local and foreign currency pseudo bonds. Since foreign currency strikes are selected to match the default probabilities of the LC pseudo bonds, the two series closely align during periods of overlapping data. Panel (c) shows the number of options used to construct the aggregate credit spread indices. For LC spreads, we include all available options, revealing a clear upward trend in market liquidity. In contrast, the number of FC options is lower, as we restrict the sample to those that closely match the ex-ante default probabilities of the LC bonds.

2.5 Synthetic Local and Foreign Currency Pseudo Credit Spreads

In the absence of USD-denominated ETF options, we construct synthetic foreign currency (FC) pseudo bonds and corresponding risk-free benchmarks. Specifically, we compute a twin

FC pseudo bond $\widehat{B}_t^{\$}(K^{\$}, T)$, whose no-arbitrage price is given by:

$$\widehat{B}_t^{\$}(K^{\$}, T) = K^{\$} \widehat{Z}_t^{\$}(T) - \widehat{P}_t^{ESX, \$}(K^{\$}, T), \quad (7)$$

and an implied leverage ratio determined by $K^{\$}/A_t^{\$}$. The value of the ESX index in foreign currency is given by $A_t^{\$} = A_t \cdot S_t$, where S_t denotes the exchange rate expressed as units of foreign currency per unit of local currency. The corresponding FC put options are computed using the classical Black-Scholes-Merton pricing formula ([Black and Scholes, 1973](#)):

$$\widehat{P}_t^{ESX, \$}(K^{\$}, \tau) = BSM(A_t^{\$}, K^{\$}, \tau, \widehat{r}_{t, \tau}^{\$}, \widehat{\sigma}_{t, \tau}^{\$}). \quad (8)$$

The inputs to the put pricing formula include the index measured in foreign currency, $A_t^{\$}$. The strike $K^{\$}$ is chosen to match the ex-ante empirical default probability in Equation (2) between the LC and FC pseudo bonds (see Appendix A.4). The option horizon τ is set to match that of the LC-denominated pseudo bond.

We require an estimate of the risk-adjusted index volatility measured in foreign currency, $\widehat{\sigma}_{t, \tau}^{\$}$. As shown in Appendix B.2, under the assumption that both the index and exchange rate follow standard geometric Brownian motions, the unconditional index volatility in foreign currency is given by:

$$\sigma^{\$} = \sqrt{\sigma_S^2 + \sigma^2 + 2\rho\sigma\sigma_S}, \quad (9)$$

where σ_S denotes the exchange rate volatility, and ρ is the correlation between LC-denominated index returns and exchange rate returns. In the implementation, we adopt a conditional version of this relation: the time- t implied volatility in LC is inferred from the option price corresponding to the relevant LC-denominated strike K , while the at-the-money implied volatility for the exchange rate is obtained from FX options. The correlation coefficient ρ is estimated using a 5-year rolling window of monthly returns. We use realized correlations as a proxy for their risk-neutral counterparts, based on prior evidence that the two are closely aligned ([Della Corte et al., 2023](#)).

Note that, when FC options are illiquid, we cannot directly estimate the box rate in foreign currency using ETF option prices. In such cases, we follow [Du and Schreger \(2016\)](#) and construct synthetic FC risk-free rates by combining LC box rates with the forward premium, consistent with the covered interest parity (CIP) condition. Details are provided in Appendix [A.5](#). Although CIP was violated for many currencies after the 2008 Global Financial Crisis (GFC), this approach allows us to infer the relevant effective funding rate to serve as a benchmark for credit spread computation ([Augustin et al., 2024](#)).

Figure [3](#) compares empirical and synthetic credit spreads. While we prioritize empirical estimates in our analysis, we use synthetic spreads when option data are insufficient. Panel (a) overlays the time series of empirical and synthetic LC credit spreads; Panel (b) presents the same comparison for FC credit spreads. Panel (c) displays the full time series of LC and FC credit spreads used in our analysis. These reflect the credit risk of twin pseudo firms issuing debt in different currencies but with identical default probabilities.

FIGURE [3](#) ABOUT HERE

2.6 Dynamics of Foreign and Local Currency Pseudo Credit Spreads

To better understand the properties of LC and FC pseudo firms, Figures [4](#) and [5](#) present several diagnostics for U.K. pseudo spreads. Panel (a) of Figure [4](#) revisits the joint time series of 6-month pseudo spreads in local and foreign currencies. FC spreads tend to be higher and slightly more volatile than their LC counterparts. Over the sample period, the average 6-month USD pseudo spread is 3.90%, compared to 2.90% for GBP spreads.

This pattern is confirmed in Panel (b) of Figure [4](#), which plots the ratio of FC to LC pseudo spreads. For most of the sample, the ratio remains above one. Panel (c) shows the level difference between the two series, indicating an average spread differential of approximately 100 basis points.

FIGURES 4 AND 5 ABOUT HERE

Panel (a) of Figure 5 reports the ratio of risk-neutral to physical default probabilities associated with LC and FC pseudo bonds.⁵ Risk-neutral probabilities are generally higher and more volatile than their physical counterparts, especially during crisis periods such as 9/11, the Global Financial Crisis, and the COVID-19 pandemic. These ratios typically range from 1 to 3 but can exceed 10. Notably, the ratio is often higher for FC pseudo bonds, even though, as shown in Panel (b), implied volatility is frequently lower in FC terms. Panel (c) plots implied leverage ratios, defined as $L_t = A_t/K$ and $L_t^{\$} = A_t^{\$}/K^{\$}$. A notable pattern is that pseudo firms exhibit more pronounced deleveraging on their FC vs. LC debt following recessions and crisis episodes.

Finally, Figure 6 plots the difference between FC and LC risk-neutral default probabilities against the difference in credit spread levels – which we refer to as the quanto pseudo spread. We find a strong positive relationship between quanto pseudo spreads and the differential in risk-adjusted default probabilities. This suggests that the cross-currency spread differential is primarily driven by a risk premium component, rather than differences in physical credit risk. In the next section, we explore the economic sources of this premium.

FIGURE 6 ABOUT HERE

3 Interpreting the Evidence with Theory

We develop a stylized framework to understand the economic underpinnings of the difference between USD and LC pseudo spreads. We continue to use the example of the U.K. to calibrate the model and discuss the evidence. Thus, GBP serves as the reference LC.

⁵Risk-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.

3.1 Exchange Rates

We assume that the exchange rate S_t follows a Geometric Brownian motion under the physical measure $\mathbb{P}$:

$$dS_t/S_t = \mu_S dt + \sigma_S dW_t^S, \quad (10)$$

where μ_S denotes the expected exchange rate return, σ_S captures the exchange rate volatility, and dW_t^S are standard Brownian shocks. Consistent with Section 2, the exchange rate S_t represents the number of USD (\$) needed to purchase one unit of the local currency, so that an increase in S_t reflects an appreciation of the LC relative to the USD.

Consider a simple currency trade that converts one unit of the local currency (GBP) into USD, invests the converted cash in a USD-denominated riskless bond, and then converts the USD proceeds back to the local currency. We assume a constant return of the USD-denominated riskless bond $B_t^\$$, given by:

$$dB_t^\$/B_t^\$ = r^\$ dt, \quad (11)$$

where $r^\$$ denotes the USD risk-free interest rate, the FC counterpart to the LC riskless interest rate r .

The return of this currency trade, measured in local currency, is $d(B_t^\$/S_t)/(B_t^\$/S_t)$. According to the fundamental theorem in asset pricing, it must be true that (see Appendix D.1):

$$\mathbb{E}_t \left[\frac{d(M_t B_t^\$/S_t)}{M_t B_t^\$/S_t} \right] = 0, \quad (12)$$

where $\mathbb{E}$ is the expectation operator (under $\mathbb{P}$) and M_t is the stochastic discount factor (SDF) that prices assets denominated in LC.⁶

After solving for this expression, we can show that the expected exchange rate return is

⁶This expression is the continuous-time equivalent to $\mathbb{E}[M_{t+1}R_{t+1}] = 1$, 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.

given by (see Appendix D.2):

$$\mathbb{E}_t \left[\frac{dS}{S} \right] = (r^\$ - r + \sigma_S^2) dt - \mathbb{E} \left[\frac{dM_t}{M_t} \frac{dS_t}{S_t} \right] dt \quad (13)$$

$$= (r^\$ - r + \sigma_S^2 + \lambda_S) dt, \quad (14)$$

where $\lambda_S = -\mathbb{E} \left[\frac{dM_t}{M_t} \frac{dS_t}{S_t} \right]$ captures the LC currency risk premium, whose sign depends on the covariance between the exchange rate and the SDF. Consider, for example, that the local currency (i.e., GBP) tends to depreciate relative to the USD in bad states of the world, i.e., when M_t increases. We then have $\mathbb{E} \left[\frac{dM_t}{M_t} \frac{dS_t}{S_t} \right] < 0$ and $\lambda_S > 0$. That is, investors require a positive risk compensation for holding the GBP, given its cyclical property. Conversely, the USD is a safe haven currency, earning a negative risk premium.

Under the risk-neutral expectation $\mathbb{E}_t^\mathbb{Q}$, the covariance term disappears and we obtain the Uncovered Interest Parity (UIP) condition, which predicts a depreciation (appreciation) of the higher (lower) interest rate currency:

$$\mathbb{E}^\mathbb{Q} \left[\frac{dS_t}{S_t} \right] = (r^\$ - r + \sigma_S^2) dt, \quad (15)$$

where σ_S^2 captures a Jensen's convexity correction term.

Starting with [Hansen and Hodrick \(1980\)](#) and [Fama \(1984\)](#), empirical work has consistently shown that the UIP condition fails to predict future exchange rate returns. Therefore, the expected exchange rate return must depend not only on the interest rate differential (and the convexity adjustment) but also on the risk compensation λ_S . As we will show, this term also plays a critical role in explaining the cross-currency difference in credit spreads.

3.2 Stock Market Dynamics in LC and USD

To parallel our empirical approach, we consider two twin pseudo firms that invest in the stock market index denominated in LC and USD, respectively. Thus, the asset value of both pseudo firms is fully observable.

We denote the stock market index denominated in LC (e.g., FTSE in GBP) by A_t , which has the following $\mathbb{P}$ -dynamics:

$$dA_t/A_t = \mu dt + \sigma dW_t, \quad (16)$$

where μ is the expected index return, σ is the stock return volatility, and dW_t are Brownian shocks. These shocks are possibly correlated with exchange rate shocks, with a correlation coefficient $\text{Corr}(dW_t, dW_t^S) = \rho dt$. The expected stock market return is the sum of the LC risk-free rate r and the stock market risk premium given by $\lambda_A = -\mathbb{E}_t \left[\frac{dM_t}{M_t} \frac{dA_t}{A_t} \right] > 0$.

The country's stock market dynamics in FC (i.e., USD) is pinned down by the product of the LC index and the exchange rate, $A_t^\$ = A_t \cdot S_t$. Following Itô's Lemma, the $\mathbb{P}$ -dynamics of $A_t^\$$ is given by:

$$dA_t^\$/A_t^\$ = \mu^\$ dt + \sigma^\$ dW_t^\$, \quad (17)$$

where the expected USD-denominated stock return equals:

$$\mu^\$ = \mu + \mu_S + \rho\sigma\sigma_S \quad (18)$$

$$= r^\$ + \underbrace{\sigma_S^2 + \lambda_A + \lambda_S + \rho\sigma\sigma_S}_{\lambda_A^\$}, \quad (19)$$

with $\lambda_A^\$$ capturing the stock market risk premium in USD. The volatility of the country's stock market measured in USD is given by:

$$\sigma^\$ = \sqrt{\sigma^2 + \sigma_S^2 + 2\rho\sigma\sigma_S}. \quad (20)$$

3.3 Default Probabilities and Credit Spreads

Following [Merton \(1974\)](#), default occurs when the pseudo firms' asset value drops below their debt's face value at maturity. Given the lognormal dynamics of A_t , the default probability

in LC under $\mathbb{P}$ is given by:

$$\mathbb{P}[A_T < K] = N \left(-\frac{\log(A_t/K) + \left(\mu - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \right), \quad (21)$$

where K references the face value of debt in LC, T represents the debt maturity, and N denotes the cumulative normal density function. Equivalent expressions can be derived for the probability of default in USD, expressed as $\mathbb{P}^\$[A_T^\$ < K^\$]$, with $\mu^\$$ replacing μ and $\sigma^\$$ replacing σ .

The default probability under $\mathbb{Q}$ for the pseudo firm invested in A_t is given by Equation (21), with the risk-free rate r replacing μ , given that $\mathbb{E}^\mathbb{Q} \left[\frac{dA_t}{A_t} \right] = r$. In the USD case, the risk-free rate $r^\$$ replaces $\mu^\$$, as $\mathbb{E}^\mathbb{Q} \left[\frac{dA_t^\$}{A_t^\$} \right] = r^\$$. Note that volatility is constant and thus remains unchanged under $\mathbb{Q}$.

In this framework, the LC and USD-denominated credit spreads are given by:

$$cs = -\frac{1}{T-t} \ln \frac{D_t}{K} - r \quad (22)$$

$$cs^\$ = -\frac{1}{T-t} \ln \frac{D_t^\$}{K^\$} - r^\$, \quad (23)$$

where the date- t debt prices are:

$$D_t = Ke^{-r(T-t)} - \text{Put}(A_t, K, r, \sigma, T) \quad (24)$$

$$D_t^\$ = K^\$e^{-r^\$(T-t)} - \text{Put}(A_t^\$, K^\$, r^\$, \sigma^\$, T), \quad (25)$$

and where the put options $\text{Put}(\cdot)$ can be evaluated using the Black-Scholes-Merton option pricing formula.

3.4 Calibration and Results

We calibrate the model to the dynamics of the FTSE 100 index measured in LC and FC, i.e., GBP and USD. We use historical data over the sample period for which we can compute

credit spreads in both currencies.

The LC risk-free rate is set to $r = 0.019$, which corresponds to the average 3m GBP-denominated box rate. We set the expected LC stock return to $\mu_A = 0.06$, which implies a stock market risk premium of $\lambda_A = 0.041$. Stock market volatility is set to $\sigma_A = 0.14$, as given by the average volatility of FTSE 100 index returns. The correlation between stock market and exchange rate returns is $\rho = 0.13$, indicating that the GBP tends to appreciate when the UK stock market rises. The USD risk-free rate is set to $r^\$ = 0.014 < r$, as the GBP is a high yield currency compared to the USD. The currency risk premium is set to $\lambda_S = 0.02$, given the cyclical property of the GBP.

Exchange rate volatility equals $\sigma_S = 0.1$, so that stock market volatility in USD is $\sigma^\$ = 0.182$. The expected stock return in USD is then $\mu^\$ = 0.087$, which implies a stock market risk premium in USD equal to $\lambda_A^\$ = \mu^\$ - r^\$ = 0.073$. Finally, we calibrate the face value of debt K in LC to generate a physical default probability $\mathbb{P}[A_T < K] = 0.05$ at the one-year horizon ($T = 1$) and then determine the face value of debt $K^\$$ such that $\mathbb{P}[A_T^\$ < K^\$] = \mathbb{P}[A_T < K]$. Table A.4 summarizes the parameter values.

Figure 7 illustrates the levels of LC and FC denominated credit spreads (Panels a, d, g), their implied leverage (Panels b, e, h), and their corresponding risk-neutral default probability Q (Panels c, f, i). Panel (a) shows that credit spreads in USD are significantly higher than those denominated in LC (GBP), consistent with our main empirical findings. We now investigate the source of such difference.

FIGURE 7 ABOUT HERE

A priori, one could expect that $cs^\$ > cs$ given that the assets in USD ($A_t^\$$) carry additional exchange rate risk. Given the positive correlation between the FTSE 100 index and USD/GBP, a fall in the FTSE tends to be accompanied by a depreciation of the GBP, thereby amplifying the fall in the index measured in USD. To see that in the baseline calibration,

the level of stock market volatility in USD is significant higher than the LC counterpart ($\sigma^\$ = 0.182$ vs. $\sigma = 0.14$).

However, this risk amplification channel cannot directly affect cross-currency credit risk, as we calibrate the two pseudo firms to have identical physical default probability: they indeed face the same *quantity* of default risk. Hence, a higher index volatility in USD ($\sigma^\$ > \sigma$) must be accompanied with lower leverage ($K^\$/A^\$ < K/A$), as illustrated in Panel (b). Effectively, we have to consider a more distant strike $K^\$$ so that the default probabilities remain the same in both currencies.

The difference in USD and GBP credit spreads must, therefore, come from a difference in risk premia. A key measure is the difference between the risk-neutral and the physical default probability, which reflects the price of default risk. Given that $P = P^\$$, the difference in price of default risk across currencies is given by $Q^\$/P^\$ - Q/P = (Q^\$ - Q)/P$. Panel (c) shows that $Q^\$ - Q > 0$ when the model is calibrated to the UK, irrespective of the level of default risk.

A key mechanism is the relative high risk premium in USD. Based on Equation 19, we have $\lambda_A^\$ - \lambda_A = \sigma_S^2 + \lambda_S + \rho\sigma\sigma_S = 0.083 - 0.051 > 0$. This risk premium differential notably increases with: i) the currency premium λ_S , where a positive level indicates that the currency depreciates in bad times for investors; and ii) the correlation ρ between the USD/LC exchange rate and the LC stock index, where a positive correlation amplifies stock market volatility in USD.

We now explore each of these channels. First, Panel (f) shows that a higher currency premium λ_S increases $Q^\$ - Q$. A direct effect is via an increase in the relative risk premium, $\lambda_A^\$ - \lambda_A$. As a complementary effect, a higher currency premium λ_S increases the expected growth rate $\mu^\$$ under $\mathbb{P}$, which must be compensated by a higher leverage in USD (see Panel e) to maintain a default probability identical to that in local currency. So higher leverage combined with a constant risk-neutral drift ($r^\$$) implies a higher $\mathbb{Q}$ -default probability for USD bonds, while the $\mathbb{Q}$ -default probability local currency remains unaffected by the currency premium. Together, the model predicts that λ_S positively drives the difference in credit spreads between

USD and LC (Panel d). Note that when λ_S is sufficiently negative, the risk premium in USD bonds becomes lower than in LC bonds, and the difference in credit spreads between USD and LC switches sign.

Second, the stock-FX correlation ρ enters into the pricing of USD bonds via two distinct channels. On one hand, it increases the risk premium $\lambda_A^\$$ and thus the credit spread in USD relative to the LC one. On the other hand, it increases the volatility of the stock index measured in USD (see Equation 20), which implies that leverage in USD should be reduced to keep the default probability unchanged (see Panel h). This force decreases the $\mathbb{Q}$ -default probability for USD bonds, as illustrated in Panel (i). Overall, the risk premium channel dominates the volatility channel, such that the difference in credit spreads between USD and LC increases with the correlation ρ (Panel g).

This stylized model, calibrated to the data of the FTSE 100 index, is sufficiently rich to explain the positive difference in USD and GBP credit spreads, in addition to generating novel cross-sectional predictions. The main driving forces are the currency premium and the joint dynamics of the exchange rate and the local currency stock market index. These forces generate different levels of risk premia across currencies and, as a consequence, distinct credit spread levels.

4 Pseudo Credit Spreads Around the World

We first describe in Section 4.1 our international options sample that we use to construct local and foreign currency denominated pseudo spreads around the world. We next study the drivers of local currency pseudo spreads in Section 4.2. In Section 4.3, we study pseudo quanto spreads defined as the difference between USD and local currency denominated pseudo spreads.

4.1 Data and Summary Statistics

We construct an international sample LC- and USD-denominated pseudo credit spreads. For that purpose, we undertake a comprehensive search for data on international stock market indices with traded options, as well as on exchange-traded funds (ETFs) denominated in U.S. dollars that track these indices and have listed options. We start with the list of emerging and developed countries used in [Du and Schreger \(2016\)](#) and [Kelly et al. \(2016\)](#) and complement it with Thailand, Malaysia, India, and China due to increasing options data coverage in recent years.

We obtain index and options price and trade data from Refinitiv Datastream and from OptionMetrics via Wharton Research Data Services (WRDS). Specifically, we retrieve end-of-day put and call option data on international stock indices from Datastream, accessed through Refinitiv Eikon, and on USD-denominated index-tracking ETFs from OptionMetrics. We describe the data filtering and cleaning process in [Appendix A](#).

[Table 1](#) summarizes the information on our final sample that contains 29 countries (8 emerging and 21 developed countries) and the Eurozone region. For each country or region, we report the name, the ticker of the corresponding stock market index, the mnemonic of the option series on the index, the currency denomination of the options, the sample start and end dates, and the average number of available option observations per month. The subsequent columns present the same information for USD-denominated options on ETFs that track the respective country’s stock market index.

The start date of options availability differs across currencies. For LC, the U.S. is the first country to have traded options in our sample, starting in 1996, due to the data availability in OptionMetrics. The Netherlands are the second country with options data availability starting in 2001, and Brazil is the latest country with a starting date in 2018. For USD options, the earliest starting date in our sample is recorded for China in 2004, while Poland features the latest starting date in 2019.

Options tend to be more liquid in LC, as described by the number of available put options

that survive our data filtering process. Notable exceptions are Brazil, Canada, China, Mexico, Singapore and Malaysia. For each country, we start with the most liquid option market to compute the aggregate country pseudo spread using all available options. To ensure a representative country index, we restrict pseudo firms to have an ex-ante empirical default probability no higher than the Standard&Poor’s CCC Global Corporate Average Cumulative Default Rate between 1981 and 2023. We construct pseudo credit spreads by aggregating all pseudo yields within a given month to compute a time-to-maturity weighted average pseudo yield for maturities of 3, 6, 12, and 24 months. For 6-month (3, 12, 24 months) bonds, we restrict the option maturity to be within [91, 365] ([7,182], [182, 547], [365, 1095]) days.

To construct the empirical foreign currency counterpart to the initial pseudo spread (or the local currency counterpart if USD options are more liquid), we consider all options written on the USD denominated ETF index. We choose options with strike and maturity to perfectly match the aggregate ex-ante default probability of the benchmark index. Hence we obtain two twin pseudo yields with identical default probabilities.

In a final step, we infer riskless benchmark rates for the computation of credit spreads. Specifically, we follow [Brenner and Galai \(1986\)](#), [Van Binsbergen et al. \(2022\)](#), and [Diamond and Van Tassel \(2021\)](#) and infer implied interest rates from the put-call parity relation applied to European-style options on the local stock market index. For some countries options liquidity is insufficient to reliably estimate country-specific box rates. In that case, we construct regional box rate indices for the Euro area, non-Euro European countries, and Asian economies. For details, see [Appendix A](#). For the few instances where LC box rates are unreliable or unavailable for our sample period (Australia, Brazil, Canada and Mexico), we use the USD-denominated box rate estimated from options on the S&P500 index and convert it to a LC risk-free rate using the CIP condition.

[Table 2](#) presents summary statistics for the 6-month pseudo spreads at the country level with a monthly frequency. Similar statistics for pseudo spreads at the 3-, 12-, and 24-month horizon are available in [Appendix Figures A.5, A.6, and A.7](#). We separate statistics for developed economies (Panel A) and emerging economies (Panel B). The average LC pseudo spread for developed economies is 3.44%, ranging between a low of 71bps for the Netherlands

to 780bps for New Zealand. The average FC pseudo spread is 4.64%, 120bps higher than the LC average. The same ranking applies to most countries, although the average FC spread is lower than the LC spread for Denmark, Greece, New Zealand and Taiwan. Pseudo spreads in emerging economies are higher than for developed economies, since the average LC (FC) pseudo spread in Panel B is 5.32% (5.67%).

We illustrate in Figure 8 the dynamics of the LC and FC pseudo spreads across three regions (Europe, Asia, Americas). While these time series exhibit some degree of commonality, they illustrate a significant amount of cross-regional heterogeneity with different sensitivities to macroeconomic events. For example, FC denominated spreads react more strongly for European countries around the Brexit referendum. The last column in Table 2 shows the average correlation between FC and LC pseudo spreads, which ranges between 43% for Italy to 97% for Greece. This supports the view that FC denominated pseudo spreads have independent dynamics because they are exposed to the interaction between default and exchange rate risk.

In Panel A of Table 3, we present aggregate statistics (all countries together) for various maturities. These equally-weighted values suggest that the term structure of credit spreads tends to be downward sloping, on average. However, we show in Figure 9 the significant degree of heterogeneity across countries. We scale the term structure of pseudo spreads of each country by subtracting the 3-month spread, allowing us to directly compare the term structures across countries. This figure illustrates that the sample has both countries with steeply upward and steeply downward term structures. In Panel B of Table 3, we report the average implied volatility from the options that we use to construct the credit indices. Implied volatilities similarly reflect a downward sloping pattern with values ranging between 23.72% and 38.35%.

Finally, in Panel C of Table 3, we report the empirical ex-ante default probabilities by currency denomination and maturity horizon. The average 6-month default probability implied by traded options is 8.54% (11.53%) for advanced (emerging) economies. The values are identical across LC and FC denominates because FC options are chose to match the aggregate default probability of the representative country index. Statistics at the country

level are available in Appendix Table [A.8](#).

TABLES [2](#) & [3](#) ABOUT HERE

4.2 Determinants of Local Currency Pseudo Credit Spreads

We begin by examining the economic determinants of pseudo credit spreads denominated in local currency. While our primary analysis focuses on 3-month pseudo bonds, we find qualitatively similar results across other maturities. Summary statistics for the predictors are reported in the Appendix Table [A.10](#).

TABLE [4](#) ABOUT HERE

In column (1) of Table [4](#), we demonstrate the economic relevance of our LC pseudo credit spreads by regressing the 3-month spreads on their fundamental risk components: the physical default probability P and the excess compensation for default risk, defined as the difference between the risk-adjusted Q and physical default probabilities. The panel regression includes country fixed effects to isolate within-country time series variation. Both components – default risk and its risk premium – exert a strong influence on LC spreads and jointly explain 83.2% of the within-country variation.

The estimated coefficient of 0.346 implies that a one percentage point increase in the physical default probability is associated with a 35 basis point increase in spreads. The effect of the risk premium is even more pronounced: a one-point increase in $Q - P$ raises spreads by approximately 55 basis points. This finding is consistent with prior evidence that corporate credit spreads reflect compensation for expected loss given default and the associated risk premium (e.g., [Gilchrist and Zakrajšek, 2012](#); [Berndt et al., 2018](#); [Culp et al., 2018](#)).

In column (2) of Table 4, we show that the level of LC pseudo credit spreads is positively (negatively) associated with the expected return (volatility) of the local-currency-denominated stock market index, which proxies for the assets of the pseudo firm. This result is consistent with the intuition of the structural credit risk framework, where default risk is linked to the likelihood of the stock index falling below a strike that corresponds to a default threshold. Specifically, an increase in asset volatility raises the probability of default by increasing the likelihood that the stock index will breach the strike price. Conversely, higher expected returns reduce the probability of default and are associated with narrower credit spreads.

Column (3) examines the relationship between LC pseudo credit spreads and both the return and volatility of the local currency (LC) exchange rate against the USD.⁷ A one percentage point increase in foreign exchange rate volatility is associated with an average increase of 30 basis points in pseudo spreads. In addition, LC pseudo spreads rise as the local currency depreciates, as indicated by the statistically significant negative coefficient of -0.090 . These findings suggest that LC credit spreads reflect heightened default risk when the local currency weakens or becomes more volatile. Accordingly, investors require greater compensation for holding debt denominated in currencies that are more prone to large fluctuations or depreciation.

Neither risk-free rates in local nor foreign currency contain significant information for pseudo credit spreads, as indicated by the statistically insignificant coefficients in column (4) of Table 4. This is likely because risk-free rates primarily affect the option-implied credit spread through the risk-neutral drift, which has a limited impact on short-maturity bonds. As a result, the risk of short-term LC pseudo bonds is more closely linked to factors specific to the local economy and currency, rather than to global interest rates or broader monetary policy conditions.

We examine several country-specific and global risk factors in columns (5) to (7) of Table 4. A one standard deviation increase in foreign exchange reserves is associated with a rise in pseudo spreads of nearly 300 basis points, on average – an economically significant

⁷We measure foreign exchange rate volatility using the implied volatility of USD/LC options with a 3-month maturity. Similar results are obtained using GARCH(1,1) estimates based on exchange rate returns.

effect. One possible interpretation is that the level of FX reserves may serve as a signal of monetary policy credibility and the central bank’s capacity to counteract inflation and local currency depreciation (e.g., [Bank for International Settlements, 2023](#)). Consistent with this interpretation, we also find that pseudo spreads are positively related to local inflation levels. Thus, higher inflation erodes a currency’s purchasing power, raises uncertainty about future economic conditions, and increases the likelihood of default, thereby widening credit spreads.

Moreover, we find that stronger economic conditions, as measured by the Chicago Fed National Activity Index (CFNAI), are associated with lower pseudo spreads. In contrast, heightened macroeconomic uncertainty – captured by the index of [Jurado et al. \(2015\)](#) – and tighter U.S. credit conditions, proxied by the GZ spread of [Gilchrist and Zakrajšek \(2012\)](#), are associated with wider pseudo spreads. These findings underscore the global interconnectedness of credit markets, suggesting that uncertainty and adverse credit conditions in global financial markets can spill over into local credit markets.

4.3 Determinants of Pseudo Quanto Spreads

We next examine the drivers of pseudo quanto spreads, defined as the difference between USD and local currency denominated pseudo spreads. The economic framework suggests that the pseudo quanto spread reflects differences in the price of risk across spreads denominated in different currencies: $Q^{\$} - Q$. Thus, the pseudo quanto spread captures differences in how default risk correlates with investors’ stochastic discount factor in each local currency. Since the risk premium depends on the level of default risk, we expect both the physical default probability P and the difference in excess compensation between the two currencies to drive variation in pseudo quanto spreads.

Table 5 reports that, consistent with our stylized framework, both the physical probability of default and the different risk-adjusted default probabilities between USD and LC denominated pseudo spreads significantly pseudo quanto spreads. This holds true across

specifications, including pooled regressions, cross-sectional regressions with time fixed effects, and time-series regressions with country fixed effects. While the level of default risk bears greater explanatory power in the cross-section to explain the gap between USD and LC denominated pseudo spreads, the excess risk premium explains more variation in the time series. The statistically significant coefficient of 0.493 is also three times as large as that of the default probability, 0.168.

TABLES 5 AND 6 ABOUT HERE

In Table 6, we examine whether the determinants of LC-denominated pseudo spreads help explain within-country variation in pseudo quanto spreads. Column (1) shows that lower LC index returns and higher return volatility are associated with lower pseudo quanto spreads. This reflects the fact that these factors raise LC-denominated pseudo spreads, thereby narrowing the spread between USD and LC pseudo spreads. Conversely, column (2) shows that lower FC index returns and higher FC return volatility increase pseudo quanto spreads, as they raise USD-denominated pseudo spreads. Together, these results highlight the asymmetry in how local and foreign risk factors shape the cross-currency pricing of credit risk.

Higher foreign exchange (FX) volatility increases the riskiness of USD-denominated pseudo spreads relative to those in LC, thereby widening the CS quanto pseudo spread. The economic magnitude is, however, more muted. Moreover, the riskless rate differential influences the credit quanto spread, with a higher USD rate indicating a safer USD bond and thus a lower CS quanto.

Finally, we find that the pseudo quanto spread increases with higher central bank FX reserves, stronger economic activity – as measured by the CFNAI – and greater macroeconomic uncertainty. These effects are largely driven by the differential sensitivity of LC- and USD-denominated pseudo spreads to global risk factors.

5 Information Content of the Pseudo Credit Spreads

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

5.1 Predictability of Aggregate Economic Activity

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

$$\Delta Y_{t+1} = \alpha + \beta \Delta Y_t + \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_t + \varepsilon_{t+1}, \quad (26)$$

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

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

In column (1) of Table 7, we find that CS^{LC} significantly predicts future aggregate output growth with a negative sign. This result is consistent with previous evidence that widening credit spreads signal worsening economic conditions (e.g., Culp et al., 2018; Gilchrist and Zakrajšek, 2012). Regarding the economic magnitude, the estimated coefficient of column (1) implies that a one percentage point increase in the LC pseudo spread predicts a 0.023 percentage points decline in output growth, or about 0.1 percentage points on an annualized basis. While the economic effect is modest—as one would expect from a single country-level spread forecasting a broad cross-country aggregate—it is statistically and economically meaningful. In contrast, column (2) shows that the pseudo quanto spread, CS^{Quanto} —which reflects how a country’s currency co-moves with the global pricing kernel—does not significantly forecast real activity. Since pseudo quanto spreads primarily capture currency-related risk, they are less likely to contain information about aggregate economic fundamentals.

TABLE 7 ABOUT HERE

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

We further include control variables to account for macroeconomic and monetary policy conditions. These controls comprise the term spread (10-year minus 3-month Treasury yield), the real federal funds rate, and the Macroeconomic Uncertainty Index of Jurado et al. (2015). As shown in columns (3) and (4) of Table 7, the coefficient on CS^{LC} remains statistically significant even after controlling for these factors, indicating that country-level option-implied

credit spreads contain predictive information beyond that captured by conventional U.S.-based indicators. Notably, both CS^{USA} and the GZ Spread continue to be significant with the expected signs, reaffirming their role as important predictors of macroeconomic outcomes.

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

In practice, disentangling the expected default risk and the risk premium from bond or CDS spread data is challenging, as both components tend to comove and respond similarly to shifts in market sentiment and macroeconomic conditions. To address this, prior studies have adopted model-based approaches. For instance, [Gilchrist and Zakrajšek \(2012\)](#) proxy default risk using the “distance to default” (DD) derived from the Merton (1974) model, while [Berndt et al. \(2018\)](#) rely on Moody’s Analytics Expected Default Frequencies (EDF) as a forward-looking measure of firm-level conditional default probabilities.

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

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

Table A.11 demonstrates that our main results are robust to a range of alternative regression specifications. First, the findings hold regardless of whether aggregate economic growth is constructed using GDP-weighted or equally weighted country averages, indicating that the observed predictability is not driven by a small number of large economies. Second, the results are robust to the inclusion or exclusion of the United States in the construction of the aggregate series, suggesting that the predictive power of pseudo credit spreads extends beyond U.S.-specific dynamics. In addition, we confirm robustness across different forecast horizons and option maturities. Specifically, the results remain significant when predicting economic growth three months ahead using the physical default probability P and credit risk premium $Q - P$ derived from options centered at the three-month horizon. Similarly, the findings persist when forecasting twelve-month-ahead growth using predictors constructed from options across all maturities.

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

5.2 Country-Level Predictability of Economic Growth

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

$$\Delta Y_{i,t+4} = \beta \Delta Y_{i,t} + \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_t + \alpha_i + \eta_t + \varepsilon_{i,t+4}, \quad (27)$$

where $\Delta Y_{i,t+4}$ denotes the one-year-ahead real GDP growth of country i . The specification

includes country fixed effects (α_i) to control for time-invariant heterogeneity across countries and time fixed effects (η_t) to control for aggregate conditions. Standard errors are clustered by both country and time to account for potential cross-sectional and temporal dependence in the residuals ($\varepsilon_{i,t+1}$).

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

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

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

TABLE 8 ABOUT HERE

5.3 Exchange Rate Predictability

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

$$\Delta s_{i,t+4} = \gamma_1 \text{CS}_{i,t}^{LC} + \gamma_2 \text{CS}_{i,t}^{\text{Quanto}} + \delta \text{Controls}_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t+4}, \quad (28)$$

where $\Delta s_{i,t+4}$ denotes the one-year-ahead exchange rate return of country i , with a positive Δs indicating an appreciation of the country's local currency relative to the USD. The specification includes country fixed effects (α_i) to control for time-invariant heterogeneity across countries and time fixed effects (η_t) to control for aggregate conditions. Standard errors are clustered by both country and time to account for potential cross-sectional and temporal dependence in the residuals ($\varepsilon_{i,t+1}$). The results are presented in Table 9.

TABLE 9 ABOUT HERE

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

Second, we show that the pseudo quanto credit spread statistically predict future currency returns with a positive sign. Based on Column (4), for example, a 100 basis point increase

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

Our empirical findings support this interpretation. Currencies of countries with higher pseudo quanto spreads tend to experience greater future appreciation. To test the underlying mechanism more directly, we sort the sample based on the correlation between local stock market returns and the USD/LC exchange rate. Table 10 reports the results. We find that the pseudo quanto spread predicts future currency returns only when this correlation is high, indicating a stronger link between currency depreciation and adverse local market outcomes. Similar results obtain when we sort countries by the correlation of their local stock returns with either U.S. equity returns (S&P 500) or U.S. consumption growth. These findings are consistent with a covariance-based risk premium: the predictive power of the pseudo quanto spread arises specifically when the local currency covaries negatively with the global pricing kernel.

TABLE 10 ABOUT HERE

The evidence is grounded in our structural model framework, in which the covariance between the pricing kernel and default risk, captured by parameter λ_S , raises both the pseudo quanto spread and the expected excess return on the local currency. A key feature of the

model is that default probabilities are held constant across currencies, so differences in credit spreads purely reflect variation in the price of risk rather than in default expectations. This identification strategy enables us to isolate a clean measure of currency risk premia embedded in pseudo credit spreads, disentangled from confounding effects related to credit events.

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

Finally, our approach complements and extends the methodology of [Della Corte et al. \(2023\)](#), who construct a credit-implied risk premium using euro-area sovereign CDS spreads in multiple currencies. While their measure captures depreciation risk conditional on sovereign credit events, our analysis focuses on a broader set of countries and captures systematic risk pricing in normal times. Moreover, by relying on short-maturity pseudo credit spreads, we avoid some of the liquidity and regulatory distortions affecting long-dated CDS contracts. Our broader cross-country coverage and emphasis on risk pricing rather than event-driven risk represent key contributions to both the asset pricing and currency forecasting literatures.

6 Conclusion

Internationally comparable measures of local and foreign currency corporate credit risk at the firm level are scarce due to several challenges: (1) limited data and illiquid bond markets, (2) the rarity of firms issuing debt in both currencies, (3) cross-currency differences in legal

and tax treatment, and (4) the difficulty of identifying consistent benchmark risk-free rates across currencies. To overcome these limitations, we develop a novel measure of local and foreign currency credit risk using traded equity index options.

We propose credit spread measures based on bonds issued by pseudo firms that invest in the domestic stock market index. Drawing on structural credit risk models, we treat debt as a short put option on firm assets – here, the index – yielding firms with fully observable balance sheets. We construct a sample of local and foreign currency pseudo credit spreads for 29 countries from 2006 to 2023. Although these spreads are designed to reflect identical physical default probabilities, they embed distinct economic information.

Our findings yield two key insights. First, local currency credit spreads predict aggregate GDP growth, while the USD-LC pseudo spread differential does not. Second, pseudo quanto spreads forecast exchange rate returns. Together, these results provide a comprehensive view of credit risk across currencies, revealing distinct credit spread dynamics and their sensitivity to monetary policy.

Table 1: International Options Data

This table presents the sample of countries with joint availability of stock market index and index options data traded in local currency. We also report information on the availability of index exchange traded funds (ETF) that track the local stock market index in USD and the corresponding ETF index options data valued in USD. For each country/region, we report the country's/region's name, the ticker of the corresponding stock market index, the mnemonic of the option series on the underlying index, the currency denomination of the option, the start and end date of the sample, the average number of available put options per month, and the average box rates observations per month when we use a lower threshold R^2 of 0.9999 to validate the box rate regressions. The subsequent columns report the same information for foreign currency (i.e., USD) options on ETFs that track the country's stock index in USD. We include in our sample the countries used in [Du and Schreger \(2016\)](#), [Kelly et al. \(2016\)](#), [Du et al. \(2018\)](#) and, [Diamond and Van Tassel \(2021\)](#) for which we have available options data. We add Thailand, Malaysia, India, and China to improve on our coverage of Asian countries. We highlight using grey bars emerging economies, as defined by the IMF. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS).

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

Table 2: Local and Foreign Currency Pseudo Credit Spreads – 6-Month Horizon

This table presents summary statistics of the 6-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 six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendices A and B for details. The units are in percentage terms: for example, the average LC credit spread for all developed countries is 3.44%. The last two columns report the correlation between the LC and USD credit spreads, and the correlation between the LC stock index and USD/LC exchange rate returns. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

Panel A: Developed countries

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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
Belgium	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

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

Table 3: Pseudo Credit Spreads by Currency and Maturity – Aggregate Statistics

This table presents summary statistics of the pseudo credit spreads and default probabilities by currency and maturity. Pseudo bonds in local currency are constructed from put options on the corresponding domestic stock market index, while those in foreign currency 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, six-month, one-year, and two-year bonds, we restrict the option maturity to be within [7,182], [91, 365], [182, 547] and [365, 1095] days, respectively. See Appendices A and B for details. The statistics aggregate all countries into an 'Advanced' or 'Emerging' average, such that the first two lines of the table can be found in the last lines of Panel A and Panel B of Tables A.5, 2, A.6, and A.7. The units are in percentage terms: for example, the average 3-month credit spread for all advanced countries is 3.85%. In Panel B, we report the corresponding ex-ante physical default probabilities. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

Panel A: Credit Spread

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

Table 4: Determinants of Local Currency Pseudo Credit Spreads

This table reports coefficients of regressing 3-month pseudo credit spreads in local currency (LC) on various determinants. The physical default probability is denoted by P , while the risk-neutral counterpart is denoted by Q . Both are for pseudo bonds with a 3-month maturity. The frequency of the data is quarterly, computed as the average monthly observations within a quarter. The regressions include country fixed effects. The table reports t -statistics in parentheses computed with standard errors clustered at the quarter and country levels. Section 2 provides details on the computation of the local variables. The global determinants are detailed in Section 4.

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

Table 5: Decomposition of Pseudo Quanto Spreads

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

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

Table 6: Determinants of Pseudo Quanto Spreads

This table reports coefficients of regressing pseudo quanto spreads on a set of risk factors. The pseudo quanto spread is defined as the difference between the USD and the local currency (LC) denominated 3-month pseudo credit spreads. The frequency of the data is quarterly, computed as the average monthly observations within a quarter. The regressions include country fixed effects. The table reports t -statistics in parentheses computed with standard errors clustered at the quarter and country levels. Section 2 provides details on the computation of the local variables. The global determinants are detailed in Section 4.

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

Table 7: Predictability of Aggregate GDP Growth

This table reports the results of the following predictive regression:

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

where ΔY_{t+1} reflects the one-quarter-ahead real GDP growth averaged across countries (excluding the US), with weights given by the mean GDP over the sample period. The main variables of interest in Panel A are the local currency (LC) pseudo credit spread for country i in quarter t , denoted by $\text{CS}_{i,t}^{LC}$, and the difference between $\text{CS}_{i,t}^{USD}$ and $\text{CS}_{i,t}^{LC}$, denoted by $\text{CS}_{i,t}^{\text{Quanto}}$. In Panel B, the main variables of interest are the default probability (P) and the default risk premium, measured as the difference between the physical (P) and risk-neutral (Q) default probabilities. All measures are centered around the 3-month maturity to match our measures with the forecast horizon. The controls include the (updated, LC) quarterly SPX pseudo spread of [Culp et al. \(2018\)](#) denoted by ‘CS USA’, the term spread, the Macroeconomic Uncertainty Index of [Jurado et al. \(2015\)](#), the real Federal Funds rate (FFR), and the ‘GZ Spread’ of [Gilchrist and Zakrajšek \(2012\)](#) available up to 2015. We adjust the standard errors using the Newey and West (1987) kernel, where the bandwidth is selected optimally to account for potential serial correlation across residuals (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)
	Pseudo credit spreads				Risk decomposition		
	Controlling for CNV		Controlling for GZ		Controlling for CNV		Controlling for GZ
	Full sample	Full sample	Full sample	Up to 2015	Full sample	Full sample	Up to 2015
CS LC	-2.342** (-2.21)	-2.714** (-2.44)	-10.568*** (-8.82)	-6.834*** (-15.44)			
CS Difference (USD - LC)		0.095 (0.17)	0.254 (0.49)	0.133 (0.52)			
Default Probability					-1.575*** (-3.62)	-3.832*** (-8.68)	-1.811*** (-8.40)
Default Premium (Q - P)					-1.142*** (-2.71)	-3.453*** (-7.98)	-1.763*** (-7.88)
CS US			-0.796*** (-15.87)	-0.331*** (-15.17)		-0.788*** (-15.93)	-0.243*** (-10.40)
Term Spread			0.402*** (10.60)	-0.079*** (-2.75)		0.337*** (9.26)	-0.026 (-0.79)
Macro Uncertainty			4.475*** (11.61)	0.497 (1.62)		3.965*** (10.92)	-1.054*** (-3.43)
FFR				-0.125*** (-7.06)			-0.088*** (-4.38)
GZ Spread				-0.769*** (-19.09)			-0.658*** (-15.26)
Constant	0.850*** (13.23)	0.875*** (12.78)	-3.043*** (-9.23)	1.037*** (5.18)	0.971*** (13.09)	-2.433*** (-7.70)	-2.433*** (-7.70)
Observations	1,770	1,718	1,659	730	1,743	1,634	1,634
R-squared	0.051	0.052	0.181	0.681	0.056	0.185	0.185

Table 8: Predictability of Country-level GDP Growth

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

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

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

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

Table 9: Exchange Rate Predictability

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

$$\Delta s_{i,t+4} = \gamma_1 CS_{i,t}^{LC} + \gamma_2 CS_{i,t}^{Quanto} + \delta Controls_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t+4},$$

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

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

Table 10: Exchange Rate Predictability by Currency Characteristics

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

$$\Delta s_{i,t+4} = \gamma_1 CS_{i,t}^{LC} + \gamma_2 CS_{i,t}^{Quanto} + \delta Controls_{i,t} + \alpha_i + \eta_t + \varepsilon_{i,t+4},$$

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

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

Figure 1: Empirical Credit Spreads of Two-Year SPX Pseudo Bonds

In this figure, we illustrate credit spreads of two-year pseudo bonds in the US. Pseudo bonds are constructed from risk-free debt minus put options on the S&P500 Index (SPX). Investment Grade (IG) and High Yield (HY) credit ratings of pseudo bonds are assigned to Moody's credit rating categories, based on the ex-ante default probabilities of pseudo bonds computed from the empirical distribution of SPX returns. See Appendix A for details. In Panel (a), we plot the historical IG and HY credit spreads of Culp et al. (2018), which we label CNV, and our replicated series extended to 2022 (labeled AJPS). In Panel (b), we plot our replicated historical IG and HY credit spread indices computed with either the box rates inferred from the put-call parity relation (Van Binsbergen et al., 2022) or the Gürkaynak et al. (2007)'s riskless rates (labeled GSW). SPX options data is from OptionMetrics. Shaded vertical bars denote NBER recessions. The data frequency is monthly from 1996 to 2023.

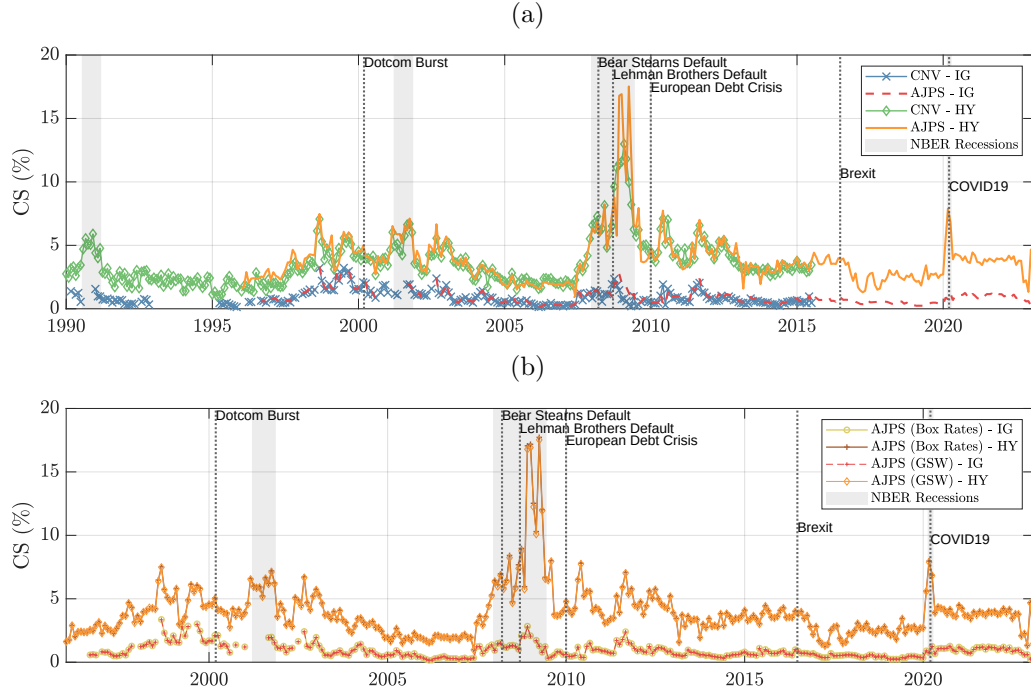


Figure 2: Empirical Credit Spreads of Six-Month ESX Pseudo Bonds

In this figure, we illustrate credit spreads and empirical default probabilities of six-month pseudo bonds for the U.K. Pseudo bonds in local currency (LC) are constructed from put options on the FTSE100 Index (ESX), while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks the FTSE100 index in USD. For six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendix A for details. In Panel (a), we plot the historical 6-month pseudo local currency (i.e., GBP) credit spread based on FTSE100 index options, and the foreign currency (i.e., USD) equivalent of the six-month pseudo credit spread. In Panel (b), we plot the corresponding ex-ante default probabilities for both time series. In Panel (c), we report the monthly number of options used to construct the local and foreign currency empirical credit spreads. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). Shaded vertical bars denote NBER recessions. The data frequency is monthly from 2005 to 2024.

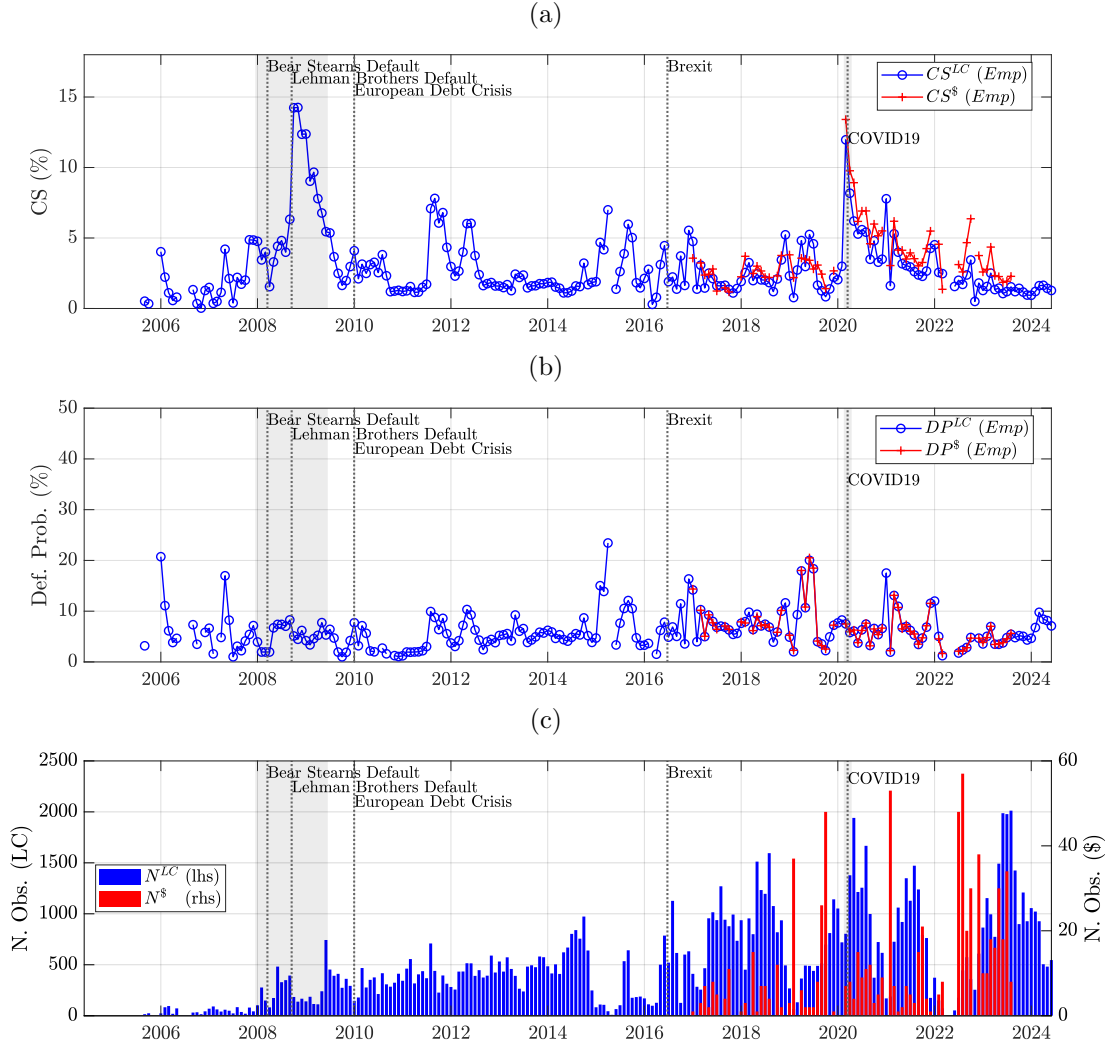


Figure 3: Synthetic Credit Spreads of Six-Month ESX Pseudo Bonds

In this figure, we illustrate credit spreads of six-month pseudo bonds for the U.K., comparing the empirical pseudo spreads to their synthetic counterparts. Pseudo bonds in local currency (LC) are constructed from put options on the FTSE100 Index (ESX), while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks the FTSE100 index in USD. Synthetic foreign (local) currency options are constructed from the empirical local (foreign) options using the Black-Scholes-Merton model to price put options written on the synthetic foreign (local) currency stock market index. For six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendices A and B for details. In Panel (a), we plot the historical 6-month pseudo local currency (i.e., GBP) credit spread based on FTSE100 index options and compare it to the synthetic counterpart. In Panel (b), we plot the foreign currency (i.e., USD) equivalent of the six-month pseudo credit spread and compare it to the synthetic counterpart. In Panel (c), we plot the combined series of local and foreign currency pseudo credit spreads. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). Shaded vertical bars denote NBER recessions. The data frequency is monthly from 2003 to 2024.

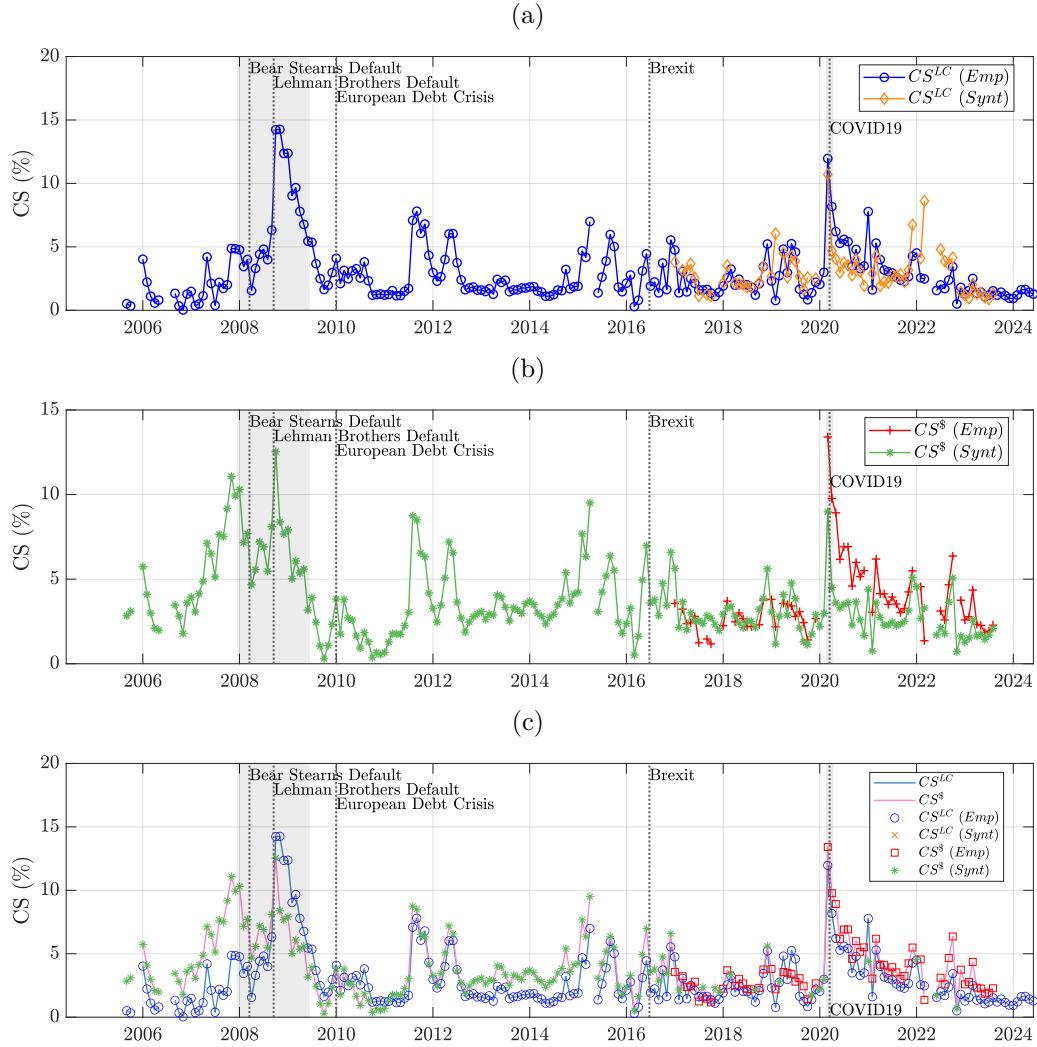


Figure 4: Credit Spreads of Six-Month ESX Pseudo Bonds - By Currency

In this figure, we illustrate credit spreads of six-month pseudo bonds for the U.K., comparing the pseudo spreads in local and foreign currency. Pseudo bonds in local currency (LC) are constructed from put options on the FTSE100 Index (ESX), while those in foreign currency (labeled with \$) are constructed using USD denominated options on the exchange traded fund (ETF) that tracks the FTSE100 index in USD. Synthetic foreign (local) currency options are constructed from the empirical local (foreign) options using the Black-Scholes-Merton model to price put options written on the synthetic foreign (local) currency stock market index. For six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendices A and B for details. In Panel (a), we plot the historical six-month pseudo local currency (i.e., GBP) credit spread based on FTSE100 index options and compare it to the synthetic counterpart. In Panel (b), we plot the ratio of the historical 6-month pseudo LC credit spread based on FTSE100 index options to its foreign currency counterpart. In Panel (c), we plot the credit spread differential, defined as the difference between the historical 6-month foreign and local currency pseudo credit spreads. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). Shaded vertical bars denote NBER recessions. The data frequency is monthly from 2003 to 2024.

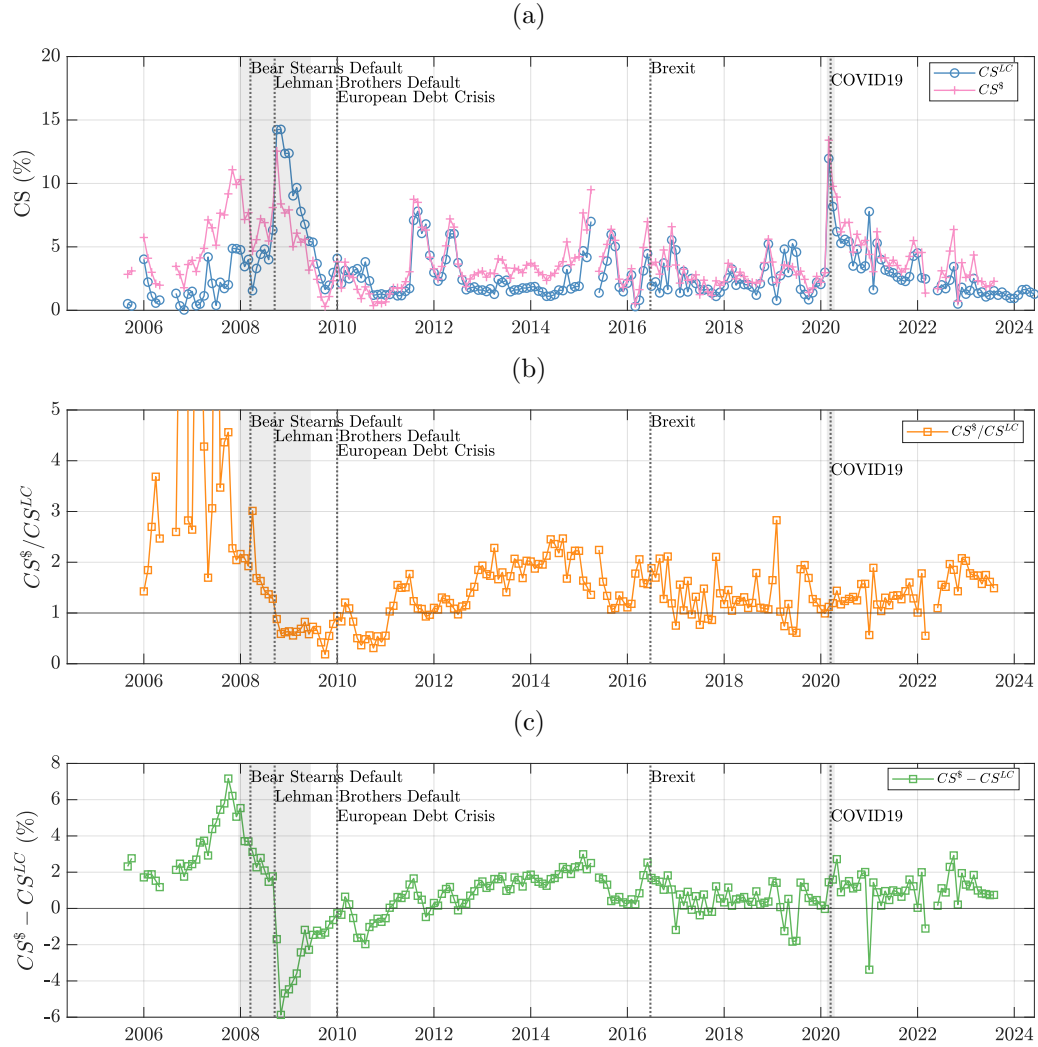


Figure 5: Six-Month ESX Pseudo Bonds - Model Diagnostics

In this figure, we illustrate default probabilities, implied volatilities and implied leverages of six-month pseudo bonds for the U.K. Pseudo bonds in local currency (LC) are constructed from put options on the FTSE100 Index (ESX), while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks the FTSE100 index in USD. Synthetic foreign (local) currency options are constructed from the empirical local (foreign) options using the Black-Scholes-Merton model to price put options written on the synthetic foreign (local) currency stock market index. The empirical default probability for each pseudo bond under the physical measure P is based on the historical default frequency. The risk-neutral (Q) default probability is computed with the Black-Scholes-Merton model over the same horizon. For six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendices A and B for details. In Panel (a), we plot for both foreign and local currency ratio of default probabilities under the risk-neutral (Q) and physical (P) probability measures, respectively. In Panel (b), we report the implied volatility of the ESX in foreign and local currencies. In Panel (c), we illustrate the implied leverage of the corresponding pseudo bonds. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). Shaded vertical bars denote NBER recessions. The data frequency is monthly from 2003 to 2024.

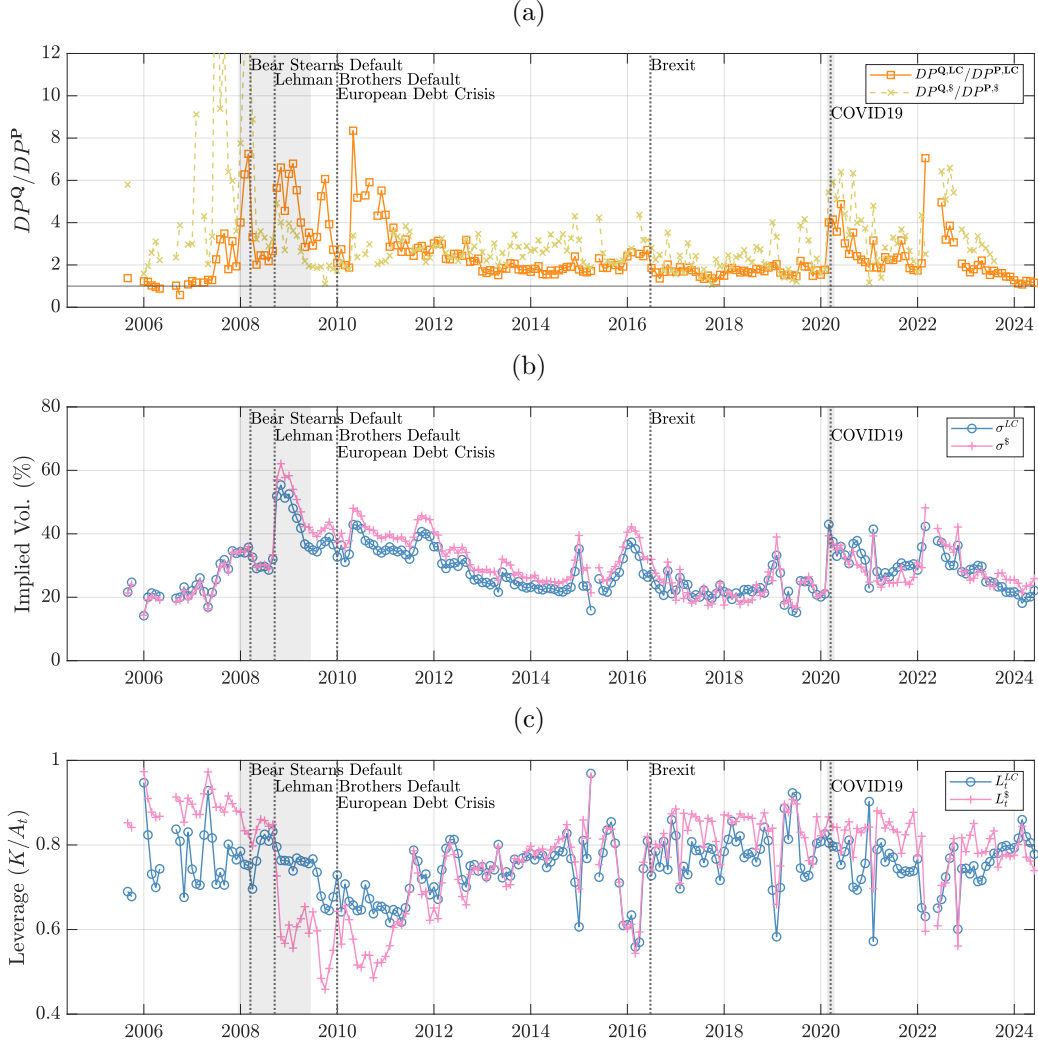


Figure 6: Pseudo Quanto Spreads and Risk Premia

In this figure, we illustrate the relation between the pseudo quanto spread and the cross-currency difference in risk premium for the U.K. The pseudo quanto spread is defined as difference between foreign and local currency credit spreads. The cross-currency difference in risk premium is measured as the difference between foreign and local currency risk-neutral default probabilities. Pseudo bonds in local currency (LC) are constructed from put options on the FTSE100 Index (ESX), while those in foreign currency (labeled with \$) are constructed using USD-denominated options on the exchange traded fund (ETF) that tracks the FTSE100 index in USD. Synthetic foreign (local) currency options are constructed from the empirical local (foreign) options using the Black-Scholes-Merton (BSM) model to price put options written on the synthetic foreign (local) currency stock market index. Default probabilities under the risk-neutral measure Q are computed with the Black-Scholes-Merton model. For six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendices A and B for details. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). The data frequency is monthly from 2003 to 2024.

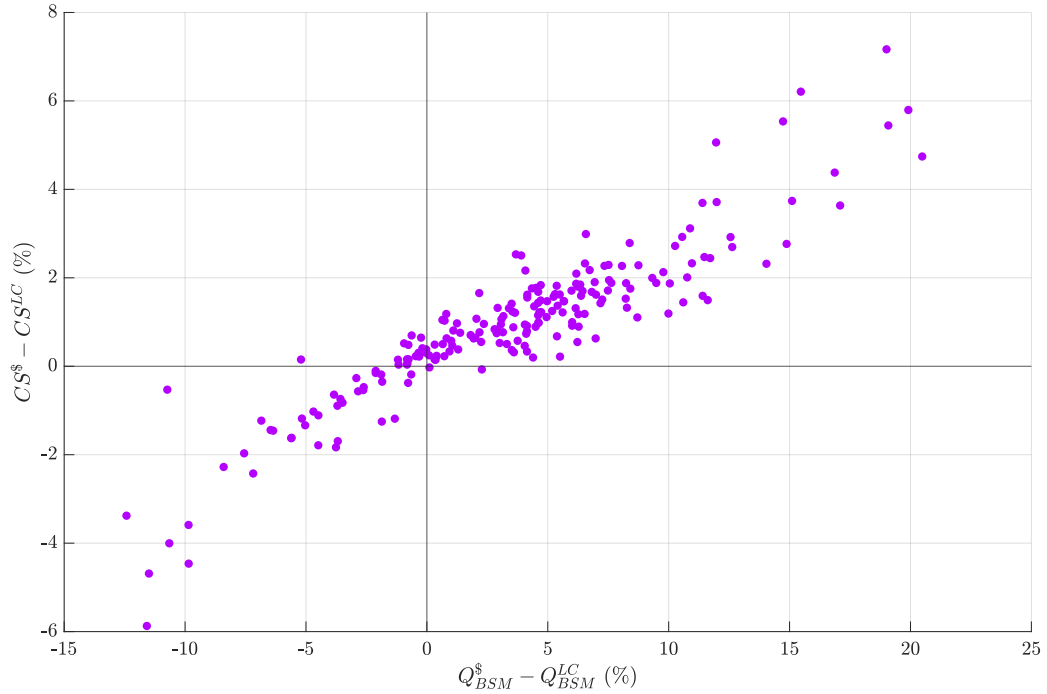


Figure 7: Theoretical Predictions

In this figure, we illustrate the economic mechanism of our stylized model for pseudo credit spreads denominated in different currencies. The figure shows how credit spreads, leverage, and the risk-neutral default probability react to changes in the default probability (Panels a, b, c), changes in the currency premium (Panels d, e, f), and changes in the correlation between the local stock market index and the USD-GBP exchange rate (Panels g, h, i). Measures in local currency (GBP) are reported using dashed red lines, while measures in foreign currency (USD) are reported using solid blue lines. The calibration of model parameters is summarized in Table A.4.

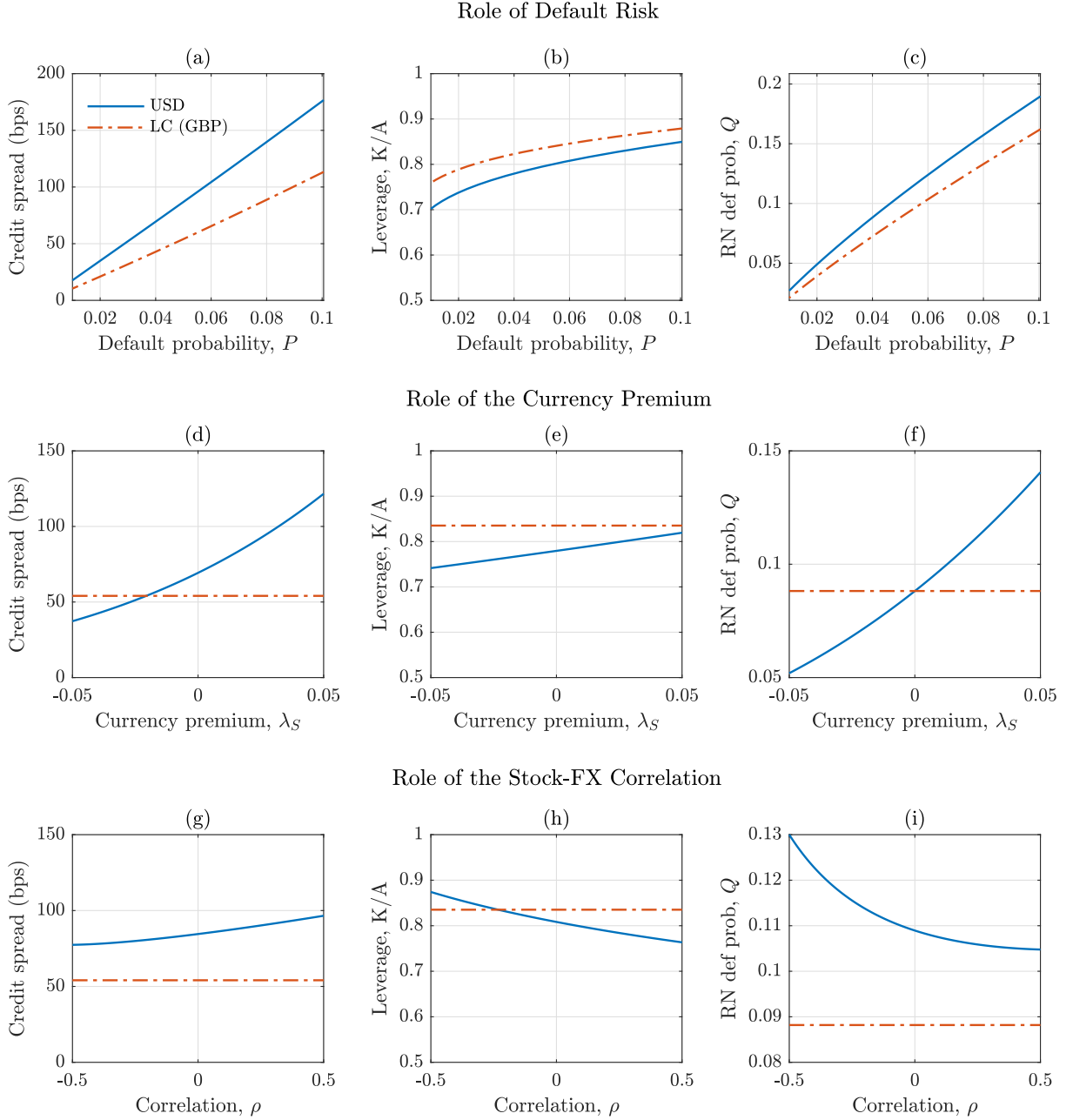


Figure 8: Regional Credit Spreads of Six-Month Pseudo Bonds

In this figure, we illustrate regional GDP-weighted averages of the credit spreads of six-month pseudo bonds in local and foreign currencies. 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. For six-month bonds, we restrict the option maturity to be within [91, 365] days. See Appendices A and B for details. In Panel (a), we plot the local currency pseudo spread for three regions: Europe, Asia-Pacific, and the Americas, using the GDP-weighted average pseudo spread across countries. In Panel (b), we plot the USD denominate pseudo spread for the same three regions. Europe: Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Norway, Poland, United Kingdom, Spain, Sweden, Switzerland and Turkey; Asia-Pacific: China, India, Japan, South Korea, Malaysia, Singapore and Thailand; Americas: Brazil, Canada, Chile, Colombia, Mexico. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS); and from IMF for GDP data. Shaded vertical bars denote NBER recessions. The data frequency is monthly from 2003 to 2024.

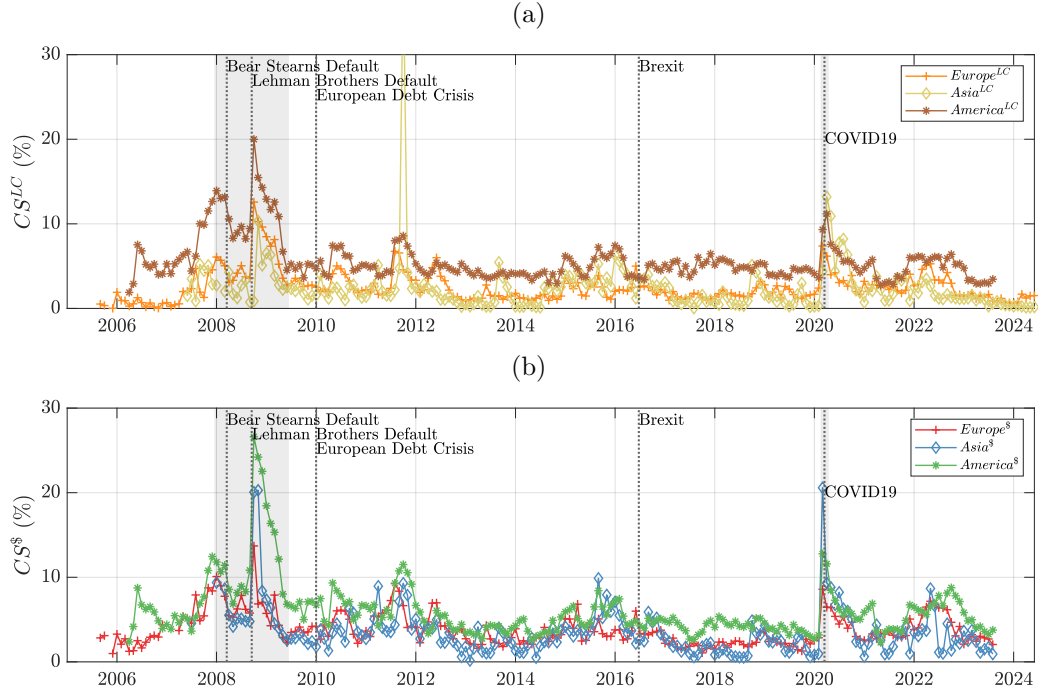
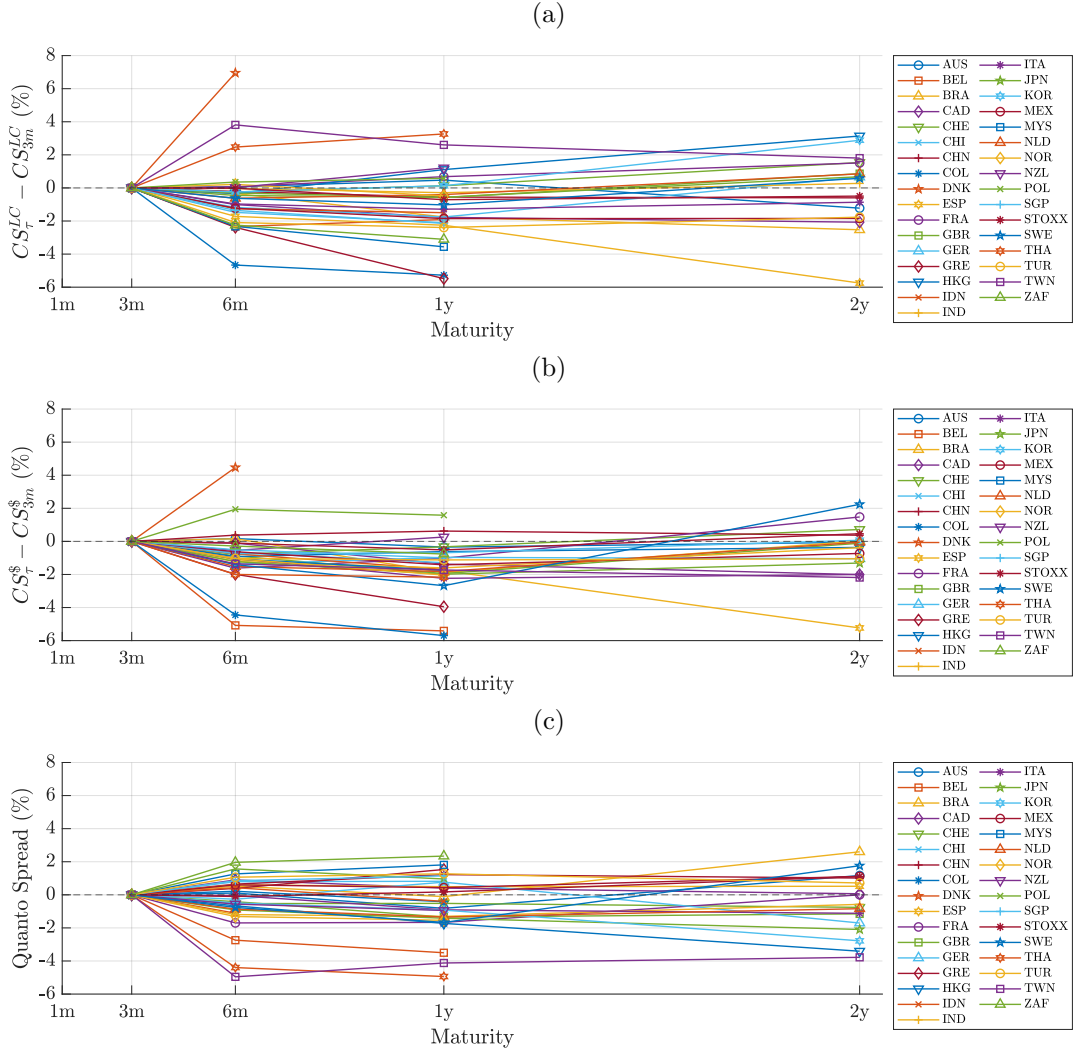


Figure 9: Term Structure of Pseudo Credit Spreads

In this figure, we illustrate the average term structure of credit spreads of pseudo bonds in local and foreign currencies. 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. For three-month, six-month, one-year, and two-year bonds, we restrict the option maturity to be within [7,182], [91, 365], [182, 547] and [365, 1095] days, respectively. See Appendices A and B for details. In Panel (a), we plot the local currency term structure of pseudo spreads across countries with respect to the respective three-month local currency average credit spread. In Panel (b), we plot the foreign currency term structure of pseudo spreads across countries with respect to the respective three-month local currency average credit spread. In Panel (c), we plot the average term structure of pseudo quanto spreads, i.e., the difference between USD and LC denominated spreads, with respect to the respective three-month quanto spread. The data are sourced from Refinitiv Eikon Datastream and from OptionMetrics through Wharton Research Data Services (WRDS). Shaded vertical bars denote NBER recessions. The data frequency is monthly from 2003 to 2024.



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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.

Appendix

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A Estimation of Empirical Credit Spreads

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

A.1 ETF and Index Options Data

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

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

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

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

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

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

A.2 Forecasting Expected Returns

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

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

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 $\sigma_{t,\tau}$.

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

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

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

For non-SPX indices, we estimate the time- t expected return parameter $\mu_{t,\tau}$ for some forecast horizon 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:

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

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 iteratively forecast and accumulate returns over the desired τ -month horizon.

A.3 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:

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

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:

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

A.4 Estimating Ex-Ante Default Probabilities

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

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

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

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

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 $\hat{\varepsilon}_{t,\tau} = (\ln(A_{t+\tau}/A_t) - \hat{\mu}_{t,\tau})/\hat{\sigma}_{t,\tau}$. The estimation of $\hat{\mu}_{t,\tau}$ and $\hat{\sigma}_{t,\tau}$ is described in Sections A.2 and A.3, respectively. Using the empirical shock distribution, we estimate the physical default probability for pseudo-firm i as $\hat{p}_{i,t}(\tau) = \mathbb{P}[A_{t,\tau} < K_i \mid \mathcal{F}_t] = \mathbb{P}[\hat{\varepsilon}_{t,\tau} < X_{i,t} \mid \mathcal{F}_t]$, where $X_{i,t} = (\ln(K_i/A_t) - \hat{\mu}_{t,\tau})/\hat{\sigma}_{t,\tau}$. This probability is computed as the in-sample frequency of historical shocks falling below the threshold $X_{i,t}$, i.e., $\hat{p}_{i,t}(\tau) = n(\hat{\varepsilon}_{t,\tau} < X_{i,t})/n(\hat{\varepsilon}_{t,\tau})$, 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 $\hat{\varepsilon}_{s,\tau} = (\ln(A_{s+\tau}/A_s) - \hat{\mu}_{s,\tau})/\hat{\sigma}_{s,\tau}$ for all $s + \tau < t$. Practically, this requires re-estimating $\hat{\mu}_{s,\tau}$ and $\hat{\sigma}_{s,\tau}$ 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., $\hat{\varepsilon}_{s,\tau} < \hat{X}_{i,t}$.

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

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

A.5 Risk-Free Rates

We estimate local-currency (LC) risk-free rates using options on the domestic stock market index. Specifically, we follow [Brenner and Galai \(1986\)](#), [Van Binsbergen et al. \(2022\)](#), and [Diamond and Van Tassel \(2021\)](#) in inferring implied interest rates from the put-call parity relation applied to European-style options on the local stock market index. The resulting rates, commonly referred to as box rates, are considered free of credit and convenience yield components.⁸

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:

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

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

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

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

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

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

⁸Following [Van Binsbergen et al. \(2022\)](#), we further limit the sample for box rate estimation to option contracts with more than 21 days to maturity.

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

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

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

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

$$\hat{r}_{t,T}^{\$} = \hat{r}_{t,T}^{LC} - \rho_{t,T}, \quad (\text{A.9})$$

where $\rho_{t,T} = (T - t)^{-1}(f_{t,T}/s_t)$ is the log forward premium defined as the difference between the log forward rate $f_{t,T}$ and the log exchange rate s_t . To construct the forward premium, we use the forward rates, spot rates, and days to settlement obtained from Bloomberg. Table [A.1](#) 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 $\hat{r}_{t,T}^{LC} = \hat{r}_{t,T}^{\$} + \rho_{t,T}$. 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.2 presents summary statistics for the box rates in LC and FC at the monthly frequency. The last three columns of the Table indicate if the box rate is obtained directly from the options on the local index, from the options on the local index but converted in the appropriate currency using the CIP condition, or obtained from applying the CIP condition to the US box rates.

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

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

We assign a pseudo credit rating to each pseudo-bond by matching its ex-ante default probability, computed as described in Section A.4, with a credit rating category provided by Moody’s 2022 Annual Default Study Report (Moody’s, 2022). Exhibit 39 in Moody’s (2022) provides average cumulative global default rates by letter rating for various default horizons, ranging from one year to 20 years. These default rates are computed from 1970 to 2022. Since pseudo bonds are mostly computed for short maturities, we primarily rely on the 1-year and 2-year cumulative default probabilities, which we report in Table A.3 for convenience.

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

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

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

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

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

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

A.7 Country-Level Aggregation of Credit Spreads

For countries other than the U.S., we construct aggregate pseudo credit spreads representing the credit risk of the 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.

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

B Estimation of Synthetic Credit Spreads

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

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

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

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

$$\hat{B}_t^{\$}(K^{\$}, T) = K^{\$} \hat{Z}_t^{\$}(T) - \hat{P}_t^{\$}(K^{\$}, T), \quad (\text{B.1})$$

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

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

For each option in our sample, we construct a twin option in foreign currency. We obtain the foreign currency denominated underlying counterpart by multiplying the local currency stock market index with the exchange rate, $A_t^{\$} = A_t \cdot S_t$, where S_t denotes the exchange rate expressed in units of FC per LC.⁹ The time to maturity τ and the dividend yields are fixed to be identical for both twins. We compute the riskless rate in FC by applying the covered interest rate parity condition to the riskless rate denominated in LC, as described in Section A.5. We construct the implied volatility in FC by using a combination of the twin option's implied volatility in LC and the implied volatility of the options on the exchange rate, as

⁹As reflected in Table A.1, we could have directly used prices of the stock market indices tracking the local stock market index in FC. We use a synthetic underlying asset to remain consistent with our model in Section B.2.

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

$$\hat{p}_{i,t}(\tau) = \mathbb{P}[A_{t,\tau} < K_i \mid \mathcal{F}_t] \equiv \hat{p}_{j,t}^\$(\tau) = \mathbb{P}[A_{t,\tau}^\$ < K_j^\$ \mid \mathcal{F}_t]. \quad (\text{B.3})$$

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

B.2 Synthetic Foreign Currency Volatility Estimations

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

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

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 $A_t^\$$, which evolve as:

$$\begin{aligned} dA_t^\$ &= A_t S_t dS_t / S_t + A_t S_t dA_t / A_t + A_t S_t dS_t / S_t dA_t / A_t \\ &= A_t S_t \left[\mu^S dt + \sigma^S \left(\rho dW_t + \sqrt{1 - \rho^2} dW_t^\perp \right) \right] + A_t S_t (\mu dt + \sigma dW_t) + A_t S_t \rho \sigma \sigma^S dt \\ &= A_t^\$ \left[(\mu^S + \mu + \rho \sigma \sigma^S) dt + (\sigma + \rho \sigma^S) dW_t + \sigma^S \sqrt{1 - \rho^2} dW_t^\perp \right] \\ &= A_t^\$ \left[(\mu^S + \mu + \rho \sigma \sigma^S) dt + \sigma^\$ dW_t^\$ \right], \end{aligned}$$

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

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

with

$$(\sigma^\$)^2 = (\sigma^S)^2 + (\sigma)^2 + 2\rho\sigma\sigma^S, \quad (\text{B.4})$$

which we can compute using implied volatilities of foreign exchange and stock index options. We use at-the-money implied volatilities of exchange rate options to estimate σ_S . To estimate σ , we rely on local currency options with similar moneyness to avoid biases associated with differences in implied volatility smiles. If necessary, we also maturity-match the implied volatilities on the exchange-rate options by interpolating along the maturity axis. At-the-money implied volatilities of European options are directly available from Bloomberg. The correlation between exchange rate returns and asset returns is obtained using a 5-year rolling window.¹⁰

B.3 Matching Pseudo Bonds Across Currencies

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

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

Using this method, we can generate two sets of pseudo credit spreads, depending on what currency-denomination we use as benchmark: LC or FC (USD). We select the currency benchmark for each country based on the highest number of observation for the CS index time series after filling as many missing empirical estimates with their synthetic counterparts as possible. Table A.12 presents what benchmark currency we use for each country and maturity in our empirical implementation.

¹⁰Our results are similar when we use dynamic conditional correlations (Engle, 2002).

C Data Appendix

Indices and ETFs returns and dividend yield. We download price and dividend data for the primary stock indices of each country in our sample. For the majority of countries, we find also find price and dividend data on the ETF on the MSCI country index, in USD. When the dividend data is unavailable, we download total returns and back out the dividends using the total returns and ex-dividend returns. The daily time series are downloaded from Datastream. Columns (4), (5), and (6) in Table A.1 present show data availability for the LC stock indices, and columns (7) and (8) for the FC stock indices. Note that the last row of the Table describes the downloading ticker format for each time series. The starting date of each country’s time series in LC varies greatly across the sample. The data on the US stock market dates back to 1871, but for the majority of the countries, we only have data dating from the early 1980s. For the FC indices, most ETFs were not traded before the mid-to-late 1990s. This data is notably used to estimate the ex-ante probability of default of pseudo debt as described in Section A.4.

Spot exchange rates. We obtain the last spot exchange rate from Bloomberg. The local currency time series ticker is expressed in units of USD and writes “USDCCY Curncy”. Our spot exchange rate data spans twenty currency pairs at a daily frequency. Table A.1 lists the various exchange rates used in our analysis; note that we use the CNH (offshore market Chinese Yuan), not the CNY, to represent the Renminbi value as there are trading restrictions on the latter.

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

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

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

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

D.1 Fundamental Equation of Asset Pricing in Continuous Time

We here verify that

$$\mathbb{E}_t \left[\frac{d(M_t X_t)}{M_t X_t} \right] = 0 \quad (\text{B.5})$$

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

$$\frac{dB_t}{B_t} = r dt, \quad (\text{B.6})$$

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

We indeed have

$$\mathbb{E}_t \left[\frac{d(M_t B_t)}{M_t B_t} \right] = \underbrace{\mathbb{E} \left[\frac{dM_t}{M_t} \right]}_{-r dt} + \underbrace{\mathbb{E} \left[\frac{dB_t}{B_t} \right]}_{r dt} + \underbrace{\mathbb{E} \left[\frac{dM_t}{M_t} \frac{dB_t}{B_t} \right]}_0 = 0, \quad (\text{B.7})$$

which verifies that Equation (B.5) holds.

D.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 (12), we obtain (ignoring time subscripts for convenience):

$$\begin{aligned} df(M, S, B^\$) &= \frac{B^\$}{S} dM - \frac{MB^\$}{S^2} dS + \frac{M}{S} dB^\$ \\ &\quad + \frac{1}{2} \left(2M \frac{B^\$}{S^3} (dS)^2 + 0(dM)^2 + 0(dB^\$)^2 \right) \\ &\quad - \frac{1}{S^2} B^\$ dM dS + \frac{1}{S} dM dB^\$ - M \frac{1}{S^2} dS dB^\$. \end{aligned} \quad (\text{B.8})$$

After taking expectations, we obtain

$$\begin{aligned}
\mathbb{E}_t [df(M, S, B^\$)] &= \mathbb{E}_t \left[\frac{B^\$}{S} dM \right] - \mathbb{E}_t \left[\frac{MB^\$}{S^2} dS \right] + \mathbb{E}_t \left[\frac{M}{S} dB^\$ \right] \\
&\quad + \underbrace{\mathbb{E}_t \left[M \frac{B^\$}{S^3} (dS)^2 \right]}_{M \frac{B^\$}{S} \sigma_S^2 dt} - \mathbb{E}_t \left[\frac{1}{S^2} B^\$ dM dS \right] \\
&\quad + \underbrace{\mathbb{E}_t \left[\frac{1}{S} dM dB^\$ \right]}_0 - \underbrace{\mathbb{E}_t \left[M \frac{1}{S^2} dS dB^\$ \right]}_0.
\end{aligned} \tag{B.9}$$

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

$$\mathbb{E}_t \left[\frac{df(M, S, B^\$)}{M(1/S)B^\$} \right] = \underbrace{\mathbb{E}_t \left[\frac{dM}{M} \right]}_{-r dt} - \mathbb{E}_t \left[\frac{dS}{S} \right] + \underbrace{\mathbb{E}_t \left[\frac{dB^\$}{B^\$} \right]}_{r^\$ dt} + \sigma_S^2 dt - \mathbb{E}_t \left[\frac{dM}{M} \frac{dS}{S} \right]. \tag{B.10}$$

Finally, after re-arranging, we obtain

$$\mathbb{E}_t \left[\frac{dS}{S} \right] = (r^\$ - r + \sigma_S^2) dt - \mathbb{E}_t \left[\frac{dM}{M} \frac{dS}{S} \right]. \tag{B.11}$$

Table A.1: Data Source

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

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

Table A.2: Local and Foreign Box Rate Indices – 3-Month Horizon

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

Panel A: Developed Countries

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

Panel B: Emerging Countries

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

Panel C: Foreign (SPX) Box Rates

Country	Index Type	N	Mean	Median	SD	5 th prc.	95 th prc.
United States	SPX box rate	250	0.019	0.012	0.016	0.003	0.053

Table A.3: 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.4: Model Calibration.

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

Parameter	Notation	Values
<i>Panel A: Risk-free rates and exchange rate</i>		
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
<i>Panel B: Stock index in local currency (GBP)</i>		
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
<i>Panel C: Stock index in USD</i>		
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	$\sigma^{\$} = \sqrt{\sigma^2 + \sigma_S^2 + 2\rho\sigma\sigma_S}$	0.182
Face debt value	$K^{\$}$	set s.t. $\mathbb{P}^{\$} = \mathbb{P}$

Table A.5: Local and Foreign Currency Pseudo Credit Spreads – 3-Month Horizon

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

Panel A: Developed Countries

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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
Israel	120	4.30	2.11	6.62	0.51	18.66	107	47.44	47.66	22.53	11.89	87.71	-0.12	0.40
Italy	187	2.55	1.65	2.89	0.52	7.91	177	3.41	2.77	2.89	0.18	9.84	0.34	0.30
Japan	205	2.26	1.59	2.32	0.51	5.24	189	3.57	3.09	2.89	0.81	9.22	0.75	-0.44
Netherlands	220	2.20	1.15	3.13	0.35	8.81	210	4.60	3.76	3.11	1.29	10.95	0.54	0.18
Norway	174	4.31	3.61	2.86	1.15	9.46	164	10.35	9.34	6.30	2.88	20.78	0.60	0.48
New Zealand	38	7.78	7.80	2.46	4.02	12.22	38	8.11	8.47	2.35	4.21	11.84	0.79	-
Singapore	82	5.77	5.54	2.48	2.45	11.13	82	4.24	4.00	1.50	2.26	6.82	0.60	0.52
South Korea	193	5.36	5.11	3.35	1.08	11.96	194	6.18	5.22	4.60	2.48	13.62	0.37	0.46
Spain	181	7.21	6.15	4.33	2.42	17.19	181	7.43	5.81	5.28	2.70	18.74	0.80	0.35
Sweden	184	6.60	5.52	4.40	1.61	14.25	180	10.26	8.84	5.80	3.14	20.99	0.73	0.26
Switzerland	200	2.47	1.85	2.53	0.30	6.90	203	4.67	3.36	3.63	1.54	11.56	0.64	-0.08
Taiwan	132	2.34	1.60	2.30	0.18	6.90	125	5.92	5.31	2.90	2.34	12.00	0.65	0.53
United Kingdom	222	3.40	2.33	3.00	0.91	8.71	212	4.84	3.98	3.14	1.50	11.32	0.75	0.21
All	3,453	3.85	2.65	3.72	0.44	10.68	3,332	7.04	4.61	9.44	1.31	18.31	0.26	-

Panel B: Emerging Countries

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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.6: Local and Foreign Currency Pseudo Credit Spreads – 12-Month Horizon

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

Panel A: Developed Countries

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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	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

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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.7: Local and Foreign Currency Pseudo Credit Spreads – 24-Month Horizon

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

Panel A: Developed Countries

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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

Country	Local Currency CS						Foreign Currency CS						Correlations	
	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.8: Local and Foreign Currency Ex-ante Default Probabilities – 6-Month Horizon

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

Panel A: Developed Countries

Country	Local Currency						Foreign Currency						ρ_{D^{PLC}, DP^S}
	N	Mean	Median	SD	5 th prc.	95 th prc.	N	Mean	Median	SD	5 th prc.	95 th prc.	
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

Country	Local Currency						Foreign Currency						ρ_{D^{PLC}, DP^S}
	N	Mean	Median	SD	5 th prc.	95 th prc.	N	Mean	Median	SD	5 th prc.	95 th prc.	
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.9: Descriptive Statistics – Analysis of the Drivers

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

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

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

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

Table A.10: Descriptive Statistics – Predictability Analysis

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

Dependent Variables							
	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
Agg growth (NoUS,VW,3m)	1770	0.006	0.0158	-0.0677	0.0815	0.0034	0.01
Agg growth (NoUS,EW,3m)	1754	0.0059	0.0194	-0.108	0.0874	0.0019	0.0124
Agg growth (VW,3m)	1770	0.0058	0.0156	-0.0721	0.0796	0.0024	0.0095
Agg growth (EW,3m)	1754	0.0059	0.0191	-0.106	0.0864	0.0024	0.0123
Agg growth (NoUS,VW,12m)	1770	0.0237	0.0271	-0.1032	0.124	-0.0089	0.0383
Agg growth (VW,12m)	1770	0.0229	0.0256	-0.0956	0.1215	-0.0093	0.0346
Agg growth (NoUS,EW,12m)	1696	0.0233	0.03	-0.1225	0.131	-0.0069	0.0448
Agg growth (EW,12m)	1696	0.0231	0.0294	-0.119	0.1297	-0.0054	0.0432
Country growth (12m)	1572	0.0197	0.039	-0.2483	0.2283	-0.0165	0.0547
FX Return (USD/LC,12m)	1572	-0.0238	0.0985	-0.7557	0.3162	-0.1465	0.0806
Credit Spreads and Risk Decomposition							
	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
CS LC (AVG)	1770	0.0474	0.0338	0.0001	0.3767	0.014	0.0892
CS Diff (USD-LC,AVG)	1718	0.0146	0.0633	-0.144	0.5257	-0.0067	0.026
Default Prob (3m)	1743	0.0828	0.1055	0	0.9065	0.0134	0.1518
Default Prob (avg)	1763	0.1121	0.1065	0	0.9065	0.0181	0.1894
Q - P (LC,3m)	1743	0.0464	0.1101	-0.8255	0.2883	0.0027	0.1403
Q - P (LC,avg)	1743	0.0464	0.1101	-0.8255	0.2883	0.0027	0.1403
Controls							
	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
CS US (orth,3m)	1634	0	1.0167	-3.3566	7.097	-0.9255	0.976
CS US (orth,avg)	1659	0	0.9952	-2.9106	6.5631	-0.8701	0.9573
Term Spread	1770	1.3121	1.2194	-1.72	3.57	-0.4383	2.73
Macro Uncertainty	1770	0.8256	0.1346	0.6679	1.2772	0.7067	0.9953
FFR	1770	1.2457	1.6541	0.06	5.33	0.0833	4.5167
GZ Spread (orth,3m)	720	0	0.4083	-1.1977	1.5105	-0.3737	0.3331
GZ Spread (orth,avg)	730	0	0.4062	-1.2199	1.5004	-0.3754	0.3597
Country growth	1646	0.005	0.0249	-0.2585	0.2035	-0.0056	0.0177
Measures of FX Cyclicalilty							
	N	Mean	SD	Minimum	Maximum	10% Pct.	90% Pct.
Corr (LC Index,FX)	1609	0.1994	0.2626	-0.5971	0.7594	-0.1776	0.5301
Corr (SPX,FX)	1646	0.3961	0.2394	-0.4449	0.8484	0.0597	0.6825
Corr (US Cons,FX)	1646	0.0742	0.1292	-0.335	0.5291	-0.0702	0.2362

Table A.11: 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	-3.543*** (-7.27)	-5.217*** (-4.89)	-3.570*** (-7.66)	-5.309*** (-5.31)	-4.798*** (-8.62)	-6.280*** (-5.78)	-4.704*** (-8.62)	-6.221*** (-5.84)
Default Premium (Q - P)	-3.410*** (-7.20)	-4.934*** (-4.65)	-3.450*** (-7.63)	-5.049*** (-5.08)	-4.540*** (-8.41)	-5.669*** (-5.25)	-4.459*** (-8.43)	-5.643*** (-5.33)
Term Spread	0.323*** (8.81)	0.822*** (9.35)	0.300*** (8.55)	0.722*** (8.76)	0.446*** (10.68)	0.997*** (11.14)	0.430*** (10.51)	0.956*** (10.90)
Macro Uncertainty	3.810*** (10.39)	9.099*** (10.79)	3.959*** (11.29)	9.273*** (11.83)	5.477*** (13.12)	12.157*** (14.52)	5.377*** (13.12)	11.942*** (14.55)
CS US	-0.776*** (-15.48)	-0.765*** (-7.72)	-0.794*** (-16.23)	-0.808*** (-8.66)	-1.035*** (-17.28)	-0.878*** (-8.57)	-1.019*** (-17.31)	-0.880*** (-8.76)
Constant	-2.424*** (-7.57)	-5.388*** (-7.32)	-2.565*** (-8.38)	-5.492*** (-8.02)	-3.929*** (-10.84)	-8.185*** (-11.25)	-3.842*** (-10.80)	-7.974*** (-11.17)
Observations	1,634	1,634	1,634	1,634	1,634	1,634	1,634	1,634
R-squared	0.175	0.165	0.167	0.164	0.158	0.213	0.157	0.210

Table A.12: Benchmark Currency Choices for Matching Procedure.

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

Panel A: Developed Countries

Country	Maturity			
	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

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