The Global Credit Cycle*

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Abstract

Using a large cross-section of corporate bond returns around the world, we construct a novel global credit factor that prices international corporate bonds in both the time-series and the cross-section. We estimate the global credit factor as a function of both the VIX and U. S. credit spreads, and show that incorporating information from nonlinearities and from interactions between the two is important for the forecasting performance of the global credit factor. In the cross-section, riskier bonds and bonds of issuers in riskier countries have a higher loading on the global credit factor. Periods of tight credit conditions correspond not only to larger probabilities of negative bond returns and higher future bond return volatility but, importantly, to a persistent deterioration in firms' credit risk and increases in credit spreads, especially for riskier firms. This suggests that increases in the global price of credit risk have real consequences for corporate bond borrowers.

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1 Introduction

As of the end of 2024, the global outstanding of nonfinancial corporate bonds was more than $18 trillion, with $11.6 trillion of that outstanding issued by firms in G-7 countries, $4.6 trillion by firms in China, and the remaining $2.4 trillion by firms in the rest of the world.[1] Despite the growing importance of corporate bond markets to the global economy, and as a source of financing for nonfinancial firms,[2] understanding of how risk is priced in international corporate bond markets – and whether the pricing of corporate credit risk is global – is limited.

In this paper, we document a global component to corporate bond returns around the world. Using a nonparametric method, we estimate a global credit factor from the nonlinear relationship between a panel of future excess returns on credit-rating-sorted portfolios of advanced economy corporate bonds , U. S. equity market volatility (as measured by the VIX) and U. S. credit spreads (as measured by the Gilchrist and Zakrajšek (2012) default-adjusted spread, EBP). Building on Adrian et al. (2019a), we use a sieve reduced-rank regression to construct our estimate of the global credit factor. The sieve reduced-rank estimator proceeds in two steps. First, future returns on the test assets are regressed in the time series on a bi-variate sieve expansion of the VIX and U. S. credit spreads. Second, the rank of the matrix of forecasting coefficients is reduced using an eigenvalue decomposition, and only the reduced rank approximation that optimizes out-of-sample predictability is retained.

We find strong evidence that there is a single (nonlinear) global credit factor that prices advanced economy corporate bond portfolios in both the time-series and the cross-section. Furthermore, the global credit factor incorporates information from both the VIX and credit spreads and their interactions; specifications that use only the VIX *or* U. S. credit spreads

[1] Source: BIS debt securities statistics as of Q4 2024, for debt securities of all original maturities and currencies, as collected from national financial accounts.

[2] In the U. S., where corporate debt markets are most prevalent, bonds represent around 77% of firm debt while outside the U. S. they represent more than 16% of total debt (SIFMA, 2025).

are systematically rejected by the data. The global credit factor also has low correlation with alternative proxies for the global financial cycle, including the VIX itself, the traded-weighted dollar exchange rate, and the Miranda-Agrippino and Rey (2015) global financial cycle factor.

Moving beyond the test assets used to construct the global credit factor, we show that, at the bond level, the global credit factor forecasts returns, with exposure to the global credit factor increasing in bond and country risk. On average, high yield bonds are more exposed to the global credit factor than AAA/AA-rated bonds are, and, for a given credit rating, bonds in emerging market economies are more exposed than bonds in advanced economies. When we further expand the set of test assets to include returns on sovereign bonds and equity indices, the ranking of estimated global credit factor β across security risk remains consistent: sovereign bonds have the lowest exposure, followed by corporate bonds, and equities have the biggest exposure.

When we consider what sources of risks are priced, we find that the global credit factor predicts the compensation for both duration and credit risk, with duration risk compensation rising in credit quality (highest exposure for AAA/AA-rated bonds and lowest exposure for high yield bonds) and credit risk compensation declining in credit rating (lowest exposure for AAA/AA-rated bonds and highest exposure for high yield bonds). Thus, not only does the global credit factor act as a price of risk in the global market for corporate credit risk, but exposures to the global credit factor are larger when the observable amount of risk is higher. Furthermore, when we consider which countries are more exposed to fluctuations in the global price of credit, we find that measures of financial market integration systematically predict higher exposure to the global credit cycle, especially for emerging market economies. As financial market openness (measured using the Chinn and Ito (2006) index) increases from the 25th percentile to the 75th percentile, the exposure of emerging market corporate bonds to the global credit factor increases by almost 50%.

So what are the broader implications of an increase in the global price of risk? Starting with financial market risk, we show that increases in the global credit factor correspond to a higher contemporaneous probability of negative one-month returns and higher realized return volatility, especially for lower-rated bonds and for bonds outside of the U. S. Extreme tightenings further predict a higher probability of negative returns for lower-rated bonds at holding horizons of up to three months, suggesting that financial market losses associated with large movements in the global credit cycle may be large.

Importantly, we also provide initial evidence of the real costs of the global credit cycle. Extreme tightenings of the global credit factor predict a prolonged tightening of credit spreads for lower-rated bonds, with credit spreads on high yield bonds remaining elevated up to 5 months following the onset of tight global credit conditions. To the extent that pricing of new corporate bond issuances is benchmarked to secondary market spreads, such prolonged periods of elevated credit spreads are likely to be detrimental to issuers needing to refinance when credit conditions are tight. Consistent with this intuition, we show that, not only credit spreads, but also firms' default probabilities rise when global credit conditions tighten. Furthermore, for high yield firms, default probabilities continue increasing up to three months after the start of global credit factor tightening and remain elevated for longer periods than credit spreads.

This paper is related to several strands of literature. First, a number of papers have studied the risk exposures (Blume et al., 1991; Fama and French, 1993; Elton et al., 1995) of U. S. corporate bonds, and how returns are affected by theoretically-predicted components, such as credit (Gebhardt et al., 2005) and liquidity risk (Lin et al., 2011). More recently, interest has grown in studying the factor structure of corporate bond returns (Israel et al., 2018; Chung et al., 2019; He et al., 2022; Kelly et al., 2023; Bartram et al., 2025; Bali et al., 2021), with a particular focus on factors based on bond characteristics and bond portfolio sorts. A subset of papers focused on the cross-sectional pricing of U. S. corporate bonds

evaluates the performance of different bond-factor pricing model (Dickerson et al., 2023; Van Binsbergen et al., 2025), with results consistently pointing to a bond market factor as the preferred specification. Unlike this literature, our focus is on measuring the price of risk reflected in corporate bond returns, so our main specification of interest is a return forecasting regression, rather than a contemporaneous relationship between returns and priced factors. Furthermore, with the exception of Kelly et al. (2023) and He et al. (2025), the extant literature focuses on portfolios of bonds, whereas we focus on predictability of individual bond returns.

We also contribute to the literature on the pricing of corporate bonds across different international markets. A number of papers have studied the contribution of global and local factors in global corporate bond returns (Bekaert and De Santis, 2021; Bekaert et al., 2024), showing that, although local corporate bond market factors contribute substantially to the cross-sectional pricing of corporate bonds, a single global corporate bond market factor prices returns in the time series. Bekaert et al. (2024) further argue that augmenting the global corporate bond CAPM with a liquidity spread factor improves the time-series pricing performance; in related work, Valenzuela (2016) and Li et al. (2022) document a role for illiquidity premia in corporate bond pricing, especially in emerging markets. The literature has also shown that global factors affect the timing and pricing of corporate bond issuance (Eichengreen and Mody, 1998; Moreno and Serena-Garralda, 2018), suggesting a transmission of global factors beyond prices in the secondary market for corporate bonds. Relative to this literature, we use the information from international corporate bond returns to infer a global price of credit risk – rather than constructing factor-mimicking portfolios – and investigate how exposures to the global price of risk vary across bond risk, country risk, predictive horizon, and financial openness.

Third, we contribute to the literature that studies nonlinearities in aggregate risk prices. From a theoretical perspective,[3] time-varying constraints of financial intermediaries corre-

[3] See e.g. Bernanke and Gertler (1989), He and Krishnamurthy (2013), Brunnermeier and Sannikov

spond to prices of risk that increase nonlinearly as economic conditions deteriorate. This literature moves beyond using market volatility (Ang et al., 2006; Adrian and Rosenberg, 2008; Chung et al., 2019) as a priced factor[4] to allowing for a flexible relationship between a market-wide price of risk and observable factors (Adrian et al., 2019a,b). Adrian et al. (2019a) show that a price of risk constructed as a non-parametric nonlinear function of the VIX captures "flight-to-safety" between U. S. equity and Treasury markets, while Adrian et al. (2019b) further extend the flight-to-safety intuition to global equity and sovereign bond markets. Importantly, by estimating the price of risk as a non-parametric function of common proxies of market risk, the approach in (Adrian et al., 2019a,b) remains agnostic on the constraints of which institutions contribute to the pricing of risk, rather than specifying the marginal intermediary as in, for example, He et al. (2022). Our paper contributes to this literature by extending the non-parametric approach of measuring the global price of risk to constructing a global price of credit risk as a nonlinear function of the VIX and U. S. credit spreads. We show that, in the context of international corporate bond returns, including information from both volatility and credit spreads is crucial for capturing time variation in the price of risk, pointing toward constraints of different types of financial intermediaries playing a role in the global pricing of credit risk.

Fourth, our paper contributes to the literature documenting a large degree of co-movement in asset prices around the globe. Rey (2013) discusses the existence of a GFCy in capital flows, asset prices, and credit growth and the effect this has on other countries' monetary policy independence. Miranda-Agrippino and Rey (2020) discuss the importance of U. S. monetary policy as a driver of the GFCy, and Miranda-Agrippino and Rey (2015) study the importance of the GFCy as a driver of world assets returns. Avdjiev et al. (2020) explore the sensitivity of both cross-border loan and international bond flows to U. S. monetary policy. Forbes and Warnock (2012, 2021) find that the strong relationship between global risk and

(2014), Gertler and Kiyotaki (2015), Adrian and Boyarchenko (2012), Vayanos (2004).

[4] The pricing factor constructed in Kelly, Palhares, and Pruitt (2023) from the cross-section of U. S. corporate bond returns is also significantly correlated with the VIX.

the incidence of extreme capital flow events observed in the pre-GFC period is reduced in the post-crisis period. More broadly, Goldberg (2023) discusses changes in the drivers of global liquidity since the crisis. We contribute to this literature by documenting that corporate bond returns can be *forecasted* by a common price of risk, expanding our understanding of the global financial cycle beyond contemporaneous comovements.

The rest of the paper is organized as follows. In Section 2, we describe the data we use. In Section 3, we motivate and describe our factor construction procedure. In Section 4, we present our main results centered around bond return predicability. Section 5 explores the economic mechanisms behind the global credit cycle. Section 6 concludes.

2 Data description

We rely on the comprehensive international debt market data collected in Boyarchenko and Elias (2023), which puts together primary and secondary corporate bond market data together with data on corporate debt outstanding, firm balance sheets, and firm default probabilities across a number of countries. The matching between individual bonds and firm-level information is done at the ultimate corporate parent level, implicitly assuming that the characteristics of the ultimate parents play a central role in corporate bond prices even for bonds issued by subsidiaries. The extant empirical literature on internal capital markets has indeed argued for the existence of group-wide optimization of financing costs, with the parent company playing an intermediation role in allocating resources across subsidiaries.

Our main source of secondary bond market quotes is ICE Global Bond Indices. As noted in Kelly et al. (2023), ICE data is considered the "gold standard" for corporate bond data because of the breadth of coverage relative to data on transactions-based prices and the analytics provided as part of the ICE dataset. Our main dataset starts in January 1998 and ends in December 2024, covering both periods of stress such as the global financial crisis

and the COVID-19 pandemic, as well as more "normal" periods. We define our universe of corporate bonds to be the underlying constituents at a monthly frequency from the ICE Global Corporate Index (G0BC) and ICE Global High Yield Corporate Index (HW00).[5] The underlying constituents data includes effective option-adjusted spread and duration for each bond-day, as well as bond and issuer characteristics, such as issuer domicile, issuer industry, currency of issuance, coupon type and rate, bond seniority, and call and put provisions. We use observations on the last day of every month, which allows us to use the month-to-date returns computed by ICE directly.

While ICE global data provides us with coverage for the major bond-issuing countries around the world, the time series is somewhat limited – it starts in 1998. We thus supplement the global secondary market data with a longer time series of U. S. corporate secondary market data from the Lehman-Warga Fixed Income Database. This dataset allows us to extend the time series of returns and spreads on U. S. bonds back to 1973; see Warga (1991) for details. As with the ICE global data, the Lehman-Warga Fixed Income Database includes returns, yield-to-maturity, and duration for each bond-month, as well as bond and issuer characteristics, such as issuer industry, coupon type and rate, bond seniority, and call and put provisions.

We follow Boyarchenko and Elias (2023) in merging the secondary market corporate bond quotes with bond characteristics from consolidated SDC Platinum – Mergent FISD, ultimate parent balance sheet information, and expected default frequency (EDF) data from Moody's KMV CreditEdge. For both balance sheet information and EDFs, we use data that most closely precedes the date of the observed secondary bond market quote. This ensures that the firm characteristics and EDF data are observable to market participants as of the pricing date. Thus, we use annual balance sheet data for the fiscal period ending at least three

[5] One potential concern with using the secondary market pricing from the ICE Global Bond Indices is coverage relative to the universe of corporate bonds outstanding. However, Boyarchenko and Elias (2023) show that a substantial fraction of the offering amount from a consolidated SDC Platinum – Mergent FISD dataset appears in the two ICE Global Bond Indices we use at some point over its lifetime.

months prior to the pricing date, and EDF data as of the last day of the month prior to the pricing date.

We restrict our sample of issuer ultimate parents to be nonfinancial corporations. That is, we include bonds issued by e.g. financing arms of nonfinancial ultimate parents but exclude bonds issued by nonfinancial subsidiaries of financial ultimate parents.[6] Moreover, we restrict the sample of bonds we use to be senior, unsecured, fixed-coupon bonds.

In Appendix B, we describe the procedure for computing duration-matched and default-adjusted bond-level credit spreads in our context of bonds denominated in different currencies, issued by ultimate parent companies domiciled in different countries. This allows us to construct our own time series of U. S. aggregate duration-matched spreads, using the panel of bonds issued by U. S.-domiciled *ultimate parents*, rather than U. S. domiciled issuers, aligning the construction of the U. S. aggregate credit spreads series with our definition of the corresponding bond universe. Furthermore, constructing our own spreads allows us to compute the average default-adjusted and the average predicted U. S. credit spread on the same sample of bonds (rather than taking the difference between the G-Z spread and the published EBP series, which represent different sets of bonds).[7]

We take the perspective of a U. S. investor in computing the excess returns on bond b at date t. Thus, we convert the currency-specific return $R^c_{b(f),t}$ to implied USD returns using exchange rates and use the one-month return on the three-month U. S. Treasury bill as our measure of the relevant one-month risk-free rate. That is, the USD-based one-month excess

[6] We define an ultimate parent as being a nonfinancial corporation if the balance sheet data assigns a one digit SIC code that is not a 0, 6, or 9. Note that this definition excludes public sector bonds –including supranational organizations– as well as bonds issued by real estate companies. Boyarchenko and Elias (2023) show that the financing costs faced by subsidiaries of foreign parents are substantially different from those faced by domestic firms and, as such, capture the financing conditions in the parent's country more so that the financing conditions in the issuer's country.

[7] Figure A.8 in the Appendix shows that our duration-matched and default-adjusted U. S. credit spread series closely track the official Gilchrist and Zakrajšek (2012) series.

return, $Rx_{b(f),t}$, is computed as

$$Rx_{b(f),t+1} = \left(1 + R^{c}_{b(f),t+1}\right) \frac{S^{c}_{t+1}}{S^{c}_{t}} - \left(1 + R^{tsy}_{3\text{m},t+1}\right),$$

where S^{c}_{t} is the spot exchange rate of currency c with respect to the USD at date t and $R^{tsy}_{3\text{m},t+1}$ is the one-month return on a three-month U. S. Treasury bill rate from date t to $t+1$. For both the exchange rate and the risk-free rate observations, we match the date of the observation to the exact date of the corporate bond price (and spread) observation. Finally, we construct multi-period corporate bond excess returns by cumulating the one-month ahead corporate bond excess returns

$$Rx_{b(f),t+h} = \sum_{s=1}^{s=h} Rx_{b(f),t+s-1,t+s},$$

and we annualize monthly returns by computing $Rx_{b(f),t+h} \times 12/h$.

Our baseline sample includes more than 2.9 million bond-month return observations, from January 1986 to December 2024. The number of bonds and bond-issuing ultimate parents increases over time, with the largest number of bonds issued in USD, by both domestic and foreign ultimate parents. We summarize key properties of our sample by currency in Table 1. Finally, Figure 1 plots the time series of weighted-average 12-month ahead corporate bond excess returns for the countries in our sample. The figure shows that, despite the breadth of coverage of our data in geographic and rating terms, country-level average excess returns are remarkably correlated across countries, motivating our approach to consider a global credit cycle.

3 Measuring the global credit cycle

In this section, we motivate our approach to constructing the global credit factor through the lens of theoretical models with time-varying risk aversion. We then use this insight to construct the global credit factor as a nonlinear function of the VIX and U. S. credit spreads, using reduced rank regressions to identify the nonlinear function that maximizes out-of-sample return predictability.

3.1 Motivation

Our starting point is an unconditional CAPM of the form

$$Rx_{i,t+h} = a_{i,h} + b_{i,h} Rx_{M,t+h} + \hat{\epsilon}_{i,t+h},$$

where $Rx_{i,t+h}$ is the h-period holding return on asset i in excess of the return on a risk-free asset and $Rx_{M,t+h}$ is the h-period excess return to holding the market portfolio. The unconditional CAPM implies that the expected excess return on any asset i can be represented as

$$\mathbb{E}_t \left[Rx_{i,t+h} \right] = a_{i,h} + b_{i,h} \mathbb{E}_t \left[Rx_{M,t+h} \right],$$

where we have allowed for the asset (market) β and deviations from the market security line to be potentially holding horizon specific. Substituting into the above, we can thus represent the h-period ahead excess return as

$$Rx_{i,t+h} = a_{i,h} + b_{i,h} \mathbb{E}_t \left[Rx_{M,t+h} \right] + \epsilon_{i,t+h}, \tag{1}$$

where

$$\epsilon_{i,t+h} = \hat{\epsilon}_{i,t+h} + b_{i,h} \left(Rx_{M,t+h} - \mathbb{E}_t \left[Rx_{M,t+h} \right] \right).$$

We are interested in understanding the joint pricing of corporate bonds in a large set of countries around the world. As such, rather than pre-specifying the appropriate market portfolio and estimating (1) through correlations between asset excess returns and an observed return on a market portfolio, our estimation procedure constructs a proxy for the expected excess market return as a function of aggregate measures of risk. What should we expect the relationship between expected excess market returns and risk proxies to be, and which proxies do we expect to be relevant?

Recent literature has advocated for an intermediary-based view of asset prices, in which the shadow price of an occasionally-binding constraint on financial intermediaries drives the aggregate effective risk aversion priced in asset returns. The occasionally-binding nature of such constraints generates nonlinearities in the relationship between aggregate risk and aggregate effective risk aversion, translating into a nonlinear relationship between risk and expected excess returns. For example, Vayanos (2004) shows that, in a model with liquidation of under-performing mutual funds, with the probability of fund liquidation driven by aggregate risk v_t, expected excess returns on risky assets can be expressed as

$$\mathbb{E}_t \left[Rx_{i,t+1} \right] = \alpha_i \left(v_t \right) + A \left(v_t \right) \mathrm{Cov}_t \left(Rx_{i,t+1}, Rx_{M,t+1} \right) + Z \left(v_t \right) \mathrm{Cov}_t \left(Rx_{i,t+1}, v_{t+1} \right).$$

In the Vayanos (2004) model, time-varying risk aversion $A \left(v_t \right)$ evolves endogenously as a function of the probability of the value of the mutual fund falling below a liquidation threshold, so that episodes of elevated aggregate risk increase the probability of fund liquidation and thus aggregate risk aversion. Similar mechanisms can also be derived in models with, for example, value-at-risk (VaR) constraints, with episodes of elevated aggregate risk corre-

sponding to periods of tighter VaR constraints. While disentangling the precise mechanisms that link the endogenous evolution of aggregate risk aversion to evolution in aggregate risk is beyond the scope of this paper, we use the insights from this literature to postulate a nonlinear relationship between expected excess market returns and aggregate measures of risk.

In particular, we assume that the nonlinear relationship between expected excess market returns and aggregate measures of risk can be parametrized as a function of the VIX and U. S. credit spreads. Intuitively, by allowing expected excess market returns to load on different proxies of risk aversion, we both allow for neither proxy to be an error-free metric of the true effect risk aversion of the marginal investor in the market and for different proxies to capture constraints of different types of intermediaries. For example, the VIX is a commonly-used proxy for the tightness of constraints faced by institutions subject to VaR constraints. Indeed, a number of papers (Pan, 2002; Bates, 2008; Santa-Clara and Yan, 2010; Campbell et al., 2018) have suggested aggregate volatility as a pricing factor for risky assets, measured either using the VIX or realized volatility. Intuitively, higher volatility corresponds to higher effective risk aversion for market participants, leading to higher expected excess returns. Additionally, a number of papers have suggested that fixed income asset returns should be related to the level of spreads in the corresponding fixed income market, so that the expected excess returns on corporate bonds are related to the level of credit spreads (see e.g. Campello et al., 2008). The relationship between expected excess returns and credit spreads captures the intuitive "drift to par" inherent in fixed income asset valuation.

3.2 A reduced rank regression approach to return predictability

We now describe our empirical approach to constructing the time series of conditional expected excess market returns. As discussed above, our focus will be on the unconditional CAPM representation of returns (1). We follow Adrian et al. (2019a,b) in using a reduced-

rank, sieve-based procedure to estimate non-parametrically the conditional expected excess market return as a function of credit spreads and volatility, $\varphi\left(cs_t, \text{VIX}_t\right) \equiv \mathbb{E}_t\left[Rx_{M,t+1}\right]$, under only weak assumptions. The sieve reduced-rank regression (SRR) replaces the true evolution of excess returns (1) with

$$Rx_{i,t+h} = a_{i,h} + b_{i,h}\left(\gamma_h' X_{m,t}\right) + u_{i,t+h}, \quad u_{i,t+h} = \epsilon_{i,t+h} + b_{i,h}\left(\varphi\left(cs_t, \text{VIX}_t\right) - \gamma_h' X_{m,t}\right), \quad (2)$$

where $X_{m,t}$ is a (spline) basis with m basis functions in the $\mathbb{R}^2$ space formed by credit spreads and the VIX, and γ_h is an $m \times r$ matrix of coefficients that maps the m basis functions into r approximate risk factors. As shown in Adrian et al. (2019a), as m grows in sample size, the approximation error $\left(\varphi\left(cs_t, \text{VIX}_t\right) - \gamma_h' X_{m,t}\right)$ of the true nonlinear factors by the best approximation from the function space spanned by $X_{m,\cdot}$ vanishes in the appropriate sense.

To construct the estimated nonlinear factors, we stack the observation equation (2) across n assets to obtain

$$\overrightarrow{Rx}_{t+h} = \vec{a}_h + \vec{b}_h\left(\gamma_h' X_{m,t}\right) + u_{t+h}.$$

For any fixed m, or, in other words, chosen spline basis, the above is a reduced rank regression, with $A_h \equiv \vec{b}_h \gamma_h'$ assumed to be of rank r. As discussed below, we pick both an optimal rank and an optimal spline basis via cross-validation. The parameters $\vec{a}_h$, $\vec{b}_h$, and γ_h may all be estimated in closed form. However, to separately identify $\vec{a}_h$ and $\vec{b}_h$, additional restrictions have to be imposed. In particular, we impose the normalization $\varphi\left(0, \text{VIX}_t\right) = \varphi\left(cs_t, 0\right) = 0$, which allows us to identify separately the constant term for each asset. We further impose that the normalization (which helps identify the scale of the estimated global credit factor) that the loading of the high yield corporate bond portfolio on the estimated global credit factor is 1. For a symmetric, positive-definite weight matrix W and unrestricted (OLS)

estimates $\hat{a}_{h,OLS}$ and $\hat{A}_{h,OLS}$, from Adrian et al. (2019a), we then have

$$\hat{b}_h = W^{\frac{1}{2}} L; \quad \hat{\gamma}_h = \hat{A}'_{h,OLS} W^{-\frac{1}{2}} L; \quad \hat{a}_h = \hat{a}_{h,OLS} + \left(\hat{A}_{h,OLS} - \hat{b}_h \hat{\gamma}'_h \right) X_m \mathbb{1}'_T \left(\mathbb{1}_T \mathbb{1}'_T \right)^{-1},$$

where L are the eigenvectors corresponding to the r principal eigenvalues of $W^{-\frac{1}{2}} \hat{A}_{h,OLS} \left(X_m M_Z X'_m \right) \hat{A}'_{h,OLS} W^{-\frac{1}{2}}$, and $M_Z = I_T - \mathbb{1}_T \left(\mathbb{1}_T \mathbb{1}'_T \right)^{-1} \mathbb{1}'_T$. If it were the case that $u_{t+h} \sim \mathcal{N}(0, W)$ and the spline basis were fixed, then $\hat{a}_h$, $\hat{b}_h$, and $\hat{\gamma}_m$ would be the maximum likelihood estimates of $\vec{a}_h$, $\vec{b}_h$, and γ_h.

3.3 Estimated factor

We implement the procedure described above to construct the optimal approximation to $\varphi(cs_t, \text{VIX}_t)$ based on the information in the one-month-ahead excess returns on 4 advanced economy portfolios: AAA/AA, A, BBB, and high yield (below BBB) corporate bonds.[8] We use the U. S. EBP as our measure of credit spreads.[9] We set W to the variance-covariance matrix of return predictability errors from the unrestricted OLS regression of excess returns on the spline basis, avoiding overweighting high variance assets in the estimation.

As intimated in the above discussion, there are a number of choices that have to be made in constructing the approximation $\gamma'_m X_{m,t}$ to $\varphi(cs_t, \text{VIX}_t)$. The first is the reduced rank r, which corresponds to the number of factors in the ICAPM representation of excess returns. The second is the spline basis order o (corresponding to piecewise polynomials of degree $d = o - 1$) and the number k of (interior) knots used for the spline basis for each variable (cs_t, VIX_t). The final choice is whether the spline basis is constructed to be bivariate with

[8] We construct the returns for each of the advanced economy credit indices as the amount outstanding (in USD equivalents) weighted average return on non-financial corporate bonds with the appropriate credit rating and issued by firms with ultimate parents domiciled in advanced economies.

[9] Gilchrist and Zakrajšek (2012) argue that the EBP – unlike the duration-adjusted spread – captures the credit risk *premium* priced in U. S. corporate bonds. Furthermore, unlike the duration-matched spread, the EBP does not exhibit a level shift between pre- and post-LTCM time sub-samples.

interactions, (that is, as the tensor product of the univariate bases), bivariate without interactions (that is, by stacking the two univariate bases), or univariate (so that one of the two proxies for risk is superfluous).[10] To make the spline basis discussion more concrete, let $\mathcal{C}_{m_c,t}$ be the univariate b-spline basis in the credit spread space, with $m_c = o_c + k_c - 1$, and $\mathcal{V}_{m_v,t}$ be the univariate b-spline basis in the VIX space, with $m_v = o_v + k_v - 1$. For a given order o_c and number of interior knots k_c of the credit spread basis, and order o_v and number of interior knots k_v of the VIX basis, the bivariate basis with interactions is then given by $\mathcal{C}_{m_c,t} \otimes \mathcal{V}_{m_v,t}$, while the bivariate basis without interactions is given by $[\mathcal{C}_{m_c,t} \quad \mathcal{V}_{m_v,t}]$.

In choosing the optimal approximation, we allow up to 3 factors ($r = 3$), splines bases of order 4 (corresponding to piecewise cubic polynomials), and up to 6 interior knots, spaced evenly along the quantiles of the corresponding variable. In constructing the bivariate bases with interactions, we consider the bivariate basis constructed with $o_c = 2$ and $o_v = 3$ (piecewise linear in credit spreads, piecewise quadratic in VIX); $o_c = 3$ and $o_v = 2$ (piecewise quadratic in credit spreads, piecewise linear in VIX); $o_c = 3$ and $o_v = 3$ (piecewise quadratic in both); and $o_c = 4$ and $o_v = 4$ (piecewise cubic in both). While the first two specifications restrict the overall degree to be cubic within any rectangle formed by adjacent knots in each direction – thus making these bases closely analogous to the univariate spline bases of order 4 – the last two specifications consider additional flexibility by allowing the overall degree to be higher than cubic. In all bases constructions, we allow for a different number of interior knots between the credit spread basis and the VIX basis.

Overall, our estimation procedure thus considers $42 = 2 \times 3 \times 7$ possible univariate specifications (2 variables $\times$ up to 3 factors $\times$ between 0 and 6 interior knots) and $735 = 5 \times 3 \times 7 \times 7$ possible bivariate specifications (5 versions of a bivariate basis $\times$ up to 3 factors $\times$ between 0 and 6 interior credit spread knots $\times$ between 0 and 6 interior VIX knots). We discriminate amongst these 777 alternatives using an out-of-sample mean-squared error (MSE) criterion.

[10] In unreported results, for ranks higher than one, we also consider separate reduced-rank coefficient matrices for each univariate basis instead of a single reduced-rank coefficient matrix.

More specifically, for a given specification, we estimate the reduced rank specification (2) using data through December 2008 (roughly 60% of our time series). Using the estimated $\left(\hat{a}, \hat{b}, \hat{\gamma}_{m_c+m_v}\right)$ and the realized credit spreads and VIX in January 2009, we then predict expected excess returns for February 2009, forming our first (pseudo) out-of-sample forecast.[11] We then iterate, adding one month of observations at a time. The out-of-sample MSE for a given specification is then given by

$$MSE\left(r; o_c, k_v, o_v, k_v; \text{basis type}\right) = \frac{1}{T - T_0 - 1} \sum_{t=T_0}^{T-1} \left\| \overrightarrow{Rx}_{t+h} - \hat{\mathbb{E}}_t \left[\overrightarrow{Rx}_{t+h} \right] \right\|^2 .$$

In choosing the optimal factor specification, we require that, for a two-factor specification to be chosen over a one-factor one, the two-factor specification offers at least a 5% improvement in out-of-sample MSE relative to the best one-factor specification. Similarly, we require that the best three-factor specification offers at least a 5% improvement in out-of-sample MSE relative to the best two-factor specification for a three-factor specification to be chosen.

The out-of-sample MSE criterion selects a one-factor specification, with the bivariate basis with interactions constructed using a piecewise quadratic credit spread basis with 4 interior knots and piecewise linear VIX basis with 3 interior knots ($X_{m,t} = \mathcal{C}_{6,t} \otimes \mathcal{V}_{4,t}$). The approximation $\gamma_m' X_{m,t}$ to $\varphi\left(cs_t, \text{VIX}_t\right)$ is thus highly nonlinear with respect to both the credit spread and the VIX. As we will argue below, the estimated single factor captures the global pricing of credit risk. We thus call the factor the global credit factor.[12]

[11] Since we estimate $\left(\hat{a}, \hat{b}, \hat{\gamma}_{m_c+m_v}\right)$ using a predictive relationship, returns in January 2009 are included in the initial estimation sample.

[12] Table A.1 in the Appendix reports the out-of-sample MSE for best-performing factor construction alternatives.

3.4 The global credit factor and VIX and credit spread contributions

We illustrate the relationship between the global credit factor, the VIX and credit spreads in Figure 2. Starting with the top panel, which plots the overall relationship of the global credit factor with the VIX and credit spreads as measured by the EBP, we see that the factor is nonlinear in both of the two underlying metrics. Figure 2b isolates the theoretical relationship with the VIX for three different levels of the credit spread (historical 25th, 50th, and 75th percentiles). The figure illustrates the piecewise linear shape of the VIX basis, and shows how the effective slope across the spline segments changes with the level of credit spreads. The relationship with the VIX exhibits the most volatility for low levels of credit spreads, suggesting that, in periods of low credit spreads and high volatility, the evolution of the global credit factor is primarily driven by changes in the VIX. Instead, in Figure 2c, we see that intermediate levels of the VIX amplify the relationship between the global credit factor and credit spreads. Finally, Figures 2d and 2e show the empirical relationship between the global credit factor and the VIX (conditional on EBP terciles), and the global credit factor and the EBP (conditional on VIX terciles). The global credit factor is the highest when both credit spreads and VIX are high, and declines in credit spreads when the VIX is at intermediate levels.

Figure 3 plots the time series of the estimated global credit factor. The global credit factor rises during periods when both credit spreads and the VIX are high, such as the COVID-19 pandemic (March 2020) and in the aftermath of Lehman Brothers liquidation (starting in October 2008). Instead, when only the VIX is high, such as in the pre-Lehman phase of the global financial crisis, the level of the global credit factor is historically low, predicting extremely low corporate bond returns going forward.

To understand how the credit spread and the VIX each contribute to monthly changes in the global credit factor, we decompose monthly changes into those due to changes in the

VIX and changes in the EBP predictable with changes in the VIX, and changes due to EBP changes not predictable by the VIX. More specifically, we first estimate

$$EBP_t = \alpha_0 + \alpha_1 VIX_t + \epsilon_{cs,t},$$

and construct the EBP predicted conditional on a VIX level as $\widehat{EBP}_t = \hat{\alpha}_0 + \hat{\alpha}_1 VIX_t$. Then, since the global credit factor (GCC) is a function of credit spreads and the VIX, we can represent

$$\begin{aligned}\Delta GCC_t &\equiv \varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right) - \varphi\left(\mathrm{EBP}_{t-1}, \mathrm{VIX}_{t-1}\right) \\ &= \underbrace{\varphi\left(\widehat{EBP}_t, \mathrm{VIX}_t\right) - \varphi\left(\mathrm{EBP}_{t-1}, \mathrm{VIX}_{t-1}\right)}_{\text{“Common changes”}} + \underbrace{\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right) - \varphi\left(\widehat{EBP}_t, \mathrm{VIX}_t\right)}_{\text{“Orthogonal EBP changes”}}.\end{aligned}$$

Figure 4a plots the resulting decomposition of monthly changes in the global credit factor. The figure shows that large decreases in the global credit factor occur when there is a substantial (negative) contribution from movements in the EBP not predicted by the VIX. In practice, these are periods when the VIX increases but the EBP does not, leading to a large error in the predicted EBP level, $\widehat{EBP}_t$.

Figure 4b then estimates the 12-month rolling window estimate of the fraction of overall variance of monthly global credit factor explained by the common changes component. In the full sample, 68% of overall variation is explained by common changes (and 32% by the orthogonal EBP changes). Figure 4b, however, shows that there is substantial variation over time in the contribution of each component. Common changes in EBP and the VIX tend to be negatively correlated with global credit factor changes when the EBP is in its historical bottom tercile (EBP lower than -30 basis points). In contrast, when both EBP and the VIX are in their respective historical top tercile, common changes in EBP and the VIX tend to explain more than 67% of the global credit factor changes.

An alternative way of evaluating how credit spreads and the VIX contribute to the overall

global credit factor is to compare our bivariate construction with two alternatives: one that parametrizes the global price of risk as a nonlinear function of just the VIX, and one that parametrizes the global price of risk as a nonlinear function of just credit spreads. For both of the univariate specifications, we follow Adrian et al. (2019a) and consider the piecewise cubic spline as an approximation to the true nonlinear function $\varphi(\cdot)$, and optimally choose the number of knots for each using the cross-validation procedure described above.[13] Table 2 reports the estimated coefficients a_i and b_i from SRRR (2) for each of these three formulations, together with the t-statistics on a_i and χ^2 statistics on $b_i\varphi_h(\cdot)$ as derived in Adrian et al. (2019a), Theorem 1. The table also reports the joint test p-value (J p-val) reports the likelihood that the sample was generated under $\mathbb{H}_{1,0}$: $\forall \text{VIX} \in V$, $\forall \text{EBP} \in C$, $\varphi_h(\text{VIX}, \text{EBP}) = 0$ for each specification.

Table 2 shows that, for the baseline global credit factor $\varphi(\text{EBP}, \text{VIX})$, all four advanced economy portfolios load on the estimated global credit factor, and the joint test rejects the null hypothesis that excess returns are invariant to the level of the global credit factor. In contrast, the joint test fails to reject the null hypothesis of no return predictability for both of the alternative measures of the global price of risk. Furthermore, while the three safer (investment grade) advanced economy corporate bond portfolios have statistically significant loadings on $\varphi(\text{VIX})$ (column 4), only the single A portfolio has a statistically significant loading on $\varphi(\text{EBP})$ (column 6). Thus, the interactions between the VIX and EBP adds valuable information to the measurement of the global price of credit risk.

3.5 Initial evidence of cross-sectional asset pricing

Equation (2) agues that expected returns are affine functions of $\varphi(cs_t, \text{VIX}_t)$. From the perspective of asset pricing theory, the intercepts a_i and slopes b_i in (2) are cross-sectionally

[13] That is, we select the univariate specifications that minimize the MSE within the set of univariate specifications for each variable. For both the credit spread and the VIX, the optimal specification still has one factor, with no internal knots for the VIX specification and one interior knot for the EBP specification.

related to risk factor loading. For example, if the equilibrium pricing kernel has prices of risk that are affine in the global credit factor (see e.g. Adrian et al., 2015), then the cross-sectional asset pricing restriction would suggest

$$\mathbb{E}_t\left[Rx_{i,t+h}\right] = \alpha_{i,h} + \beta_{i,h}\left(\lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)\right), \tag{3}$$

where λ_0 is the constant price of risk and λ_1 is the coefficient that determines how prices of risk vary as a function of the global credit factor. The cross-sectional asset pricing representation of returns (3) implies that, for the portfolios used to construct the global credit factor, we should have

$$a_i = \alpha_i + \beta_i \lambda_0; \quad b_i = \beta_i \lambda_1.$$

We now conduct two cross-sectional asset pricing exercises, which justify our interpretation of $\varphi\left(cs_t, \mathrm{VIX}_t\right)$ as the global price of risk in worldwide corporate bond markets.

First, for the four advanced economy portfolios used to construct the global credit factor, we estimate the unrestricted panel forecasting relationship $Rx_{i,t+1} = a_i + b_i \varphi\left(cs_t, \mathrm{VIX}_t\right) + \epsilon_{i,t+1}$ by SRR regression. We then estimate the prices of risk and risk factor exposures for these portfolios by jointly estimating $Rx_{i,t+1} = \alpha_i + \beta_i\left(\lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)\right) + \beta_i u_{t+1} + \epsilon_{i,t+1}$, where $\varphi\left(cs_t, \mathrm{VIX}_t\right)$ is taken as given and $u_{t+1} \equiv \varphi\left(cs_{t+1}, \mathrm{VIX}_{t+1}\right) - \mathbb{E}_t\left[\varphi\left(cs_{t+1}, \mathrm{VIX}_{t+1}\right)\right]$ are the AR(1) innovations to $\varphi\left(cs_t, \mathrm{VIX}_t\right)$. Figure 5a compares the expected excess returns from the unrestricted SRR regression estimate and the restricted dynamic asset pricing model, and shows that the two estimates are strongly related to each other.

Second, we extend the testing of the restrictions implied by the dynamic asset pricing model (3) to the 11 corporate bond portfolios formed based on country and rating (the 4 U. S. portfolios, 4 advanced economy excluding U. S. portfolios, and 3 emerging market portfolios discussed above). Figure 5b plots the in-sample average excess return on these portfolios

versus $\alpha_i + \beta_i (\lambda_0 + \lambda_1 \mathbb{E}[\varphi(cs_{t+1}, \text{VIX}_{t+1})])$. Figure 5b shows that the predictions from the dynamic asset pricing that restricts loadings on the global credit factor to $\beta_i \lambda_1$ results in the correct predictions about unconditional excess returns in the cross-section, even when we expand the set of test portfolios. Overall, the tight relationship in Figure 5 between expected excess returns and the expected excess returns from a dynamic asset pricing model with prices of risk affine in the global credit factor lends credence to our interpretation of the global credit factor as a global price of risk in international corporate bond markets.

4 Bond-level return predictability

The previous section described our procedure for constructing the global credit factor (GCC) and provided some initial evidence that the GCC proxies for a global price risk of risk in international bond markets. We now investigate further the relationship between excess returns and the estimated GCC, using the richness of our bond-level data. Throughout this section, we use the forecasting relationship implied by the affine pricing kernel assumption (3):

$$Rx_{i,t+1} = \alpha_i + \beta_i (\lambda_0 + \lambda_1 \varphi(cs_t, \text{VIX}_t)) + \beta_i u_{t+1} + \epsilon_{i,t+1},$$

where, as before, $u_{t+1} \equiv \varphi(cs_{t+1}, \text{VIX}_{t+1}) - \mathbb{E}_t[\varphi(cs_{t+1}, \text{VIX}_{t+1})]$ are the AR(1) innovations to $\varphi(cs_t, \text{VIX}_t)$. For parsimony, we further assume that loadings on $\varphi(cs_t, \text{VIX}_t)$ are constant within a credit rating category, so that we can simplify the above to

$$Rx_{i,t+1} = \alpha_c + \beta \varphi(cs_t, \text{VIX}_t) + \beta_r \varphi(cs_t, \text{VIX}_t) \times \mathbb{1}_r + \gamma u_{t+1} + \gamma_r u_{t+1} \times \mathbb{1}_r + \epsilon_{i,t+1}, \quad (4)$$

where α_c are country fixed effects, β captures the average exposure to the global credit factor, and β_r the differential exposure relative to the baseline rating category (high yield bonds).

4.1 Baseline results

Table 3 reports the estimated coefficients together with the Hodrick (1992) standard errors[14] from the baseline predictive regression of one-month ahead international corporate bond excess returns on the global credit factor, for the full sample of bonds, as well as separately for bonds of ultimate parents domiciled in the U. S. (column 2), advanced economies excluding the U. S. (column 3), and emerging market economies (column 4).

Starting with the full sample results, column (1) of Table 3 shows that the global credit factor is a statistically significant predictor of excess returns at the individual bond level. Furthermore, bond return exposure to the global credit factor decreases as bond riskiness – proxied by the credit rating – decreases. The point estimate of the β with respect to the global credit factor decreases from 1.12 on average for high yield bonds (the omitted category), to 0.8 and 0.78 for BBB-rated and A-rated bonds, respectively, and further to 0.64 for AAA/AA rated bonds (the safest credit rating category). These β differences are not just statistically but also economically significant. A one standard deviation increase in the global credit factor corresponds to a 6.1 percentage point (p.p.) increase in annualized one-month ahead expected excess returns on high yield bonds, 4.4 p.p. increase in expected excess returns on BBB-rated bonds, 4.3 p.p. increase in expected excess returns on A-rated bonds, and a 3.5 p.p. increase in expected excess returns on AAA/AA-rated bonds. These represent meaningful changes relative to unconditional average excess returns of 7.3%, 4.8%, 4.7%, and 4.7% across high yield, BBB-rated, A-rated, and AAA/AA-rated bonds, respectively.

Turning to the cross-country evidence in columns (2) – (4) of Table 3, we see that the global credit factor is a consistent predictor of bond excess returns across different economies, with

[14] Ang and Bekaert (2007) strongly argue in favor of Hodrick (1992) over Newey and West (1987) standard errors in return predictability regressions with overlapping observations, as the former exhibit substantially better size control, a fact confirmed in simulation evidence in e.g. Wei and Wright (2013) and Adrian et al. (2019a).

bonds issued by firms in advanced economies having lower average estimated β with respect to the global credit factor than bonds issued by firms in emerging markets. Furthermore, while investment grade (those rated BBB and above) bonds in the U. S. do have lower average exposure to the global credit factor than high yield bonds, within investment grade, U. S. bonds do not appear to have differential exposure across rating categories. In contrast, the differential between A-rated bonds and BBB-rated bonds is largest for emerging market economies.

Our discussion so far has focused on bond returns in excess of returns on the three month U. S. Treasury bill. A recent literature (Van Binsbergen et al., 2025) has argued that we can gain insight into which sources of risk are priced in corporate bond market returns by considering also returns in excess of returns to a duration-matched Treasury. More specifically, we decompose excess returns into a credit risk component, a component due to the differential slope between U. S. Treasuries and the sovereign curve for the bond's currency denomination ("currency differential"), and the duration risk component:

$$\begin{aligned} Rx_{i,t+1} &= \left(1 + R^c_{i,t+1}\right) \frac{S^c_{t+1}}{S^c_t} - \left(1 + R^{tsy}_{3m,t+1}\right) \\ &= \underbrace{\left(\left(1 + R^c_{i,t+1}\right) - \left(1 + R^c_{DM_i,t+1}\right)\right) \frac{S^c_{t+1}}{S^c_t}}_{\text{Credit risk}} + \underbrace{\left(1 + R^c_{DM_i,t+1}\right) \frac{S^c_{t+1}}{S^c_t} - \left(1 + R^{tsy}_{DM_i,t+1}\right)}_{\text{Currency curve differential}} \\ &+ \underbrace{\left(1 + R^{tsy}_{DM_i,t+1}\right) - \left(1 + R^{tsy}_{3m,t+1}\right)}_{\text{Duration risk}}. \end{aligned} \tag{5}$$

Here, $R^c_{DM_i,t+1}$ is the one-month holding period return on a sovereign bond for currency c with the same duration DM_i as the corporate bond and $R^{tsy}_{DM_i,t+1}$ is the one-month holding period return on the corresponding duration-matched U. S. Treasury.

Table 4 reports the estimated coefficients from the forecasting relationship (4) for the three components of corporate bond returns for the full sample of bonds, as well as the total excess

return in column (1). Column (2) shows that the β of the credit risk component of bond excess returns to the global credit factor decreases monotonically with credit rating, so that the compensation for the correlation between credit risk and the global credit cycle is the highest for high yield bonds and lowest for AAA/AA-rated bonds. This is intuitive: higher rated bonds have less credit risk and thus should command a lower credit risk premium. Furthermore, the point estimate of the β with respect to the global credit factor is half as large for A-rated bonds as for high yield bonds, and half as large for AAA/AA-rated bonds as for A-rated bonds, suggesting economically meaningful differences in compensation for credit risk across ratings.

Turning to column (3) of Table 4, we see that, although statistically significant, the exposure of the currency curve differential component to the global credit factor is relatively low, and increases in credit rating, especially for AAA/AA-rated bonds. The negative sign of the estimated coefficients suggests that the sovereign slope differential relative to the U. S. Treasury slope declines when global credit conditions tighten. Finally, in column (4) we report the estimated coefficients from the forecasting relationship (4) for the duration risk component of corporate bond returns. Consistent with the results in Van Binsbergen et al. (2025) for U. S. corporate bonds, the duration risk compensation *increases* in credit rating. The duration risk component of returns for AAA/AA-rated bonds has the highest estimated β with respect to the global credit factor and the duration risk component of returns for high yield bonds the lowest, reflecting that the average duration is higher for higher rated bonds. Furthermore, comparing the adjusted R^2 across columns, we see that the adjusted R^2 of the predictive regression for the duration risk component is similar to the adjusted R^2 for the credit risk component, suggesting that predictability of both the credit risk and duration risk components contributes to the overall predictability of international corporate bond returns. This is in contrast to the findings in Van Binsbergen et al. (2025) that duration risk explains most of the variation in U. S. corporate bond returns, suggesting that credit risk compensation may be more significant outside of the U. S.

4.2 What contributes to bond return predictability?

The results in Tables 3 and 4 suggest that the global credit factor forecasts bond market returns across different credit ratings and countries, with exposures to the global credit factor increasing in bond riskiness. A natural question to ask in this setting is whether the time-series return predictability results are driven by particular extreme episodes, such as the global financial crisis, the European debt crisis, and the COVID-19 pandemic. To answer that question, we conduct two exercises aimed at evaluating which data points contribute to the overall performance of the global credit factor as a global price of credit risk.

In Table 5, we report the estimated coefficients from the forecast relationship (4) across different time series subsamples of our data: the Lehman-Warga historical sample for U. S. bonds (January 1986 – December 1997); pre-crisis (January 1998 – July 2007); global financial crisis (August 2007 – December 2009); post-crisis, pre-COVID-19 (January 2010 – December 2019); COVID-19 (January 2020 – December 2020); post-COVID (January 2021 – December 2024). A few features of Table 5 are worth highlighting. First, the estimated βs with respect to the global credit factor are statistically significant across these different subperiods, suggesting that the global credit factor is a consistent proxy for risk prices in global credit markets. Importantly, the point estimates of the global credit factor β are not outsized during the global financial crisis and COVID-19 pandemic. Instead, exposures to the global credit factor appear particularly large during the post-pandemic period. Intuitively, as we can see in Table A.3 in the Appendix, the large exposure of excess returns to the global credit factor in the post-pandemic period is driven by the duration risk component and by a reversal of the sign of the currency curve differential component. The tightening of monetary policy around the world in response to heightened inflation in the post-pandemic period corresponds to a steeping of sovereign discount curves, while the more aggressive tightening of monetary policy in the U. S. corresponds to a steepening of the U. S. sovereign discount curve relative to the discount curves of other major currencies.

Second, consistent with the results in column (2) of Table 3, the slope of exposures within investment grade bonds is flatter in the Lehman-Warga historical sample for U. S. bonds and in the pre-crisis subsample of the international bond returns (when the AAA/AA represent a much larger fraction of non-U. S. bonds than in the subsequent data). During the financial crisis and in the subsequent periods, exposure to the global credit factor declines with credit rating even within the investment grade category, with the benefits of the highest credit rating (AAA/AA) particularly large during the GFC and the COVID-19 pandemic. This suggests that a "flight to quality" emerges during periods of broad market stress, with the exposure of AAA/AA rated bonds to the global credit factor about half of that for the high yield bonds during these periods. As Appendix Table A.3 shows, this flight to safety is driven by the credit risk component of corporate bond returns.

Third, Table 5 shows that, while the adjusted R^2 is somewhat higher during both the GFC and COVID-19 pandemic, it remains sizable during both the pre-crisis period and the period between the GFC and the COVID-19 pandemic. Furthermore, the adjusted R^2 during the post-pandemic period is comparable to that during these periods of market-wide stress. These results suggest that the predictive power of the global credit factor for bond market excess returns is not only driven by particular extreme episodes.

We evaluate which data points contribute to the overall adjusted R^2 in Figure 6. In particular, Figure 6 plots the cumulative contribution of different data points to the improvements in mean square forecast error of returns relative to a model that forecasts returns only as a function of a country and a rating fixed effect:

$$\Delta\text{MSE}_{\mathcal{T}} = \frac{SST^{\mathcal{T}} - SSE^{\mathcal{T}}}{SST^{All}}; \quad SST^{\mathcal{T}} = \sum_{s\in\mathcal{T}} \left(Rx_s - \hat{\alpha}_c - \hat{\alpha}_r\right)^2$$
$$SSE^{\mathcal{T}} = \sum_{s\in\mathcal{T}} \left(Rx_s\alpha_c - \hat{\beta}\varphi\left(cs, \text{VIX}\right) - \hat{\beta}_r\varphi\left(cs, \text{VIX}\right) \times \mathbb{1}_r - \hat{\gamma}u - \hat{\gamma}_r u \times \mathbb{1}_r\right)^2,$$

where the coefficients $\hat{\alpha}_c$, $\hat{\alpha}_r$, $\hat{\beta}$, $\hat{\beta}_r$, $\hat{\gamma}$, and $\hat{\gamma}_r$ are estimated over set $\mathcal{T}$ of bond-months. We

evaluate the improvements in mean square forecast errors in both the time series, using the first 5 years of data (January 1986 – December 1990) as the initial estimation period and adding one month of data at a time, and in the cross-section, evaluating which countries and economic states contribute to the return predictability of each rating category.

Starting with the time series plot in Figure 6a, we see that, throughout the entire sample, the model with the global credit factor outperforms the simple means model. The (relative) mean square forecast error of the global credit factor increases sharply during the global financial crisis and during the COVID-19 pandemic, suggesting that the conditional model performs especially well during periods of stress. The relative mean forecast error continues to improve in the post-COVID period, so that the full sample improvement in mean square forecast errors of the model that conditions on the global credit factor is 4% relative to the fixed effects only model.

Figure 6b then examines bond returns of which countries contribute to the improvement in mean square forecast errors by credit rating. Notice first that the improvements for the AAA/AA rating category are small relative to those for the other credit rating categories, suggesting that the global credit factor is particularly informative about returns on riskier bonds. Second, while U. S. bonds contribute the most to the improvement in mean square forecast errors of the model that conditions on the global credit factor across rating categories – corresponding to the larger number of U. S. bonds in our sample – the importance of the U. S. observations declines with credit rating. Finally, for high yield bonds, bonds of issuers in advanced economy countries (excluding the U. S.) contribute a similar amount of information as bonds of issuers in emerging market economies, highlighting the truly global nature of our estimated credit factor.

Finally, in Figure 6c we consider whether the contribution to return predictability varies across the tightness of the global credit factor. In particular, we identify months in which the realization of the global credit factor is in the bottom 25th percentile of the historical

distribution ("P25 GCC"; loose credit conditions), months in which the realization of the global credit factor is in the middle 50 percentiles of the historical distribution ("normal periods"), and months in which realization of the global credit factor is in the top 25th percentile of the historical distribution ("P75 GCC"; tight credit conditions). Figure 6c shows that, relative to the predictive information of months with loose credit conditions, normal periods do not contribute substantially to the improvement in mean square forecast errors of the model that conditions on the global credit factor relative to the fixed effects only model. Indeed, for high yield bonds, the contribution from normal periods is slightly negative. Instead, periods of global credit factor realizations in either extreme contribute to the forecasting performance of the global credit factor, with the relative (additional) contribution of periods of tight global credit conditions declining with credit rating. That is, Figure 6c suggests that, for higher rated bonds, global credit conditions are particularly informative about future excess returns when global credit conditions are unusually tight. For high yield bonds, instead, global credit conditions are particularly informative about future excess returns when global credit conditions are unusually loose.

5 Economics of the global credit cycle

The bond-level return predictability results in the previous section demonstrate that a global price of credit risk constructed as a nonlinear function of the VIX and U. S. credit spreads forecasts corporate bond returns globally, with the exposure to the global credit factor increasing in bond and country risk. We now consider whether tight global credit conditions have implications beyond forecasting one-month-ahead corporate bond returns.

5.1 Return predictability for other asset classes

While we construct the global credit factor to proxy for the price of risk in global credit markets, the results on the predictability of the duration risk component of corporate bond returns in Table 4 suggest that the global credit factor may forecast returns in other asset classes. We now investigate this hypothesis in more detail. In particular, we augment our set of corporate bond returns with returns on the country's zero-coupon sovereign bond and returns on the country's MSCI equity index. We match the duration of the sovereign bond to the average duration of the corporate bonds in the highest rating category for each country, so that the return differential between the safest corporate bonds and the sovereign bond is driven by corporate credit risk. Table 6 reports the estimated coefficients from the forecasting relationship (4) for this expanded set of securities. Table 6 shows that sovereign bonds have the lowest exposure to the global credit factor, while equity indices have the largest exposures to the global credit factor. That is, even when we expand the set of assets to include asset classes not used for the construction of the global credit factor, return exposure to the global credit factor decreases as asset riskiness decreases.

5.2 Pricing across horizons

Recall that underlying our return predictability regressions is an affine representation of the equilibrium stochastic discount factor as a function of the global credit factor:

$$M_{t,t+1} = 1 - (\lambda_0 + \lambda_1 \varphi (cs_t, \text{VIX}_t))\, u_{t+1},$$

giving our estimates of $\beta\varphi (cs_t, \text{VIX}_t) + \beta_r \varphi (cs_t, \text{VIX}_t) \times \mathbb{1}_r$ the interpretation of risk premia earned by bonds with rating r at time t. We now consider whether corporate bond returns

are predictable at horizons longer than one month, and estimate

$$Rx_{i,t,t+h} = \alpha_{c,h} + \beta_h \varphi\left(cs_t, \text{VIX}_t\right) + \beta_{h,r} \varphi\left(cs_t, \text{VIX}_t\right) \times \mathbb{1}_r + \gamma_h u_{t,t+h} + \gamma_{h,r} u_{t,t+h} \times \mathbb{1}_r + \epsilon_{i,t,t+h}. \tag{6}$$

Comparing the one-period returns to the h-period return representation above, the implied cross-horizon restriction on the coefficients is

$$\beta_h = \beta \left(1 + \sum_{j=1}^{h-1} \frac{cov\left(\varphi\left(cs_t, \text{VIX}_t\right), \varphi\left(cs_{t+j}, \text{VIX}_{t+j}\right)\right)}{var\left(\varphi\left(cs_t, \text{VIX}_t\right)\right)} \right).$$

If the global credit factor $\varphi\left(cs_t, \text{VIX}_t\right)$ is highly persistent, the above restriction would imply that the coefficients β_h increase in horizon and any longer horizon predictability is due to a persistent predictor variable bias.

Table 7 reports the estimated coefficients for the h-period cumulative returns regression (6) for 1 month, 3 month, 6 month, 9 month, and 12 month returns for the full sample of bonds. Starting with the baseline coefficient β_h on the global credit factor across horizons, we see that the point estimate declines with horizon but remains statistically significant for up to 12 month cumulative returns. A one standard deviation increase in the global credit factor (which is equal to 5.5) corresponds to a 5.23 percentage point increase in expected excess returns on high yield bonds at the 3 month horizon, 4.02 percentage point increase in expected excess returns at the 6 month horizon, and a 2.97 percentage point increase in expected excess returns at the 12 month horizon. Table 7 also shows that the relationship between bond ratings and the exposure to the global credit factor remains consistent across forecast horizons, with higher rated bonds consistently having lower exposure to the global credit factor. Finally, we see that the adjusted R^2 remains stable across horizons, suggesting both that the one-month-ahead return predictability we focus on is not an artifact of the persistence of the global credit factor (as we would expect the adjusted R^2 and the estimated coefficients to rise as a function of horizon in that case) and that increases in the global credit

factor may have persistent effects.

Table 8 presents an alternative way of evaluating the longer-horizon impacts of the global credit factor: how realized return volatility evolves as a function of the global credit factor. In particular, we construct the h-period realized volatility at date t as the volatility of one-month returns over the following h months

$$vol_{i,t,t+h} = \sqrt{\frac{1}{h-1}\sum_{s=1}^{h}\left(Rx_{i,t+h} - \overline{Rx}_{i,t,h}\right)^2}; \quad \overline{Rx}_{i,t,h} = \frac{1}{h}\sum_{s=1}^{h} Rx_{i,t+s}.$$

Similarly to the return predictability regression, we then estimate

$$vol_{i,t,t+h} = \alpha_{c,h} + \beta_h \varphi\left(cs_t, \text{VIX}_t\right) + \beta_{h,r}\varphi\left(cs_t, \text{VIX}_t\right) \times \mathbb{1}_r + \gamma_h u_{t+1} + \gamma_{h,r} u_{t+1} \times \mathbb{1}_r + \epsilon_{i,t+h}.$$

Table 8 reports the estimated coefficients from the above regression for volatility computed using the following three months, six months, nine months, and twelve months of returns. Starting with the baseline β with respect to the global credit factor, we see that the realized volatility of returns on high yield bonds is higher following periods of high global credit factor, with the estimated coefficient declining only slightly as we expand the number of periods we use to construct our conditional realized volatility. Turning to the estimated coefficients for the rest of the rating categories, we see that, as with expected returns themselves, the estimated coefficient on the global credit factor declines as the credit rating of the bond improves. In fact, while the realized volatility of returns on BBB-rated bonds also increases as the global credit factor increases, the realized volatility on A-rated bonds and on AAA/AA-rated bonds declines. A one standard deviation increase in the global credit factor corresponds to a 3.68 pp. increase in the three month realized volatility for high yield bonds, a 0.36 pp. increase in the three month realized volatility for BBB-rated bonds, a 0.43 pp decrease in the volatility for A-rated bonds, and a 1.04 pp decrease in the realized volatility for AAA/AA-rated bonds. These estimates are not only statistically but also eco-

nomically significant: the average realized three month volatility for high yield bonds in our sample is 71%, while the average realized three month volatility for AAA/AA-rated bonds is 24%. It is also noteworthy that these patterns in the volatility response are consistent with a flight-to-safety dynamic, with increases in the global credit factor increasing the realized risk of high yield bonds but decreasing the realized risk of AAA/AA-rated bonds.

5.3 Risk across the global credit cycle

The results in Table 8 suggest that increases in the global credit factor not only forecast higher future returns but also higher future realized return volatility. To evaluate further how corporate bond market risk evolves over the global credit cycle, we estimate a linear probability model for the probability of a negative realized return contemporaneous to a tightening in global credit market conditions. More specifically, we estimate

$$\mathbb{1}_{Rx_{i,t}<0} = \alpha_c + \alpha_r + \beta\varphi\left(cs_t, \text{VIX}_t\right) + \beta_r\varphi\left(cs_t, \text{VIX}_t\right) \times \mathbb{1}_r + \epsilon_{i,t}. \tag{7}$$

Table 9 reports the estimated coefficients from the linear regression probability model (7), for the full sample of bonds, as well as separately for bonds of ultimate parents domiciled in the U. S. (column 2), advanced economies excluding the U. S. (column 3), and emerging market economies (column 4).

Starting with the full sample results in column (1), we see that a higher level of the global credit factor corresponds to a higher probability of negative bond market returns, and that the fraction of bonds with negative returns increases in bond riskiness, as proxied by the bond credit rating. For high yield bonds, when the global credit factor is enters its top 25th percentile, the probability of negative returns rises from 32% to 45%. Increases in the probability of negative returns for BBB-rated bonds are more modest, increasing from 38% to 44%, and even more modest still for A-rated bonds, increasing from 39% to 44%. For

AAA/AA-rated bonds, the probability of negative returns declines as global credit conditions tighten, falling from an average probability of 44% when the global credit factor outside of its top 25th percentile to 39% when credit conditions are tight. This suggests a flight-to-safety pattern, with returns on AAA/AA-rated bonds more likely to be positive, and returns on riskier bonds more likely to be negative when credit conditions are unusually tight.

Turning to the results across countries in columns (2) – (4), we see that the flight-to-safety phenomenon is dominated by U. S. bonds. For the rest of the advanced economies, the probability of negative returns for AAA/AA-rated bonds rises by 3 percentage points as credit conditions tighten. Furthermore, while the estimated coefficient from the linear probability regression model for advanced economy A-rated bonds is about an eighth of the point estimate of the high yield coefficient, the decline in coefficients for emerging market economies is less pronounced. The point estimate of the coefficient for emerging market A-rated bonds is half of the point estimate of the high yield coefficient. Thus, overall, Table 9 shows that the probability of negative returns rises as global credit conditions tighten, with lower rated bonds, and bonds in riskier countries more exposed to the global credit cycle.

5.4 Financial integration and return predictability

Having established the strong predictability of returns by our global credit factor across different asset classes, horizons, and economic states, we now examine whether bonds of issuers in countries that are more integrated in global financial markets are more exposed to the global credit cycle. Financial market integration can affect the predictability of returns by a global price of risk through two channels. First, countries that are less integrated in global financial markets may be more reliant on local – rather than global – intermediaries. To the extent that the global credit factor reflects the price of risk from the stochastic discount factor of a *global* marginal intermediary, the global credit factor may be a less relevant proxy for the price of risk in such countries. Second, countries less integrated in global financial

markets experience less volatile capital flows. If the global credit factor predicts returns because it predicts portfolio reallocations (rather than just repricing of risk), returns of securities in countries with less volatile capital flows should be less predictable by the global credit factor. We examine the relationship between financial market integration and return predictability by augmenting the regression specification (4) with interaction with proxies for financial market integration:

$$Rx_{i,t+1} = \alpha_r + \beta\varphi\left(cs_t, \text{VIX}_t\right) + \beta_g\varphi\left(cs_t, \text{VIX}_t\right) \times \text{Integration}_c$$
$$+ \gamma u_{t+1} + \gamma_G u_{t+1} \times \text{Integration}_c + \epsilon_{i,t+1}.$$

Table 10 reports the estimated coefficients from the above regression using three proxies for financial market integration, for advanced economies excluding the U. S. and emerging market economies. Columns (1) and (4) use the Chinn and Ito (2006) index of financial openness, which measures the extent of capital controls. Columns (2) and (5) instead use the equity market β with respect to the U. S. MSCI equity index, estimated via a contemporaneous regression of one-month excess returns on country-level MSCI equity indices for monthly data for January 1998 – December 2024. Similarly, columns (3) and (6) use the corporate bond market β with respect to the U. S. corporate bond market index returns, estimated via a contemporaneous regression of one-month excess returns on country-level corporate bond market indices for monthly data for January 1998 – December 2024.[15] That is, we consider proxies for financial market openness based both on statutory measures as well as those based on correlations of financial market returns.

Starting with the results using the Chinn and Ito (2006) index, in column (1) of Table 10, we see that the relative variation in the extent of financial account openness for advanced economies is not a significant predictor of the effect of global credit cycle tightening on

[15] We construct returns on all country-level indices as the amount-outstanding-weighted average of returns on bonds of nonfinancial ultimate parents domiciled in each country.

expected returns. This is intuitive: there is very little variation in the Chinn and Ito (2006) index across advanced economies. In contrast, financial account openness is a significant predictor of the exposure to the global credit factor for emerging market economies. As financial market openness increases from the bottom 25th percentile (0.16 in our sample) to the top 25th percentile (0.7), the exposure to the global credit factor increases from 0.76 to 1.1. Thus, bond market returns are more exposed to the global price of credit risk in countries with less extensive capital controls.

Turning to the rest of the columns in Table 10, we see that both equity and corporate bond market βs are statistically significant predictors of the exposure to the global credit factor, for both advanced and emerging economies. Variation in corporate bond market βs corresponds also to economically-meaningful variation in exposure to the global credit factor. For example, as the bond market β moves from the bottom 25th percentile for emerging markets (0.89 in our sample) to the top 25th percentile (1.18), the exposure to the global credit factor doubles from 0.64 to 1.24. For advanced economies, instead, as the bond market β moves from the bottom 25th percentile (0.23 in our sample) to the top 25th percentile (0.75), the exposure to the global credit factor more than doubles from 0.32 to 0.83. Sensitivity of global credit factor exposure in advanced economies to equity β is more modest, with an increase in equity market β from the bottom 25th percentile (0.85) to the top 25th percentile (1.07) corresponding to an increase in the exposure to the global credit factor from 0.47 to 0.63. For emerging market economies, an increase in equity market β from the bottom 25th percentile (0.9) to the top 25th percentile (1.3) corresponds to a doubling in the exposure to the global credit factor from 0.74 to 1.42.

Overall, the results in Table 10 suggest that bonds of issuers in countries more integrated in global financial markets are more exposed to the global credit cycle. For advanced economies, sensitivity to the global credit factor is most correlated with the country's corporate bond market β with respect to U. S. corporate bond market returns. For emerging markets, where

the corporate bond market and equity market βs are more than 50% correlated with each other, both βs capture substantial variation in exposures.

5.5 Real effects of tight credit conditions

Are periods of tight credit conditions costly for firms that borrow through the corporate bond market? Existing theories suggest that fluctuations in aggregate conditions can affect both the willingness and the ability of firms to issue (or refinance) debt. As aggregate credit conditions tighten, firms may face greater financing needs but, if credit spreads rise, may be less willing to raise new debt at higher coupon rates. At the same time, tighter credit conditions may induce a "flight-to-quality" (Caballero and Krishnamurthy, 2008; Vayanos, 2004), with investors becoming relatively more risk averse and shifting portfolio allocations towards safer assets. The flight-to-quality dynamic translates not only into an overall increase in credit spreads but also into a repricing of safer assets relative to riskier ones.

Motivated by the theoretical literature, we focus on two aspects of the response of equilibrium credit outcomes to global credit conditions' tightening. First, we examine changes in secondary market credit spreads at the bond level. Since secondary market spreads on outstanding bonds are a key determinant of the prices at which new debt is offered in the primary market, increases in secondary market credit spreads translate into increases of the spreads at which firms could issue and thus into both firms' willingness to issue new corporate bonds and the effective interest cost changes if they choose to do so.[16] Second, we tackle the question of how firm risk evolves in response to a tightening of global credit conditions by studying the evolution of expected default probabilities, as measured by the one-year expected default frequency at the firm level from Moody's KMV.

We identify periods of tight credit conditions as realizations of the global credit factor in

[16] See, for example, White (1974), Taggart (1977), Barry et al. (2008), Barry et al. (2009), Hotchkiss et al. (2021), and Erel et al. (2012).

the top 25th historical percentile. We then construct a dummy variable, Tight GCC_t that equals one in the first month of each period of global credit factor realizations in the top 25th historical percentile and 0 otherwise.

To trace the predicted dynamics of credit spreads and firm default probabilities around tight credit conditions, we estimate a sequence of Jordà (2005) local projections for horizons $h = -6, \ldots, 6$:

$$\begin{aligned}
\frac{\Delta S_{i,t+h,t-1}}{S_{i,t-1}} &= \alpha_{c,h} + \alpha_{r,h} + \beta_h \text{Tight GCC}_t + \beta_{r,h} \text{Tight GCC}_t \times \mathbb{1}_r + \epsilon_{i,t+h} \\
\frac{\Delta \text{EDF}_{f,t+h,t-1}}{\text{EDF}_{f,t-1}} &= \alpha_{c,h} + \alpha_{r,h} + \beta_h \text{Tight GCC}_t + \beta_{r,h} \text{Tight GCC}_t \times \mathbb{1}_r + \epsilon_{f,t+h},
\end{aligned}$$

where $S_{i,t}$ is the currency-adjusted duration-matched spread on bond i in month t and $\text{EDF}_{f,t}$ is the one year expected default frequency for firm f in month t. We benchmark both credit spread and default probability changes to the month before tight credit conditions are identified, capturing the initial credit conditions faced by firms in our sample before credit factor tightening episodes begin.

Figure 7 plots the estimated dynamics of credit spreads (Figure 7a) and default probabilities (Figure 7b) by rating category around a tightening in the global credit factor, with $h = 0$ marking the first month of a period of global credit factor realizations in the top 25th historical percentile. For example, during the COVID-19 pandemic, the first month of tight global credit conditions is March 2020.

Figure 7a shows that the start of a period of tight credit conditions corresponds to a substantial increase in credit spreads across credit ratings. Furthermore, increases in credit spreads for BBB and high yield bonds are much more persistent than credit spread increases for bonds rated A and above. While credit spreads on these safer bonds rebound within 3 months, credit spreads on BBB-rated bonds remain elevated four months after the onset of tight credit conditions, and credit spreads on high yield bonds remain elevated for up to 5

months. Thus, while the onset of a period of tight credit conditions corresponds to credit spread tightening across the rating spectrum, conditions for safer bonds improve relatively quickly but remain tight for riskier bonds for a prolonged period of time. To the extent that such tightenings in global credit conditions coincide with firms' refinancing needs, this suggest that riskier firms may be particularly disadvantaged by periods of tight global credit conditions and thus experience larger and more persistent increases in financial fragility.

Figure 7b confirms this intuition. For high yield firms, one year EDFs rise by almost 15% at the onset of a period of tight credit conditions, continue increasing up to 3 months after the start of a period of tight credit conditions, and only revert back to initial levels around 6 months later. In contrast, initial increases in the one year EDFs for AAA/AA-rated firms are much more modest – around 2% – and revert to initial levels within 2 months. Thus, the onset of a period of tight credit conditions not only corresponds to higher bond market volatility and higher probability of negative realized returns but also to persistently higher borrowing costs and increased default risk for lower-rated borrowers.

We investigate the statistical significance of the results in Figure 7 in Tables 11 and 12. Table 11a compares the initial increases in credit spreads across countries. The impact of tight credit conditions is larger (in percent terms) outside of the U. S., with credit spreads in the U. S. increasing by 6% in the first month of a period of tight credit conditions and spreads in the remaining countries increasing by more than 8.5%. In advanced economies, the initial percent increase is larger for BBB-rated bonds than for high yield bonds, potentially reflecting expectations of forthcoming rating downgrades for BBB-rated bonds. For advanced economies outside of the U. S., (percent) credit spread increases for AAA/AA-rated bonds are significantly lower than those for high yield bonds. Similarly, for emerging markets, (percent) credit spread increases for A-rated bonds (safest rating for corporate bonds of emerging market issuers in our sample) are significantly lower than those for high yield bonds, suggesting once again a relative flight to safety during periods of tight credit conditions.

Table 11b then confirms that the cross-rating differences in the persistence of credit spread increases discussed in the context of Figure 7a are statistically, as well as economically, significant. On average, spreads on high yield bonds increase by 6.7% at the onset of a period of tight credit conditions and remain 5% higher initial spreads three months after the start of the episode. In contrast, spreads on AAA/AA-rated bonds decrease below initial values within three months.

Turning to changes in firm-level EDFs in Table 12, we see that the initial increases in EDFs for high yield firms are similar across countries, with EDFs increasing 13.9% in the U. S., 14.3% in other advanced economies, and 15% for firms in emerging markets. In the U. S., however EDFs for AAA/AA-rated firms do not increase on impact, while default probabilities for AAA/AA-rated firms modestly increase by 4% in other advanced economies. Table 12b also confirms that the cross-rating differences in the persistence of default probability increases discussed in the context of Figure 7b are statistically, as well as economically, significant.

6 Conclusion

We construct the price of risk in international corporate bond markets as a nonlinear function of the VIX and U. S. credit spreads. Our global credit factor prices corporate bond returns in both the time series and the cross-section, with bond exposure to the global credit factor increasing with bond and country risk. Furthermore, a tighter global credit factor corresponds to a higher probability of negative contemporaneous returns and higher realized return volatility, suggesting the credit factor tightening increases the riskiness of corporate bonds. Importantly, these increases in corporate bond return risk are higher for lower rated bonds. For AAA/AA-rated bonds, instead, realized volatility decreases, as does the probability of negative returns for U. S. AAA/AA-rated bonds, capturing a flight-to-

safety dynamics. Across countries, bonds in emerging market economies are more exposed to the global credit factor, with capital account openness playing a key role in the extent to which different countries are affected.

Our results also provide initial evidence of the real costs of the global credit cycle. Extreme tightenings of the global credit factor predict a prolonged tightening of credit spreads for lower-rated bonds and a prolonged period of elevated default probabilities for riskier firms. As secondary market spreads feed through to the pricing of new corporate bond issuances, such persistent increases in secondary market credit spreads suggest that firms needing to refinance during a downturn in the global credit cycle may have to do so at higher rates or may loose access to the corporate bond market altogether.

Overall, the results in our paper provide novel moments that international macro-finance models should target. First, we document that neither the VIX nor U. S. credit spreads on their own provide sufficient information to parametrize the global price of credit risk. This suggests that the global equilibrium pricing kernel reflects variation in constraints of more than one type of intermediaries. In the corporate bond market, this is intuitive: traditional broker-dealers in the market and hedge funds are subject to value-at-risk constraints, mutual funds track index performance, and insurance companies are subject to regulatory capital constraints. Second, we show that countries with greater capital account openness are more exposed to the global credit factor. This suggests that the global credit cycle transmits not just through a global repricing of risk but also through a rebalancing of global portfolios. Consistent with this interpretation, we show that realized return volatility for riskier bonds is higher following a tightening of the global credit factor. Finally, the result that extreme tightenings of the global credit factor predict persistent increases in credit spreads as well as in default probabilities suggests that even a temporary tightening of financial intermediary constraints has long-lived effects on credit markets for riskier firms.

References

Adrian, T. and N. Boyarchenko (2012): "Intermediary leverage cycles and financial stability," Staff Report N. 567, Federal Reserve Bank of New York.

Adrian, T., R. K. Crump, and E. Moench (2015): "Regression-based estimation of dynamic asset pricing models," *Journal of Financial Economics*, 118, 211–244.

Adrian, T., R. K. Crump, and E. Vogt (2019a): "Nonlinearity and flight-to-safety in the risk-return trade-off for stocks and bonds," *The Journal of Finance*, 74, 1931–1973.

Adrian, T. and J. Rosenberg (2008): "Stock returns and volatility: Pricing the short-run and long-run components of market risk," *The Journal of Finance*, 63, 2997–3030.

Adrian, T., D. Stackman, and E. Vogt (2019b): "Global price of risk and stabilization policies," *IMF Economic Review*, 67, 215–260.

Ang, A. and G. Bekaert (2007): "Stock return predictability: Is it there?" *The Review of Financial Studies*, 20, 651–707.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006): "The cross-section of volatility and expected returns," *The Journal of Finance*, 61, 259–299.

Avdjiev, S., L. Gambacorta, L. S. Goldberg, and S. Schiaffi (2020): "The shifting drivers of global liquidity," *Journal of International Economics*, 125.

Bali, T. G., A. Subrahmanyam, and Q. Wen (2021): "The macroeconomic uncertainty premium in the corporate bond market," *Journal of Financial and Quantitative Analysis*, 56, 1653–1678.

Barry, C. B., S. C. Mann, V. Mihov, and M. Rodriguez (2009): "Interest rate changes and the timing of debt issues," *Journal of Banking & Finance*, 33, 600–608.

Barry, C. B., S. C. Mann, V. T. Mihov, and M. Rodriguez (2008): "Corporate debt issuance and the historical level of interest rates," *Financial Management*, 37, 413–430.

Bartram, S. M., M. Grinblatt, and Y. Nozawa (2025): "Book-to-market, mispricing, and the cross section of corporate bond returns," *Journal of Financial and Quantitative Analysis*, 60, 1185–1233.

Bates, D. S. (2008): "The market for crash risk," *Journal of Economic Dynamics and Control*, 32, 2291–2321.

Bekaert, G., R. De Santis, and T. Mondino (2024): "The Global Cross-Section of Corporate Bonds: Market, Maturity and Liquidity," *Maturity and Liquidity (August 07, 2024)*.

Bekaert, G. and R. A. De Santis (2021): "Risk and return in international corporate bond markets," *Journal of International Financial Markets, Institutions and Money*, 72.

Bernanke, B. and M. Gertler (1989): "Agency Costs, Net Worth, and Business Fluctuations," *American Economic Review*, 79, 14–31.

Van Binsbergen, J. H., Y. Nozawa, and M. Schwert (2025): "Duration-based valuation of corporate bonds," *The Review of Financial Studies*, 38, 158–191.

Blume, M. E., D. B. Keim, and S. A. Patel (1991): "Returns and volatility of low-grade bonds 1977–1989," *The Journal of Finance*, 46, 49–74.

Boyarchenko, N. and L. Elias (2023): "Corporate Credit Conditions Around the World: Novel Facts Through Holistic Data," Staff Report N. 1074, Federal Reserve Bank of New York.

Brunnermeier, M. K. and Y. Sannikov (2014): "A Macroeconomic Model with a Financial Sector," *American Economic Review*, 104, 379–421.

Caballero, R. J. and A. Krishnamurthy (2008): "Collective risk management in a flight to quality episode," *The Journal of Finance*, 63, 2195–2230.

Campbell, J. Y., S. Giglio, C. Polk, and R. Turley (2018): "An intertemporal CAPM with stochastic volatility," *Journal of Financial Economics*, 128, 207–233.

Campello, M., L. Chen, and L. Zhang (2008): "Expected returns, yield spreads, and asset pricing tests," *The Review of Financial Studies*, 21, 1297–1338.

Chinn, M. D. and H. Ito (2006): "What matters for financial development? Capital controls, institutions, and interactions," *Journal of Development Economics*, 81, 163–192.

Chung, K. H., J. Wang, and C. Wu (2019): "Volatility and the cross-section of corporate bond returns," *Journal of Financial Economics*, 133, 397–417.

Dickerson, A., P. Mueller, and C. Robotti (2023): "Priced risk in corporate bonds," *Journal of Financial Economics*, 150, 103707.

Eichengreen, B. and A. Mody (1998): "What explains changing spreads on emerging-market debt: fundamentals or market sentiment?" Working paper, NBER.

Elton, E. J., M. J. Gruber, and C. R. Blake (1995): "Fundamental economic variables, expected returns, and bond fund performance," *The Journal of Finance*, 50, 1229–1256.

Erel, I., B. Julio, W. Kim, and M. S. Weisbach (2012): "Macroeconomic conditions and capital raising," *The Review of Financial Studies*, 25, 341–376.

Fama, E. F. and K. R. French (1993): "Common risk factors in the returns on stocks and bonds," *Journal of Financial Economics*, 33, 3–56.

Forbes, K. J. and F. E. Warnock (2012): "Capital flow waves: Surges, stops, flight, and retrenchment," *Journal of international economics*, 88, 235–251.

——— (2021): "Capital flow waves—or ripples? Extreme capital flow movements since the crisis," *Journal of International Money and Finance*, 116.

Gebhardt, W. R., S. Hvidkjaer, and B. Swaminathan (2005): "The cross-section of expected corporate bond returns: Betas or characteristics?" *Journal of financial economics*, 75, 85–114.

Gertler, M. and N. Kiyotaki (2015): "Banking, liquidity, and bank runs in an infinite horizon economy," *American Economic Review*, 105, 2011–43.

Gilchrist, S. and E. Zakrajšek (2012): "Credit spreads and business cycle fluctuations," *American Economic Review*, 102, 1692–1720.

Goldberg, L. S. (2023): "Global Liquidity: Drivers, Volatility and Toolkits," Tech. rep., National Bureau of Economic Research.

He, X., G. Feng, J. Wang, and C. Wu (2025): "Predicting individual bond returns," *Journal of Banking and Finance*, 171, 107372.

He, Z., P. Khorrami, and Z. Song (2022): "Commonality in credit spread changes: Dealer inventory and intermediary distress," *The Review of Financial Studies*, 35, 4630–4673.

He, Z. and A. Krishnamurthy (2013): "Intermediary Asset Pricing," *American Economic Review*, 103, 732–770.

Hodrick, R. J. (1992): "Dividend yields and expected stock returns: Alternative procedures for inference and measurement," *The Review of Financial Studies*, 5, 357–386.

Hotchkiss, E. S., H. Sun, L. Wang, and Y. E. Zhao (2021): "Firms' response to credit supply: Evidence from upsized corporate bond offerings," Available at SSRN 4044157.

Israel, R., D. Palhares, and S. A. Richardson (2018): "Common factors in corporate bond returns," *Journal of Investment Management*, 16, 17–46.

Jordà, Ò. (2005): "Estimation and inference of impulse responses by local projections," *American Economic Review*, 95, 161–182.

Kelly, B., D. Palhares, and S. Pruitt (2023): "Modeling corporate bond returns," *The Journal of Finance*, 78, 1967–2008.

Li, D., M. Riddell, Y. Sun, and D. Adler (2022): "Illiquidity premiums in international corporate bond markets," *Available at SSRN 4153877*.

Liao, G. Y. (2020): "Credit migration and covered interest rate parity," *Journal of Financial Economics*, 138, 504–525.

Lin, H., J. Wang, and C. Wu (2011): "Liquidity risk and expected corporate bond returns," *Journal of Financial Economics*, 99, 628–650.

Miranda-Agrippino, S., T. Nenova, and H. Rey (2020): "Global footprints of monetary policies," Working paper, London School of Economics.

Miranda-Agrippino, S. and H. Rey (2015): "World asset markets and the global financial cycle," Working paper n. 21722, National Bureau of Economic Research.

——— (2020): "US monetary policy and the global financial cycle," *The Review of Economic Studies*, 87, 2754–2776.

Moreno, R. and J. M. Serena-Garralda (2018): "Firms' credit risk and the onshore transmission of the global financial cycle," .

Newey, W. K. and K. D. West (1987): "Hypothesis testing with efficient method of moments estimation," *International Economic Review*, 777–787.

Pan, J. (2002): "The jump-risk premia implicit in options: Evidence from an integrated time-series study," *Journal of Financial Economics*, 63, 3–50.

Rey, H. (2013): "Dilemma not trilemma: the global financial cycle and monetary policy independence," Tech. rep., In: Proceedings - Economic Policy Symposium - Jackson Hole.

Santa-Clara, P. and S. Yan (2010): "Crashes, volatility, and the equity premium: Lessons from S&P 500 options," *The Review of Economics and Statistics*, 92, 435–451.

SIFMA (2025): "Capital markets factbook," Tech. rep., SIFMA.

Taggart, R. A. (1977): "A Model of Corporate Financing Decisions," *The Journal of Finance*, 32, 1467–1484.

Valenzuela, P. (2016): "Rollover risk and credit spreads: Evidence from international corporate bonds," *Review of Finance*, 20, 631–661.

Vayanos, D. (2004): "Flight to quality, flight to liquidity, and the pricing of risk," Working paper N. 10327, National Bureau of Economic Research.

Warga, A. D. (1991): "A fixed income database," Manuscript, University of Houston.

Wei, M. and J. H. Wright (2013): "Reverse regressions and long-horizon forecasting," *Journal of Applied Econometrics*, 28, 353–371.

White, W. L. (1974): "Debt Management and the Form of Business Financing," *The Journal of Finance*, 29, 565–577.

Table 1: Sample summary statistics. This table reports the sample summary statistics for the bond characteristics by currency, averaged over the sample period, January 1973 – December 2024. Bond excess returns and duration-adjusted, currency matched spreads are annualized. Numerical rating at the letter level, with AAA=1, ..., C=9. EDF is the one-year-ahead expected default frequency, which measures the probability that a firm will default within a year. We split the sample of bonds denominated in USD between those issued by ultimate parents headquartered in the U. S. ("Dom. USD") and those issued by ultimate parents headquartered outside of the U. S. ("Fgn. USD"). We further split the domestic USD bond observations between the sample covered in the Lehman-Warga Fixed Income Database ("Dom. USD, Leh", Jan 1973 – Dec 1997), and those covered in the ICE Global Indices ("Dom. USD, ICE", Jan 1998 – Dec 2024).

	Bonds	Firms	Amt. outstanding (USD million)	Excess return (%)	Dur. matched spread (%)	Duration (years)	Rating	EDF (%)
Dom. USD, Leh	3,663	501	160	10.8	1.5	7.0	3.2	0.11
Dom. USD, ICE	5,465	954	602	5.2	2.6	6.5	4.0	0.95
Fgn USD	1,999	565	715	4.9	2.8	5.6	4.0	0.85
EUR	1,633	400	817	3.9	1.7	5.1	3.5	0.27
GBP	426	164	539	5.8	1.8	7.1	3.4	0.20
JPY	337	41	319	2.6	1.1	5.3	2.7	0.17
CAD	544	112	268	6.1	1.6	7.1	3.4	0.20
AUD	157	55	209	7.8	1.2	3.7	2.8	0.14

Table 2: Nonlinear VIX and credit spread predictability using advanced economy bond portfolios. This table reports the results from three predictive sieve reduced-rank (SRR) regressions for a forecast horizon of $h = 1$ month: (1) estimates of $a_{i,h}$ and $b_{i,h}$ from the full SRR $Rx_{i,t+h} = a_{i,h} + b_{i,h}\varphi_h(\mathrm{VIX}_t, \mathrm{EBP}_t) + \epsilon_{i,t+h}$ of portfolio i's excess returns on a nonlinear function of the VIX and U. S. credit spreads; (2) estimates of $a_{i,h}$ and $b_{i,h}$ from the SRR of portfolio i's excess returns on a nonlinear function of the VIX; and (3) estimates of $a_{i,h}$ and $b_{i,h}$ from the SRR of portfolio i's excess returns on a nonlinear function of U. S. credit spreads. The index i ranges over advanced economy corporate bond portfolios, grouped into AAA/AA, A, BBB, and high yield (rated below BBB-) bonds. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level for t-statistics on a_i and χ^2 statistics on $b_i\varphi_h(\cdot)$ as derived in Adrian et al. (2019a), Theorem 1. The joint test p-value (J p-val) reports the likelihood that the sample was generated under $\mathbb{H}_{1,0}$: $\forall \mathrm{VIX} \in V$, $\forall \mathrm{EBP} \in C$, $\varphi_h(\mathrm{VIX}, \mathrm{EBP}) = 0$. U. S. credit spreads measured by the country-level average default-adjusted spread (EBP).

	(1) $\varphi(\mathrm{EBP}, \mathrm{VIX})$		(2) $\varphi(\mathrm{VIX})$		(3) $\varphi(\mathrm{EBP})$	
	a^i	b^i	a^i	b^i	a^i	b^i
HY	1.73	1.00**	8.32	1.00	-2.08	1.00
BBB	0.82	0.85***	-4.65	22.14***	9.01**	-0.20
A	-0.41	0.96***	-7.47	26.68***	14.00	-0.70***
AAA/AA	2.40	0.51***	-1.85	15.10**	9.04*	-0.28
J p-val		0.000		0.966		0.849

Table 3: Bond-level return predictability. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global credit factor. All regressions include country fixed effects, and interactions between rating category and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) US	(3) AE, ex US	(4) EM
Global credit	1.12	1.05	0.90	1.31
	(0.01)***	(0.01)***	(0.05)***	(0.05)***
AAA/AA × Global credit	-0.47	-0.32	-0.57	
	(0.01)***	(0.01)***	(0.05)***	
A × Global credit	-0.33	-0.29	-0.33	-0.57
	(0.01)***	(0.01)***	(0.05)***	(0.04)***
BBB × Global credit	-0.32	-0.31	-0.30	-0.41
	(0.01)***	(0.01)***	(0.04)***	(0.04)***
Adj. R^2	0.02	0.06	0.01	0.02
N. of obs	2,894,573	1,656,372	1,064,018	169,860

Table 4: Decomposing returns into sources of risk. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global credit factor, decomposing excess returns into the contribution of duration risk from the perspective of a U. S. investor, the differential duration risk due to foreign (non-USD) currency sovereign curves, and credit risk. All regressions include country fixed effects, and interactions between rating category and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Total	(2) Credit risk	(3) Currency diff	(4) Duration risk
Global credit	1.12	0.84	-0.05	0.29
	(0.01)***	(0.01)***	(0.00)***	(0.00)***
AAA/AA × Global credit	-0.47	-0.60	-0.12	0.19
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
A × Global credit	-0.33	-0.42	-0.03	0.11
	(0.01)***	(0.01)***	(0.00)***	(0.00)***
BBB × Global credit	-0.32	-0.36	-0.02	0.05
	(0.01)***	(0.01)***	(0.00)***	(0.00)***
Adj. R-sqr.	0.019	0.009	0.003	0.010
N. of obs	2,894,573	2,894,455	1,238,161	2,894,464

Table 5: Bond-level return predictability across different subperiods. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global credit factor across subperiods. All regressions include country fixed effects, and interactions between rating category and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) 1986 – 1997	(3) Jan 1998 – Jul 2007	(4) GFC	(5) Jan 2010 – Dec 2019	(6) 2020	(7) Jan 2021 –
Global credit	1.12	1.61	1.83	0.74	1.22	1.49	3.36
	(0.01)***	(0.03)***	(0.02)***	(0.03)***	(0.02)***	(0.03)***	(0.02)***
AAA/AA × Global credit	-0.47	-0.41	-0.55	-0.46	-0.52	-0.71	-0.64
	(0.01)***	(0.03)***	(0.02)***	(0.03)***	(0.01)***	(0.04)***	(0.02)***
A × Global credit	-0.33	-0.38	-0.55	-0.03	-0.44	-0.58	-0.59
	(0.01)***	(0.03)***	(0.02)***	(0.03)	(0.01)***	(0.03)***	(0.01)***
BBB × Global credit	-0.32	-0.38	-0.50	-0.09	-0.35	-0.40	-0.50
	(0.01)***	(0.03)***	(0.02)***	(0.03)***	(0.01)***	(0.03)***	(0.01)***
Adj. R-sqr.	0.02	0.16	0.01	0.05	0.01	0.04	0.04
N. of obs	2,894,573	130,933	523,965	163,859	1,190,932	155,964	728,914

Table 6: Return predictability for other asset classes. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global credit factor including 10 year sovereign bonds and country-level MSCI index as additional assets. All regressions include country fixed effects, and interactions between rating category/asset class and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) US	(3) AE, ex US	(4) EM
Global credit	1.12	1.05	0.90	1.30
	(0.01)***	(0.01)***	(0.05)***	(0.05)***
Sovereign × Global credit	-0.69	-0.25	-0.76	0.26
	(0.08)***	(0.14)*	(0.09)***	(0.39)
AAA/AA × Global credit	-0.47	-0.32	-0.57	
	(0.01)***	(0.01)***	(0.05)***	
A × Global credit	-0.33	-0.29	-0.33	-0.57
	(0.01)***	(0.01)***	(0.05)***	(0.04)***
BBB × Global credit	-0.32	-0.31	-0.30	-0.40
	(0.01)***	(0.01)***	(0.04)***	(0.04)***
Equity × Global credit	0.48	0.43	0.48	0.52
	(0.07)***	(0.41)	(0.09)***	(0.16)***
Adj. R^2	0.02	0.06	0.01	0.02
N. of obs	2,915,927	1,657,303	1,077,388	176,913

Table 7: Bond-level return predictability across horizons. This table reports the estimated coefficients from the regression of h month excess holding period returns on the global credit factor. All regressions include country fixed effects, and interactions between rating category and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) 1M	(2) 3M	(3) 6M	(4) 9M	(5) 12M
Global credit	1.12	0.96	0.73	0.67	0.54
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
AAA/AA × Global credit	-0.47	-0.58	-0.56	-0.51	-0.46
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
A × Global credit	-0.33	-0.49	-0.50	-0.46	-0.44
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
BBB × Global credit	-0.32	-0.42	-0.43	-0.39	-0.37
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
Adj. R^2	0.02	0.03	0.03	0.03	0.03
N. of obs	2,894,573	2,805,443	2,629,185	2,464,041	2,307,173

Table 8: Bond-level volatility predictability across horizons. This table reports the estimated coefficients from the regression of h month volatility of 1 month excess holding period returns on the global credit factor. All regressions include country fixed effects, and interactions between rating category and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) 3M	(2) 6M	(3) 9M	(4) 12M
Global credit	0.67	0.56	0.50	0.50
	(0.02)***	(0.03)***	(0.03)***	(0.03)***
AAA/AA × Global credit	-0.86	-0.86	-0.86	-0.87
	(0.03)***	(0.03)***	(0.03)***	(0.03)***
A × Global credit	-0.75	-0.75	-0.74	-0.75
	(0.03)***	(0.03)***	(0.03)***	(0.03)***
BBB × Global credit	-0.61	-0.59	-0.58	-0.59
	(0.02)***	(0.03)***	(0.03)***	(0.03)***
Adj. R^2	0.01	0.01	0.01	0.01
N. of obs	2,847,221	2,854,846	2,856,372	2,857,398

Table 9: Probability of contemporaneous negative returns. This table reports the estimated coefficients from the linear probability regression of a negative realized one month excess return on the contemporaneos global credit factor. All regressions include country and rating bucket fixed effects. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) US	(3) AE, ex US	(4) EM
Global credit	0.63	0.54	0.85	0.96
	(0.03)***	(0.02)***	(0.14)***	(0.07)***
AAA/AA × Global credit	-0.56	-0.60	-0.70	
	(0.09)***	(0.03)***	(0.21)***	
A × Global credit	-0.49	-0.40	-0.76	-0.45
	(0.03)***	(0.02)***	(0.14)***	(0.10)***
BBB × Global credit	-0.32	-0.19	-0.69	-0.33
	(0.03)***	(0.02)***	(0.14)***	(0.09)***
Adj. R^2	0.00	0.00	0.00	0.00
N. of obs	2,886,466	1,654,500	1,062,173	169,793

Table 10: Bond-level return predictability and financial integration. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global credit factor and interactions with measures of how integrated the country is in global financial markets. Chinn and Ito (2006) measures the extent of openness in capital account transactions. "Equity β" is the equity market β with respect to the U. S. market equity index. "Bond market β" is the β of the country-level (amount-outstanding-weighted) corporate bond market index returns with respect to the U. S. corporate bond market index. All regressions include country and rating category fixed effects, the AR(1) innovations to the global credit factor and interactions between the measure of financial market integration and the AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	AE ex U. S.			EM		
	(1) Chinn and Ito (2006)	(2) Equity β	(3) Bond β	(4) Chinn and Ito (2006)	(5) Equity β	(6) Bond β
Global credit	0.36	-0.15	0.09	0.66	-0.79	-1.19
	(0.19)*	(0.06)**	(0.03)***	(0.07)***	(0.21)***	(0.17)***
Intl. exposure × Global credit	0.19	0.73	0.98	0.61	1.71	2.05
	(0.19)	(0.06)***	(0.06)***	(0.14)***	(0.20)***	(0.17)***
Adj. R^2	0.02	0.02	0.02	0.06	0.06	0.06
N. of obs	901,296	1,049,914	1,064,018	135,443	136,075	169,848

Table 11: Bond-level spread changes in extreme tightenings. This table reports the estimated coefficients from the regression of percent spread changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions. Tight global credit conditions measured as a global credit factor realization in the top 25th percentile. All regressions include country and rating fixed effects. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Contemporaneous increase across countries

	(1) Full sample	(2) US	(3) AE, ex US	(4) EM
P75 global credit	6.72	5.90	8.80	8.56
	(0.16)***	(0.15)***	(0.58)***	(0.42)***
AAA/AA × P75 global credit	-2.20	-1.66	-3.81	
	(1.53)	(2.77)	(0.80)***	
A × P75 global credit	2.36	3.01	0.90	-1.52
	(0.29)***	(0.37)***	(0.68)	(0.68)**
BBB × P75 global credit	3.34	4.05	1.88	-0.54
	(0.24)***	(0.25)***	(0.69)***	(0.63)
Adj. R^2	0.00	0.00	0.00	0.02
N. of obs	2,844,910	1,638,543	1,034,609	167,563

(b) Average increase across horizons

	(1) $\frac{\Delta S_{t-3,t-1}}{S_{t-1}}$	(2) $\frac{\Delta S_{t-2,t-1}}{S_{t-1}}$	(3) $\frac{\Delta S_{t-1,t}}{S_{t-1}}$	(4) $\frac{\Delta S_{t-1,t+3}}{S_{t-1}}$	(5) $\frac{\Delta S_{t-1,t+6}}{S_{t-1}}$
P75 global credit	-3.19	-3.39	6.72	5.13	-1.00
	(0.16)***	(0.09)***	(0.16)***	(0.13)***	(0.14)***
AAA/AA × P75 global credit	-1.97	0.80	-2.20	-6.32	-5.19
	(1.99)	(2.21)	(1.53)	(0.60)***	(0.59)***
A × P75 global credit	-2.43	-1.59	2.36	-4.95	-3.88
	(0.26)***	(0.27)***	(0.29)***	(0.24)***	(0.32)***
BBB × P75 global credit	-1.10	-0.53	3.34	-1.87	-1.37
	(0.21)***	(0.14)***	(0.24)***	(0.22)***	(0.24)***
Adj. R^2	-0.00	-0.00	0.00	0.00	0.00
N. of obs	2,724,683	2,784,606	2,844,910	2,695,105	2,529,848

Table 12: Firm-level EDF changes in extreme tightenings. This table reports the estimated coefficients from the regression of percent EDF changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions. Tight global credit conditions measured as a global credit factor realization in the top 25th percentile. All regressions include country and rating fixed effects. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Contemporaneous increase across countries

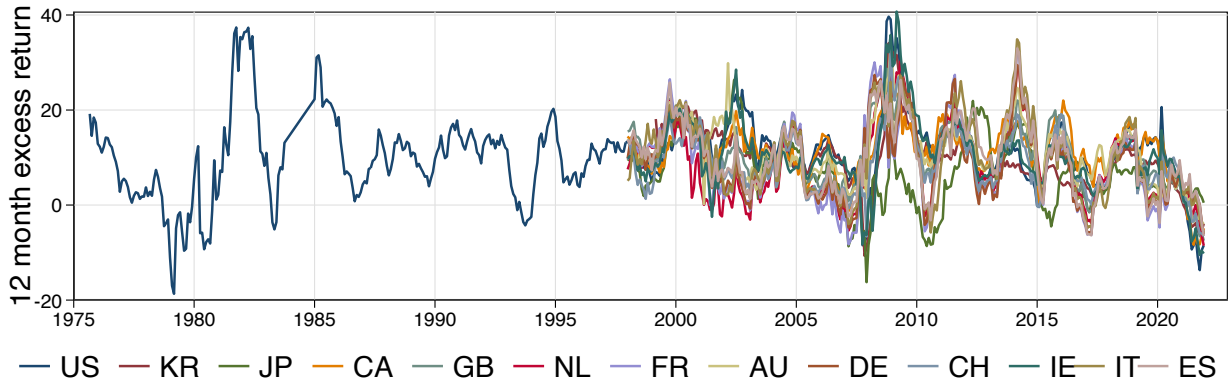
	(1) Full sample	(2) US	(3) AE, ex US	(4) EM
P75 global credit	14.13	13.89	14.32	15.15
	(0.98)***	(1.29)***	(1.79)***	(2.46)***
AAA/AA × P75 global credit	-12.17	-13.71	-10.05	
	(1.14)***	(1.45)***	(2.08)***	
A × P75 global credit	-11.51	-12.23	-10.48	-10.98
	(1.07)***	(1.39)***	(1.97)***	(3.18)***
BBB × P75 global credit	-7.92	-8.25	-7.15	-10.14
	(1.10)***	(1.50)***	(1.96)***	(2.71)***
Adj. R^2	0.00	0.00	0.00	0.00
N. of obs	188,457	102,565	67,894	17,890

(b) Average increase across horizons

	(1) $\frac{\Delta EDF_{t-3,t-1}}{EDF_{t-1}}$	(2) $\frac{\Delta EDF_{t-2,t-1}}{EDF_{t-1}}$	(3) $\frac{\Delta EDF_{t-1,t}}{EDF_{t-1}}$	(4) $\frac{\Delta EDF_{t-1,t+3}}{EDF_{t-1}}$	(5) $\frac{\Delta EDF_{t-1,t+6}}{EDF_{t-1}}$
P75 global credit	-7.59	-6.43	14.13	18.09	-0.79
	(1.20)***	(0.82)***	(0.98)***	(2.37)***	(3.96)
AAA/AA × P75 global credit	5.36	4.71	-12.17	-17.02	-0.92
	(1.35)***	(0.96)***	(1.14)***	(2.61)***	(4.32)
A × P75 global credit	3.57	3.55	-11.51	-15.57	-3.01
	(3.22)	(1.69)**	(1.07)***	(2.81)***	(4.33)
BBB × P75 global credit	4.32	3.25	-7.92	-8.74	2.29
	(1.40)***	(0.92)***	(1.10)***	(2.91)***	(4.44)
Adj. R^2	-0.00	-0.00	0.00	0.00	-0.00
N. of obs	187,960	188,250	188,457	187,615	185,795

Figure 1. 12-month-ahead bond excess returns. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) 12-month-ahead excess returns for non-financial corporate, senior fixed-coupon bonds issued by ultimate parents domiciled within the 22 countries of our sample. Sample AE countries are: United States, South Korea, Japan, Canada, United Kingdom, Netherlands, France, Australia, Germany, Switzerland, Ireland, Italy, and Spain. Sample EM countries are: China, Malaysia, Thailand, India, Mexico, Brazil, Russia, Chile, and Argentina.

(a) Advanced economies



(b) Emerging market economies

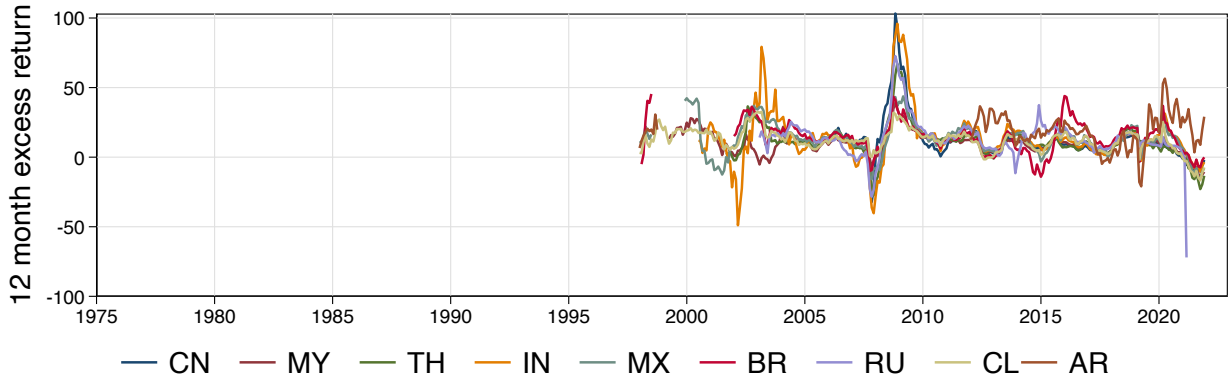
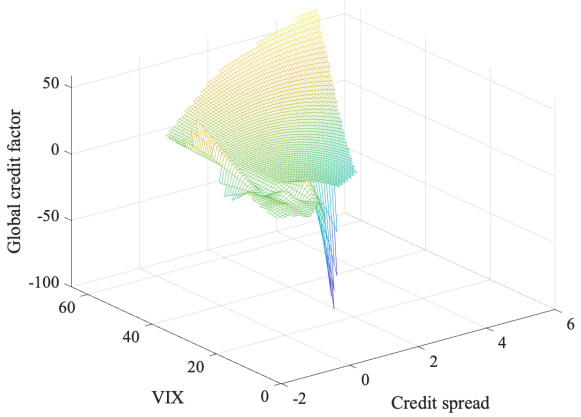
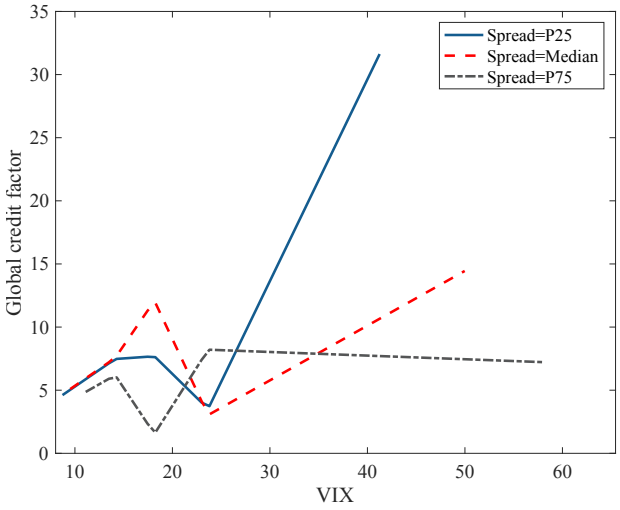


Figure 2. Estimated factor. This figure plots the estimated global credit factor as a function of realizations of the VIX and U. S. credit spreads, measured using the EBP.

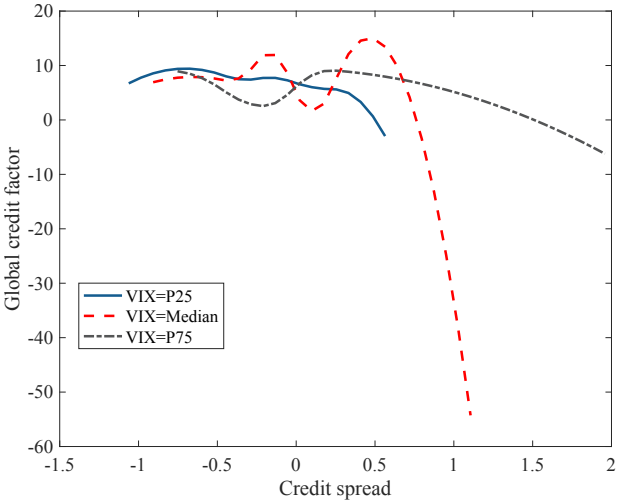
(a) Global credit factor



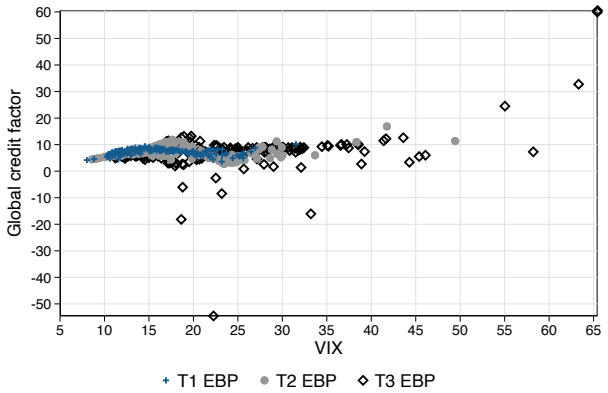
(b) Global credit factor vs VIX



(c) Global credit factor vs EBP



(d) Global credit factor vs VIX



(e) Global credit factor vs EBP

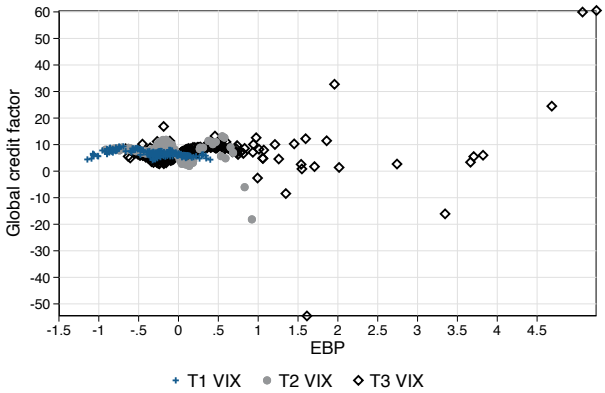


Figure 3. Time series of the estimated factor. This figure plots the time series of the global credit factor estimated by sieve reduced-rank regression. Factor scaled to have a coefficient of 1 in the predictive regression for one-month-ahead excess return on the advanced economy high yield bond portfolio.

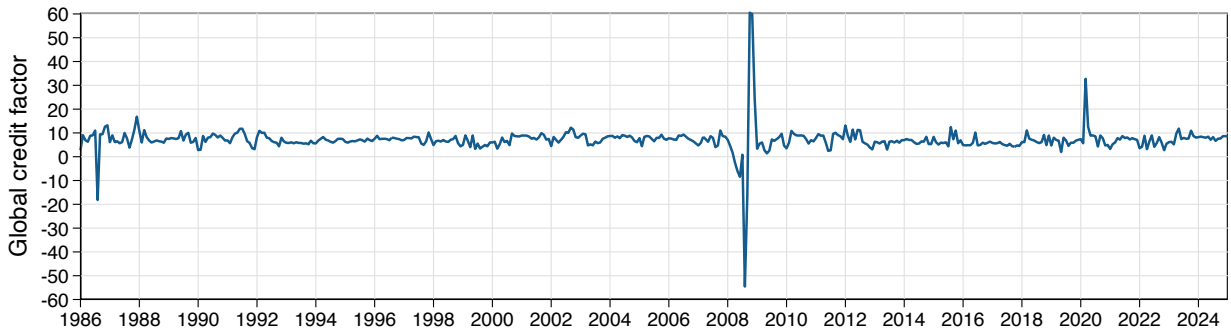
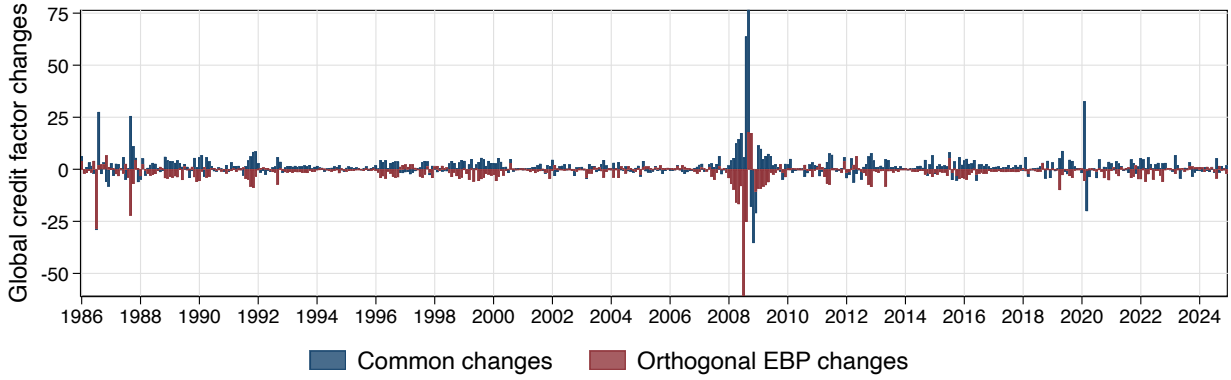


Figure 4. Decomposing monthly changes in the global credit factor. This figure plots the attribution of monthly changes in the global credit factor due to changes in the VIX and changes in U. S. credit spreads predictable by the VIX ("common changes") and changes in U. S. credit spreads orthogonal to VIX changes ("orthogonal EBP changes"). Figure 4b plots the 12 month rolling window estimate of the percent variance of monthly changes in the global credit factor explained by common changes in the VIX and U. S. credit spreads, with the average percent variance explained denoted by the solid black line.

(a) Attribution of monthly changes to common and orthogonal EBP changes



(b) 12 month rolling window percent variance explained by common changes

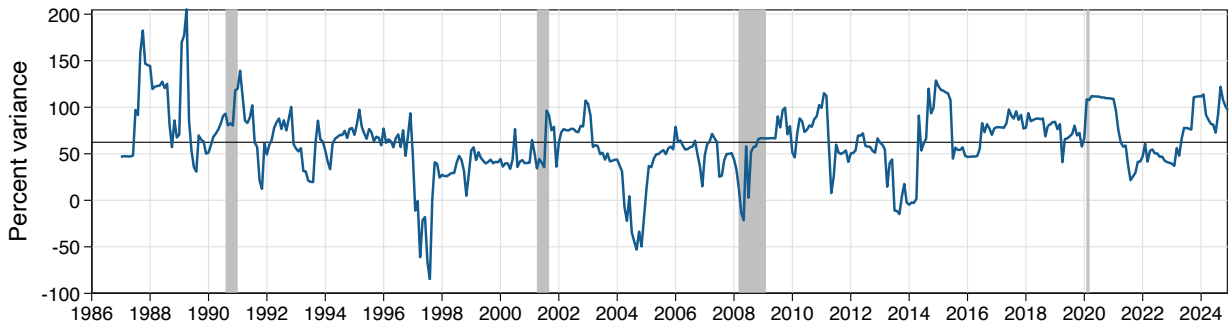
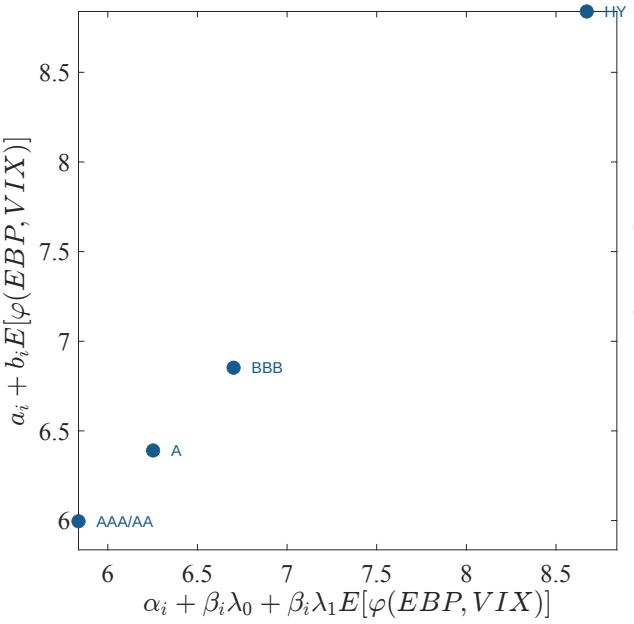


Figure 5. Cross-sectional asset pricing. This figure plots average one-month-ahead excess returns against the restricted joint forecasting regressions $Rx_{i,t+1} = (\alpha_i + \beta_i\lambda_0)+\beta_i\lambda_1\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right)+\beta_i u_{t+1}+\epsilon_{i,t+1}$ obtained from a dynamic asset pricing model with affine prices of risk. The innovations are given by $u_t = \varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right) - E_{t-1}\left[\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right)\right]$, where $\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right)$ is the nonlinear global credit factor created to predict advanced economy corporate bond portfolios in the full January 1986 – December 2024 sample. Figure 5a compares the estimates from the unrestricted sieve reduced-rank regression for the targeted (advanced economy) corporate bond portfolios, yielding parametric estimates of a_i and b_i and a nonparametric estimate of $\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right)$. In Figure 5b, one month excess returns over i correspond to 4 U. S. corporate bond portfolios, 4 advanced economy excluding the U. S. portfolios, and 3 emerging market portfolios, all constructed based on bond credit rating. The restricted joint forecasting regression is estimated following the three stage procedure in Adrian et al. (2015), taking the global credit factor as given. Sample consists of monthly observations from January 1986 (January 1998 for 5b) to December 2024.

(a) Baseline advanced economy portfolios



(b) Cross-country portfolios

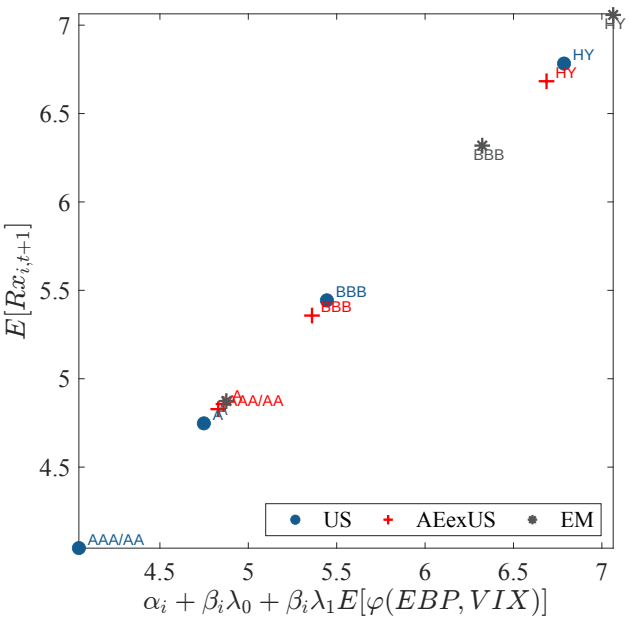
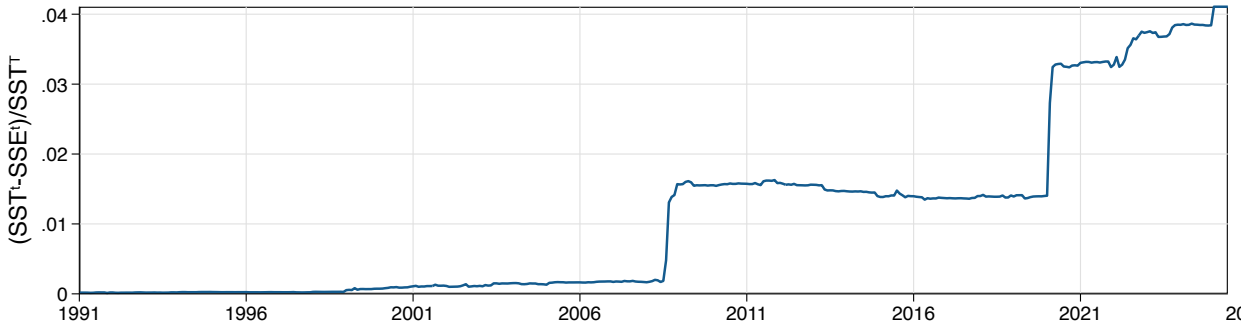
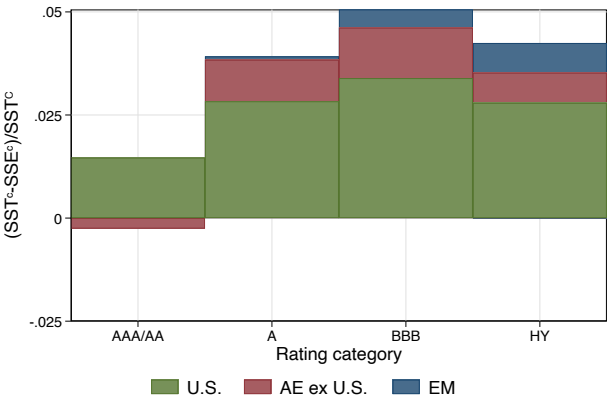


Figure 6. Contributions to the predictive R^2 of bond-level predictability regressions. This figure investigates which data points contribute to the overall fit of the bond-level predictive regression of 1 month excess holding period returns on the global credit factor. Panel 6a plots the cumulative contribution over time (across all countries and rating buckets), measured as $\left(SST^t - SSE^t\right)/SST^T$. SST^t is the mean-squared error of the regression of returns on rating fixed effects only, estimated through date t. SSE^t is the mean-squared error of the regression of returns on the global credit factor, estimated through date t. Panel 6b plots the cumulative contributions of different countries by rating categories (across all time periods), measured as $\left(SST^c - SSE^c\right)/SST^C$. For the time series plot, our first estimation uses data through January 1991, and we add one month of data at a time. All regressions include country fixed effects; the regressions on the global credit factor further include interactions between rating category and AR(1) innovations to the global credit factor.

(a) Contributions over time



(b) Contribution of different countries



(c) Contribution of different economic states

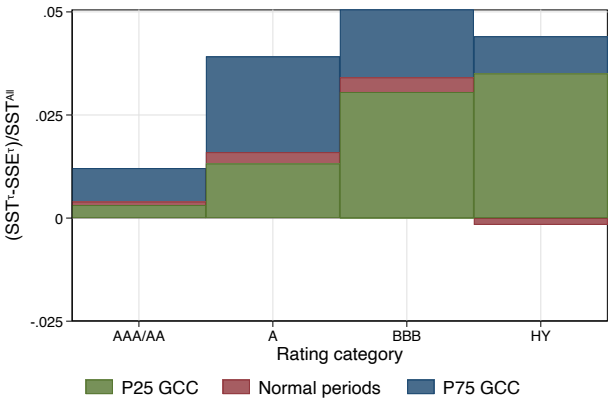
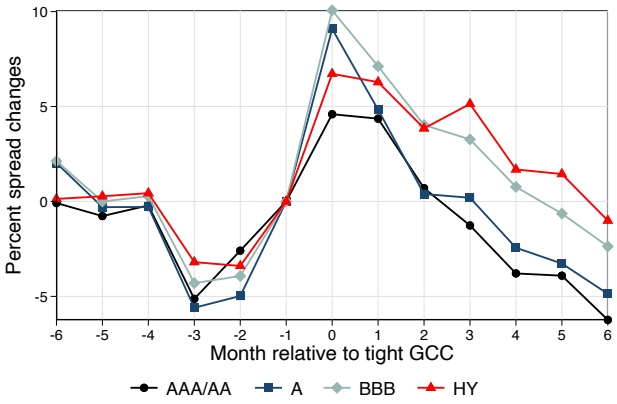
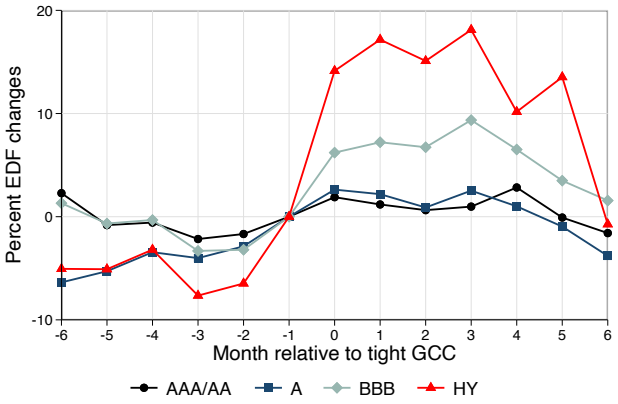


Figure 7. Effect of extreme tightenings. This table reports the estimated coefficients from the regression of percent spread and EDF changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions. Tight global credit conditions measured as a global credit factor realization in the top 25th percentile. All regressions include country and rating fixed effects.

(a) Bond-level spread changes



(b) Firm-level EDF changes



A Additional results

A.1 Alternative factor constructions

Figure A.1a plots the time series of the global credit factor together with $\varphi(\text{EBP})$ and $\varphi(\text{VIX})$. The figure shows that periods of tightness in the global credit factor are somewhat different to periods of tightness in each of $\varphi(\text{EBP})$ and $\varphi(\text{VIX})$. For example, the tightening of $\varphi(\text{EBP})$ during the global financial crisis occurs later than the tightening of either $\varphi(\text{EBP}, \text{VIX})$ or $\varphi(\text{VIX})$. Likewise, $\varphi(\text{EBP})$ tightens later than $\varphi(\text{EBP}, \text{VIX})$ does in the aftermath of Third Avenue Fund liquidation in December 2015 (and $\varphi(\text{VIX})$ does not tighten at all). $\varphi(\text{VIX})$ tightens in October 1987 but quickly reverts to more normal levels, while $\varphi(\text{EBP}, \text{VIX})$ peaks in November 1987 and remains elevated until February 1988. Overall, these episodes suggest that while a simultaneous tightening of both $\varphi(\text{EBP})$ and $\varphi(\text{VIX})$ does correspond to a tightening in the global credit factor, the global credit factor can also increase when only one of the two risk metrics remains elevated.

While our construction of the global credit factor focuses on the predictability of corporate bond portfolio returns in advanced economies, we can also consider targeting alternative portfolios. Figure A.1b plots the global credit factor together with the implied global price of risk constructed to target U. S. portfolios only, portfolios for the rest (excluding the U. S.) of the advanced economies, and emerging market portfolios.[17] The figure shows that factors constructed to target different set of corporate bond portfolios are noticeably correlated with each other, consistent with a truly global pricing of risks in corporate bond markets. In the estimation sample (1998 – 2024), the factors constructed to target either U. S. corporate bond returns or emerging market corporate bond returns have more than 85% correlation with the global credit factor (and an 82% correlation with each other). The correlation of the factor targeting the rest of the advanced economies with the global credit factor is lower – 75% in the estimation sample – and drops to 55% in the extended 1986 – 2024 sample. Inspecting the time series in Figure A.1b we see that the advance economy excluding U. S. factor reacts particularly strongly to the Asian debt crisis in 1997, while the emerging market factor reacts strongly to the 1987 stock market crash, suggesting that the emerging market factor is particularly sensitive to movements in the VIX.

A.2 Comparison to other measures of global financial conditions

An obvious question is to what extent our estimated measure of the global credit factor is related to other proxies of global financial conditions. To address this question, in Figure A.2 we plot 8 commonly used broad measures of global financial conditions together

[17] Since our global corporate bond data start in January 1998, we restrict the estimation of the U. S., the advanced economy excluding U. S., and emerging market factors to the data starting in January 1998. We then use the estimated coefficients γ to extend the history of the estimated factors to January 1986. We do not conduct that same cross-validation exercise as for the main specification to choose the optimal basis and instead use the same spline basis as in the main specification.

with our estimated global credit factor. In particular, we plot the VIX/VXO, the Gilchrist and Zakrajšek (2012) "G-Z" spread and excess bond premium (EBP), the 12-month change in the broad dollar index, the original Miranda-Agrippino and Rey (2015) and the updated Miranda-Agrippino et al. (2020) global factor, and U. S. and global Goldman-Sachs financial conditions indices (GS FCI). Figure A.2 shows that while EBP is relatively strongly correlated with our global credit factor – justifying our interpretation of the nonlinear factor we extract – the global credit factor is distinct from the factors previously proposed in the literature. In Table A.2 we report the full sample correlations, as well as correlations in the pre-crisis period (January 1986 – July 2007) and the post-crisis, pre-pandemic period (January 2010 – December 2019). Table A.2 shows that, for a number of variables, the pre– and post-crisis correlations with the global credit factor are substantively different. For example, the correlation with the EBP rises from 6% in the pre-crisis period to 23% post-crisis. Overall, the results in Figure A.2 and Table A.2 suggest that our estimated global credit factor contain differential information relative to commonly used measures of global financial conditions.

We end this section with a discussion of how our factor construction is different from that in Miranda-Agrippino and Rey (2015).[18] First, we focus on extracting factors that predict risky asset returns while the factor construction in Miranda-Agrippino and Rey (2015) targets explaining contemporaneous comovement in financial variables. Second, we specify our factors to be nonlinear combinations of observable proxies for risk (VIX and U. S. credit spreads) while Miranda-Agrippino and Rey (2015) extract a latent linear factor. Finally, the composition of the risky assets we consider is somewhat different. We focus on measuring the global price of risk in credit markets specifically, while the composition of the sample in Miranda-Agrippino and Rey (2015) tilts towards equity market variables.

B Additional data details

In this appendix, we provide additional details on the corporate bond data used in our paper, as well as describe the procedure for computing duration-matched and default-adjusted spreads in the context of bonds issued in different currencies.

Figure A.3 plots the time series of amount-outstanding-weighted nonfinancial corporate bond yields for the 10 largest (by number of nonfinancial corporate bond issues) advanced economy and emerging market economy countries. For each country $\mathcal{K}$ and each month t, we compute the country-level nonfinancial corporate bond yield as the amount-outstanding-weighted average of bond yields for all bonds associated with ultimate parent companies domiciled in that country

$$y_{\mathcal{K},t} = \sum_{b(f),f\in\mathcal{K}} \omega_{b(f),t} y_{b(f),t},$$

[18] Miranda-Agrippino et al. (2020) use the same dynamic factor model but with an expanded set of assets, and a longer time period.

where $\omega_{b(f),t}$ is the fraction of aggregate amount outstanding (in USD equivalents) in country $\mathcal{K}$ in month t represented by bond $b\,(f)$.

Figure A.3 shows that, prior to the post-COVID-19 pandemic monetary policy tightening, corporate bond yields for advanced economy countries have on average been declining in our sample period, outside of periods of stress such as the global financial crisis and the market dislocations associated with the COVID-19 pandemic. The figure also shows a large degree of commonality in the evolution of corporate bond yields in advanced economies. The convergence in advanced economy corporate bond yields to a common credit cycle comes against the backdrop of a shortening effective duration of corporate bonds in the same countries (Figure A.4). Corporate bond yields in emerging market economies instead show more individual cycles for a large part of the sample and a more stable distribution of effective duration.

We follow Boyarchenko and Elias (2023) in merging the secondary market corporate bond quotes with bond characteristics from consolidated SDC Platinum – Mergent FISD, ultimate parent balance sheet information, and expected default frequency (EDF) data from Moody's KMV CreditEdge. For both balance sheet information and EDFs, we use data that most closely precedes the date of the observed secondary bond market quote. This ensures that the firm characteristics and EDF data are observable to market participants as of the pricing date. Thus, we use annual balance sheet data for the fiscal period ending at least three months prior to the pricing date and EDF data as of the last day of the month prior to the pricing date.

To put bonds issued by firms with ultimate parents in the same country on an equal footing, we adjust the observed credit spreads for differences in bond duration and currency. More specifically, given a market price yield on security b of firm f on date t issued in currency c with duration $d^c_{b(f),t}$, we first compute the duration-matched credit spread as

$$s^c_{b(f),t} = y^c_{b(f),t} - z^c_{b,d},$$

where $z^c_{b,d}$ is the yield on the duration-matched sovereign bond in the corresponding currency. The duration-matched credit spreads make bonds issued with different coupon payment schedules and maturity but the same currency comparable across issuers.

We then follow Liao (2020) to convert duration-matched credit spreads across different currencies to the implied USD-based credit spread. Using bonds of firms that issue in multiple currencies, we estimate repeated cross-sectional regressions of the duration-matched credit spreads on currency, firm and rating fixed effects

$$s^c_{b(f),t} = \alpha_{c,t} + \alpha_{f,t} + \alpha_{rating,t} + \epsilon_{b(f),t}.$$

The currency-adjusted duration-matched credit spread is then given as the difference between the currency-specific duration-matched credit spread and the average credit spread differential to USD-denominated corporate bonds

$$s^{\$}_{b(f),t} = s^c_{b(f),t} - \left(\alpha_{c,t} - \alpha_{\$,t}\right).$$

Figure A.5 plots the time series of the average credit spread differential to USD-denominated corporate bonds for the currencies present in our sample. Similar to the results in Liao (2020), Figure A.5 shows that currency credit spread differentials were small in the pre-crisis period, increased significantly during the global financial crisis, and, though narrowed somewhat from their crisis-period highs, have remained elevated in the post-crisis sample.

Adjusting the weighted average yields we saw in Figure A.3 for duration and currency differentials reveals the global nature of the credit cycle, especially for advanced economies. The weighted-average nonfinancial currency-adjusted duration-matched credit spreads plotted in Figure A.6 comove together to a large extent, with the local credit cycle being an amplification of the global pattern.

Finally, as in Gilchrist and Zakrajšek (2012), we estimate the component of log-duration-matched spreads that can be explained by bond and firm characteristics and firm expected default frequencies

$$\log s^{\$}_{b(f),t} = \alpha_I + \alpha_{CR} + \gamma \log \text{EDF}_{f,t-1} + \vec{\beta}'_{\text{bond}} X_{bond,t} + \vec{\beta}'_{\text{firm}} X_{firm,t-1} + \epsilon_{b(f),t}, \qquad \text{(A.1)}$$

where the vector of contemporaneous bond characteristics $X_{bond,t}$ includes (log) amount outstanding in USD equivalents, (log) duration, (log) coupon rate, (log) age, and a dummy for bond callability. The regression also controls for industry and rating fixed effects and a number of lagged firm characteristics at the ultimate parent level $X_{firm,t-1}$: (log) firm size (in USD), profitability, leverage, asset tangibility, and the ultimate-parent-level one year EDFs. The default-adjusted credit spread is then the difference between the realized duration-matched spread for each bond observation and the duration-matched spread predicted from the above regression.

Table A.4 reports the estimated coefficients from regression (A.1) for the 10 largest advanced economy and emerging market economy countries. The coefficient on (log) one year EDFs is remarkably stable across countries, suggesting that global credit spreads price default risk in a systematic fashion across countries. In the time series, Figure A.7 shows that adjusting for predictable variation in credit spreads due to bond and firm fundamentals brings the country-level credit cycles even more in-line with each other, even for emerging market economies. In the rest of the paper, we explore the global credit cycle and its implications for real activity.

Table A.1: Out-of-sample MSE for best-performing factor construction alternatives. This table compares the out-of-sample forecast errors of sieve reduced-rank (SRR) regressions for different basis function construction approaches, together with the factor and knot specification chosen in the specification with the minimum RMSE for each basis function type. We split our full monthly sample from January 1986 to December 2024 into an in-sample period $t = 1, \ldots, (t* - 1)$ and an out-of-sample period $t = t*, \ldots, T$. For each considered way of constructing basis functions and rank-reduction, we then evaluate the SRR regression model and the running mean forecast $\mathbb{E}_{t*}[Rx_{i,t^*+1}]$ and compare it against the realized return $Rx_{i,t*+1}$, for i indexing the four advanced economy corporate bond portfolios, grouped into AAA/AA, A, BBB, and high yield (rated below BBB-) bonds. We start our out-of-sample evaluation in January 2009 (predicting returns in February 2009). For each basis function construction approach, we allow up to 6 interior knots, spaced evenly along the quantiles of the corresponding variable, and reduced rank up to 3, but require that the MSE improvement from each additional factor is at least 5%. "No interactions", "EBP only" and "VIX only" use order 4 B-splines; the remaining specifications use a basis constructed as the tensor product of univariate B-splines with orders as specified in the column names.

	Order 2 EBP, Order 3 VIX	Order 3 EBP, Order 2 VIX	Order 3 EBP, Order 3 VIX	Order 4 EBP, Order 4 VIX	No interactions	EBP only	VIX only
Out-of-sample MSE	505.18	493.40	506.51	518.90	508.36	510.56	506.35
Number of factors	1	1	1	1	1	1	1
Number of EBP knots	0	4	6	1	0	1	–
Number of VIX knots	6	3	2	1	6	–	0

Table A.2: Factor correlations. This table reports correlations between the global credit factor and other proxies for risk and global financial conditions. Column 1 reports results for the full sample, Column 2for the pre-July 2007 sample, Column 3 for the January 2010 – December 2019 sample. "TWI" is the 12-month change in the broad dollar index. "GFC (updated)" is the updated Miranda-Agrippino et al. (2020) global factor. "U. S." and "Global" GS FCI U. S. and global Goldman-Sachs financial conditions indices, respectively.

	(1) Full sample	(2) Pre-crisis	(3) Post-crisis
VIX	0.34***	0.20***	0.40***
G-Z spread	0.17***	0.11*	0.31***
φ (VIX)	0.64***	-0.03	0.15*
φ (EBP)	-0.63***	0.16**	0.22**
EBP	0.22***	0.06	0.23**
Predicted G-Z spread	-0.00	0.10	0.29***
USD TWI	0.13***	-0.03	0.06
GFC (updated)	-0.17***	-0.07	-0.05
U. S. GS FCI	0.20***	0.33***	0.21**
Global GS FCI	0.25***		0.20**

Table A.3: Sources of risk in bond returns across different subperiods. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global credit factor, decomposing excess returns into the contribution of duration risk from the perspective of a U. S. investor, the differential duration risk due to foreign (non-USD) currency sovereign curves, and credit risk, across different subperiods. All regressions include country fixed effects, and interactions between rating category and AR(1) innovations to the global credit factor. High yield bonds are the omitted category. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Credit risk

	(1) Full sample	(2) 1986 – 1997	(3) Jan 1998 – Jul 2007	(4) GFC	(5) Jan 2010 – Dec 2019	(6) 2020	(7) Jan 2021 –
Global credit	0.84	0.93	1.08	0.54	0.77	1.27	1.38
	(0.01)***	(0.04)***	(0.03)***	(0.03)***	(0.02)***	(0.03)***	(0.02)***
AAA/AA × Global credit	-0.60	-0.57	-0.78	-0.45	-0.61	-0.73	-0.64
	(0.01)***	(0.04)***	(0.02)***	(0.03)***	(0.01)***	(0.03)***	(0.01)***
A × Global credit	-0.42	-0.54	-0.73	-0.12	-0.53	-0.60	-0.57
	(0.01)***	(0.04)***	(0.02)***	(0.03)***	(0.01)***	(0.03)***	(0.01)***
BBB × Global credit	-0.36	-0.46	-0.64	-0.18	-0.44	-0.42	-0.47
	(0.01)***	(0.04)***	(0.02)***	(0.03)***	(0.01)***	(0.03)***	(0.01)***
Adj. R-sqr.	0.009	0.015	0.005	0.015	0.004	0.023	0.010
N. of obs	2,894,455	130,933	523,903	163,859	1,190,918	155,947	728,889

(b) Currency curve differential

	(1) Full sample	(2) Jan 1998 – Jul 2007	(3) GFC	(4) Jan 2010 – Dec 2019	(5) 2020	(6) Jan 2021 –
Global credit	-0.02	-0.04	-0.01	0.00	-0.01	0.38
	(0.00)***	(0.00)***	(0.00)***	(0.00)	(0.00)***	(0.01)***
AAA/AA × Global credit	-0.07	-0.01	-0.20	-0.02	-0.01	0.03
	(0.00)***	(0.00)***	(0.01)***	(0.00)***	(0.00)	(0.00)***
A × Global credit	-0.01	-0.01	-0.06	-0.01	-0.01	0.01
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
BBB × Global credit	-0.01	-0.00	-0.03	-0.01	-0.01	0.02
	(0.00)***	(0.00)	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Adj. R-sqr.	0.001	0.000	0.026	-0.000	-0.000	0.008
N. of obs	2,894,464	523,910	163,859	1,190,918	155,947	728,889

(c) Duration risk

	(1) Full sample	(2) 1986 – 1997	(3) Jan 1998 – Jul 2007	(4) GFC	(5) Jan 2010 – Dec 2019	(6) 2020	(7) Jan 2021 –
Global credit	0.29	0.69	0.79	0.21	0.45	0.23	1.60
	(0.00)***	(0.03)***	(0.02)***	(0.01)***	(0.01)***	(0.00)***	(0.02)***
AAA/AA × Global credit	0.19	0.16	0.24	0.18	0.11	0.03	-0.03
	(0.01)***	(0.03)***	(0.02)***	(0.02)***	(0.01)***	(0.01)***	(0.02)
A × Global credit	0.11	0.16	0.19	0.15	0.10	0.03	-0.03
	(0.00)***	(0.03)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
BBB × Global credit	0.05	0.08	0.14	0.12	0.10	0.02	-0.04
	(0.00)***	(0.03)***	(0.01)***	(0.01)***	(0.01)***	(0.00)***	(0.01)***
Adj. R-sqr.	0.010	0.045	0.008	0.061	0.006	0.017	0.020
N. of obs	2,894,464	130,935	523,910	163,859	1,190,918	155,947	728,889

Table A.4: Estimated relationship between secondary market duration-matched, currency adjusted spreads and characteristics. This table reports the estimated coefficients from the regression of secondary log duration-matched, currency-adjusted spreads on firm-level 1 year expected default frequency (EDF) and bond characteristics. All regressions include 2 digit SIC industry and rating fixed effects. Standard errors clustered at the issuer-quarter level reported in parentheses below the point estimates.*** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Advanced economies

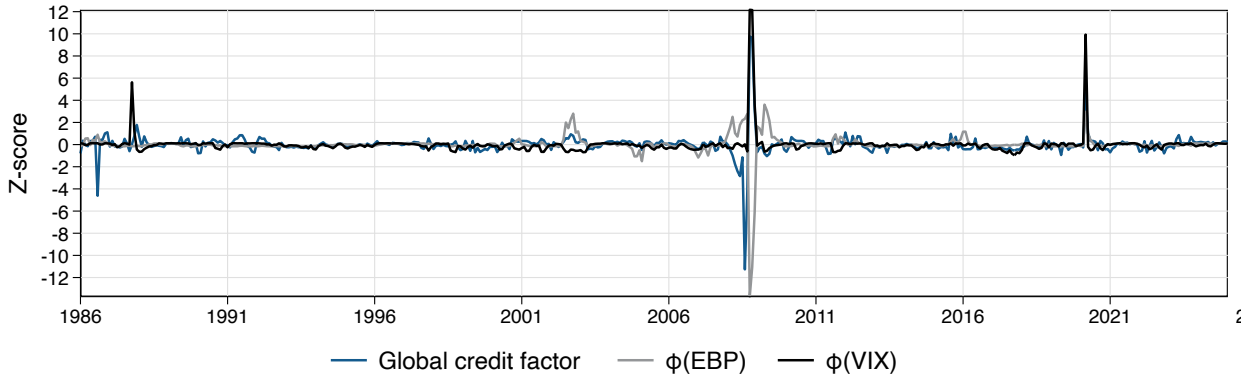
	US	KR	JP	CA	GB	NL	FR	TW	AU	DE	CH	IE	IT	ES
Log EDF	0.13	0.13	0.16	0.13	0.13	0.09	0.16	0.11	0.20	0.13	0.18	0.16	0.11	0.16
	(0.00)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.03)***	(0.02)***	(0.01)***	(0.02)***
Sub in home country	0.04	0.25	0.09	0.02	0.05	-0.05	0.18	0.40	0.06	0.04	-0.04	-0.20	0.08	0.04
	(0.01)***	(0.03)***	(0.03)***	(0.01)	(0.02)***	(0.04)	(0.03)***	(0.08)***	(0.08)	(0.02)*	(0.04)	(0.06)***	(0.03)**	(0.05)
Sub in foreign country	-0.07	-0.13	-0.15	0.06	0.01	-0.05	0.20	0.00	-0.04	0.12	-0.03	-0.27	0.13	0.07
	(0.02)***	(0.05)***	(0.03)***	(0.02)**	(0.02)	(0.04)	(0.04)***	(.)	(0.08)	(0.02)***	(0.05)	(0.04)***	(0.03)***	(0.04)
Log duration	0.35	0.15	0.17	0.35	0.33	0.30	0.30	0.17	0.27	0.28	0.36	0.22	0.35	0.29
	(0.00)***	(0.03)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.03)***	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***
Log coupon	0.35	0.09	0.08	0.39	0.22	0.21	0.17	0.03	0.25	0.18	0.10	0.18	0.20	0.36
	(0.01)***	(0.02)***	(0.01)***	(0.02)***	(0.01)***	(0.02)***	(0.01)***	(0.04)	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.02)***
Log age	0.02	0.05	-0.02	0.00	-0.01	-0.01	-0.03	-0.02	-0.03	-0.03	-0.00	-0.03	-0.01	-0.06
	(0.00)***	(0.01)***	(0.00)***	(0.00)	(0.00)***	(0.01)	(0.01)***	(0.02)	(0.01)***	(0.00)***	(0.01)	(0.01)***	(0.01)	(0.01)***
Callable	0.12	1.22	-0.05	0.03	-0.04	0.03	-0.12	-0.13	-0.03	-0.06	-0.08	-0.08	0.09	-0.01
	(0.01)***	(0.19)***	(0.02)**	(0.01)*	(0.01)***	(0.02)	(0.01)***	(0.11)	(0.03)	(0.02)***	(0.03)***	(0.03)***	(0.02)***	(0.02)
Log amt out (USD)	0.04	-0.10	-0.01	-0.03	-0.00	0.01	0.00	0.08	-0.02	0.07	0.01	0.06	0.04	0.03
	(0.00)***	(0.03)***	(0.01)	(0.01)***	(0.01)	(0.01)	(0.01)	(0.03)***	(0.02)	(0.01)***	(0.01)	(0.03)**	(0.02)**	(0.02)*
W/in adj. R-sqr.	0.35	0.14	0.19	0.37	0.32	0.29	0.32	0.39	0.36	0.34	0.30	0.27	0.36	0.41
N. of obs	696552	5645	46261	77452	87283	12415	27904	1218	7591	40600	20749	5973	20535	15102
N. of clusters	41245	486	2256	4199	4681	909	1955	113	840	2008	1015	559	1027	770

(b) Emerging market economies

	CN	MY	TH	IN	ID	MX	BR	RU	CL	AR
Log EDF	0.07	-0.04	0.13	0.14	0.17	0.09	0.12	-0.04	0.03	0.24
	(0.02)***	(0.02)*	(0.02)***	(0.01)***	(0.03)***	(0.01)***	(0.01)***	(0.58)	(0.01)**	(0.02)***
Sub in home country	0.06	-0.02	-0.32	0.09	-0.49	-0.06	-0.07		0.19	0.04
	(0.15)	(0.10)	(0.04)***	(0.04)**	(0.14)***	(0.03)**	(0.03)***		(0.16)	(0.06)
Sub in foreign country	-0.30	-0.45		-0.02	-0.37	-0.04	-0.31	0.00	0.19	-0.02
	(0.07)***	(0.16)***		(0.05)	(0.23)	(0.03)	(0.04)***	(.)	(0.06)***	(0.09)
Log duration	0.18	0.20	0.22	0.33	-0.02	0.30	0.28	0.63	0.25	-0.02
	(0.02)***	(0.04)***	(0.02)***	(0.02)***	(0.09)	(0.02)***	(0.02)***	(0.68)	(0.02)***	(0.03)
Log coupon	0.20	0.06	0.08	0.31	0.81	0.60	0.47	-4.51	0.44	0.57
	(0.04)***	(0.07)	(0.05)	(0.06)***	(0.13)***	(0.03)***	(0.04)***	(4.75)	(0.06)***	(0.14)***
Log age	-0.07	-0.01	-0.00	0.00	-0.05	-0.04	-0.01	-1.75	-0.06	0.01
	(0.01)***	(0.02)	(0.01)	(0.01)	(0.03)**	(0.01)***	(0.01)**	(0.39)**	(0.01)***	(0.02)
Callable	0.05	-0.00	-0.18	0.22	-0.06	0.14	-0.10	0.00	0.05	-0.06
	(0.04)	(0.05)	(0.03)***	(0.06)***	(0.25)	(0.02)***	(0.02)***	(.)	(0.06)	(0.04)
Log amt out (USD)	0.02	-0.24	0.06	-0.06	0.21	0.03	0.02	-0.62	-0.18	-0.09
	(0.03)	(0.05)***	(0.04)	(0.02)***	(0.10)**	(0.02)*	(0.01)*	(0.49)	(0.04)***	(0.04)**
W/in adj. R-sqr.	0.16	0.12	0.44	0.40	0.28	0.40	0.33	0.85	0.26	0.32
N. of obs	4129	1958	2084	4178	855	7984	11976	14	3317	1304
N. of clusters	626	438	231	663	269	988	1123	3	497	186

Figure A.1. Comparing the global credit factor to alternative estimation procedures. This figure plots the comparison between the global credit factor and the factors extracted from credit spreads and VIX separately, and between the global credit factor constructed to price advanced economy bond return portfolios, and those constructed to price U. S. portfolios, advance economies excluding U. S. portfolios, and emerging market portfolios. To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations.

(a) Comparison to $\varphi\left(\text{EBP}\right)$ and $\varphi\left(\text{VIX}\right)$



(b) Comparison to $\varphi\left(\text{EBP}, \text{VIX}\right)$ constructed to target alternative portfolios

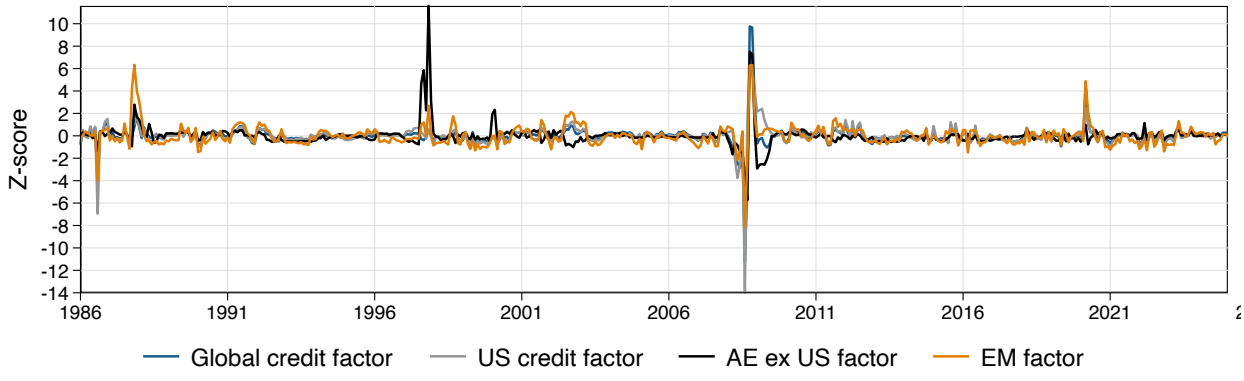
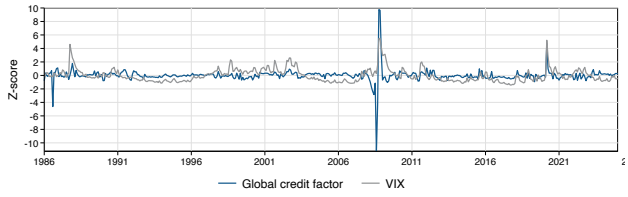
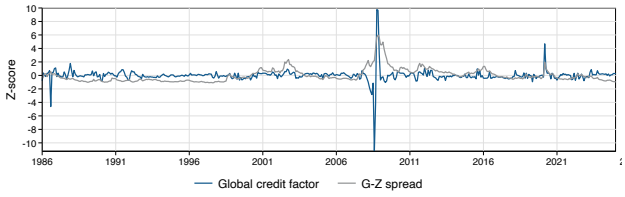


Figure A.2. Comparison to other variables. This figure plots the time series of the global credit factor estimated by reduced-rank regression against commonly used measures of financial conditions: VXO/VIX, Gilchrist and Zakrajšek (2012) "G-Z" spread and excess bond premium (EBP), the 12-month change in the broad dollar index, the original Miranda-Agrippino and Rey (2015) and the updated Miranda-Agrippino et al. (2020) global factor, and U. S. and global Goldman-Sachs financial conditions indices (GS FCI). To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations.

(a) VXO/VIX



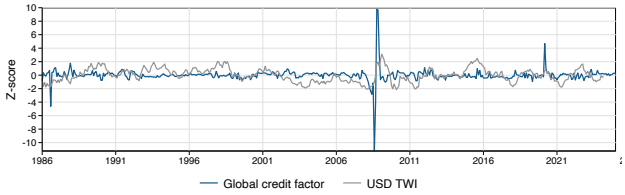
(b) GZ-spread



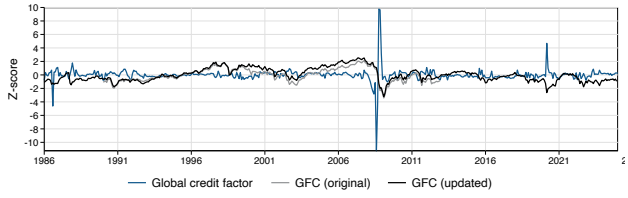
(c) EBP



(d) Broad dollar index



(e) GFC (original and updated)



(f) GS FCI and Global GS FCI

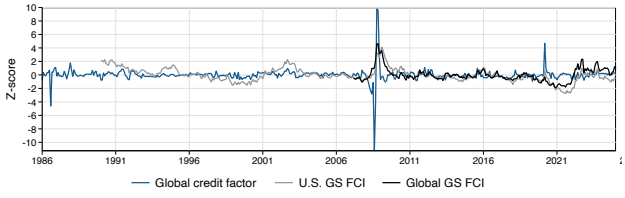
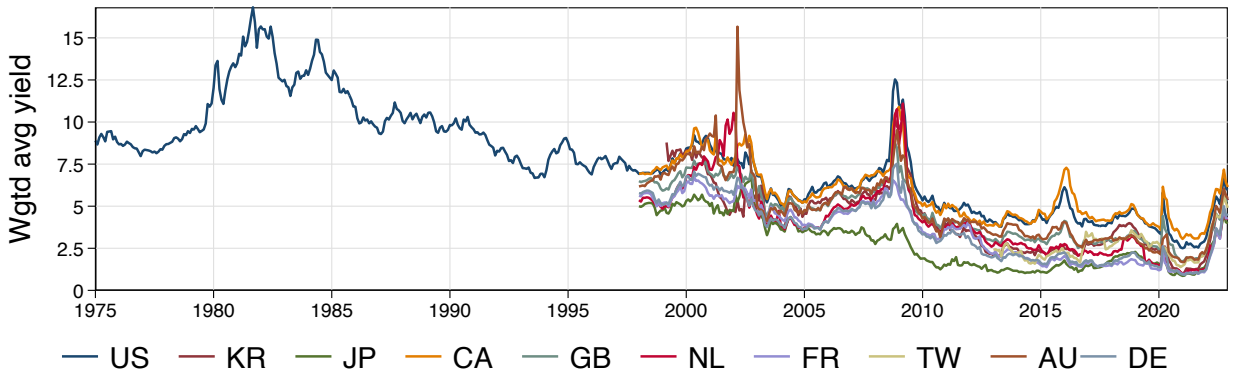


Figure A.3. Raw secondary market quote data. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) yields quoted in ICE for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

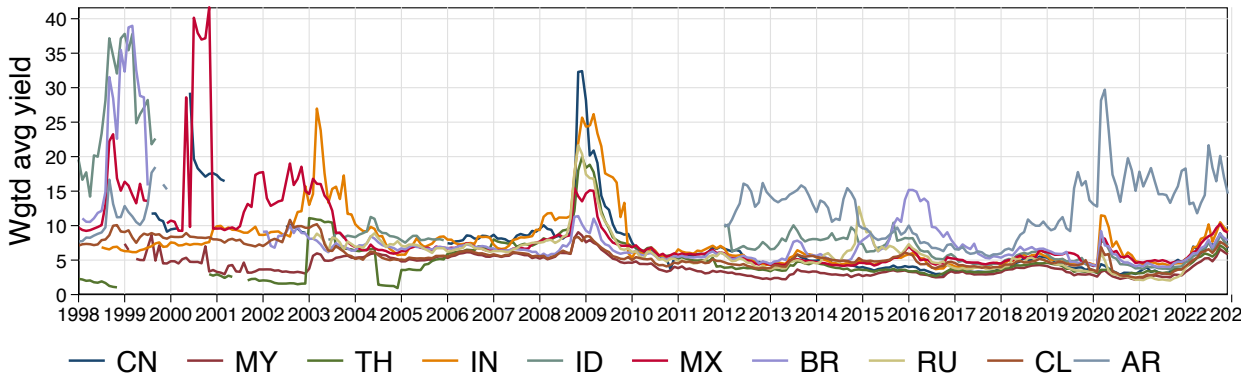
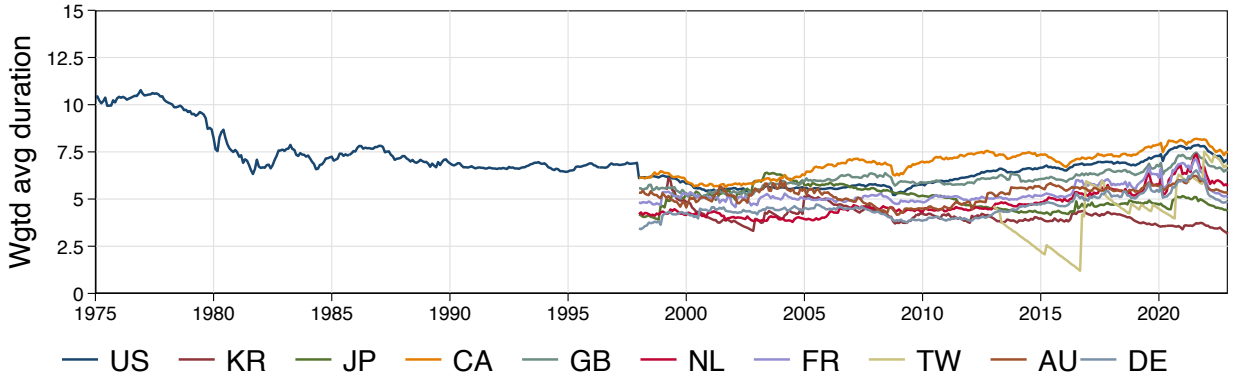


Figure A.4. Secondary market duration data. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) duration for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

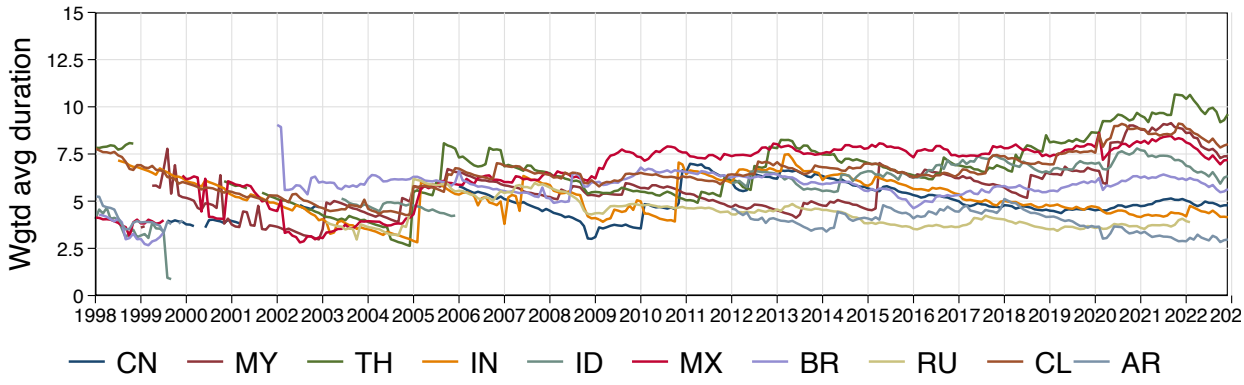


Figure A.5. Average differential to USD credit spreads. This figure plots the time series of the average credit spread between non-USD denominated bonds and USD denominated non-financial corporate, senior fixed-coupon bonds. Average credit spreads estimated from repeated cross-sectional regressions of duration-adjusted credit spreads for firms with bonds outstanding in multiple currencies on currency, firm, and rating fixed effects.

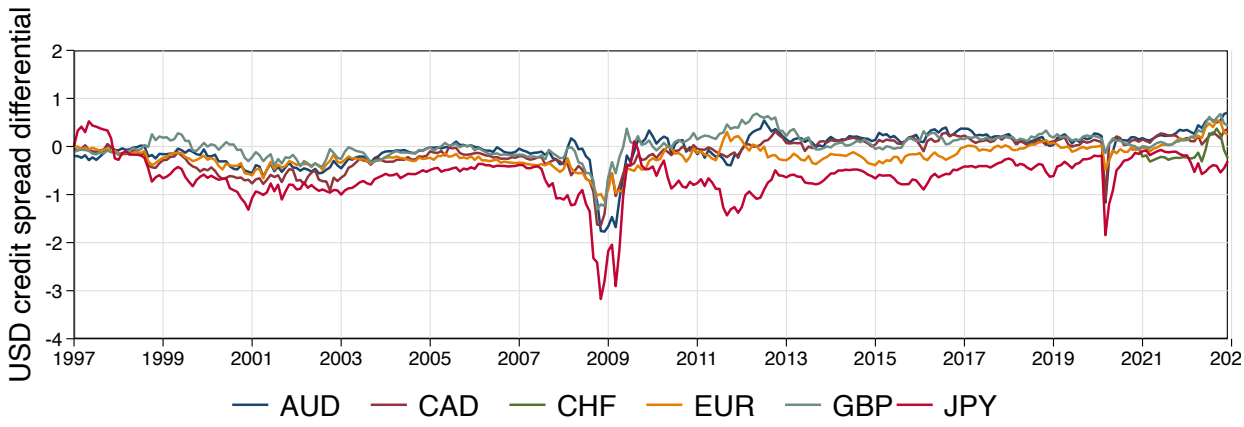
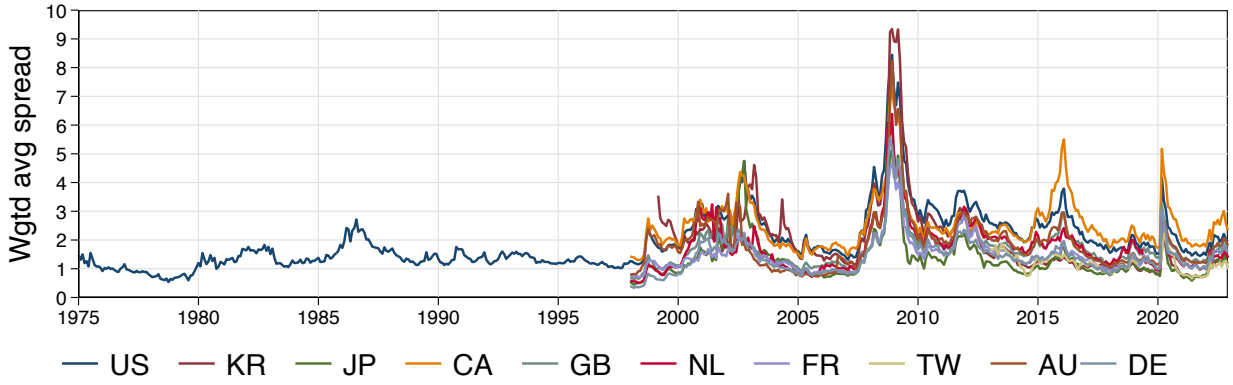


Figure A.6. Secondary market duration-matched, currency-adjusted spreads. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) duration-matched, currency-adjusted spreads for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

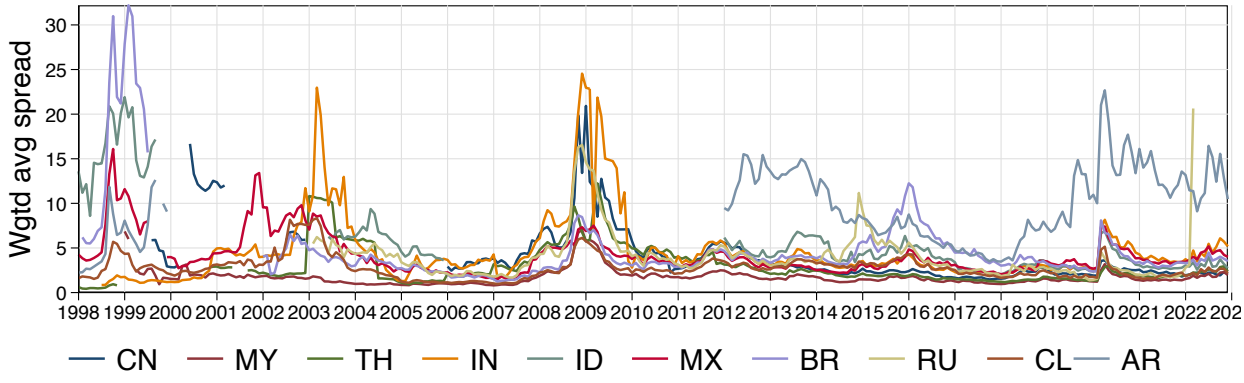
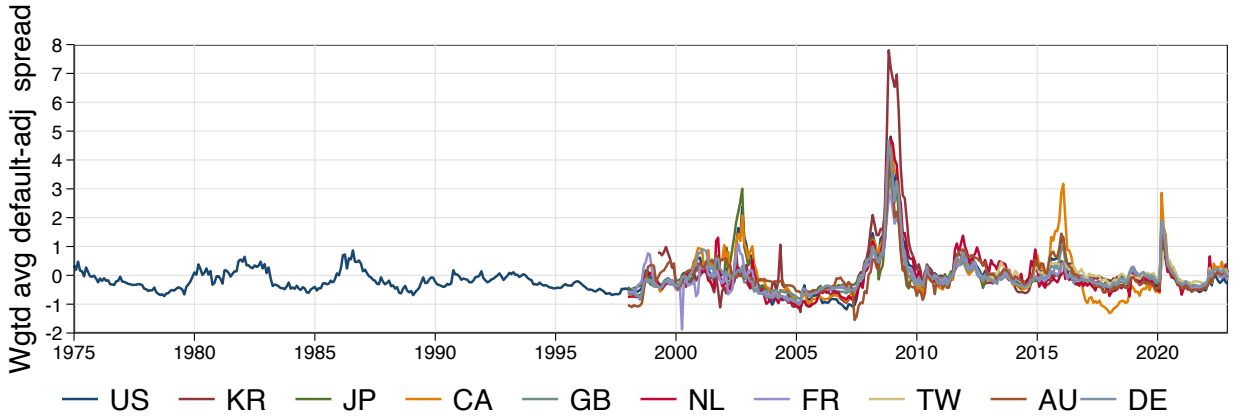


Figure A.7. Estimated default-adjusted spreads. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) default-adjusted credit spreads for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

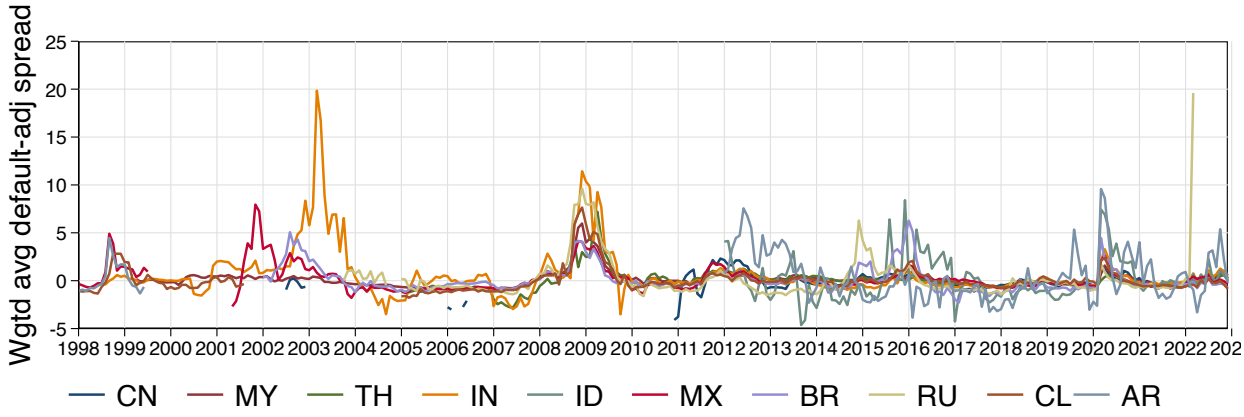
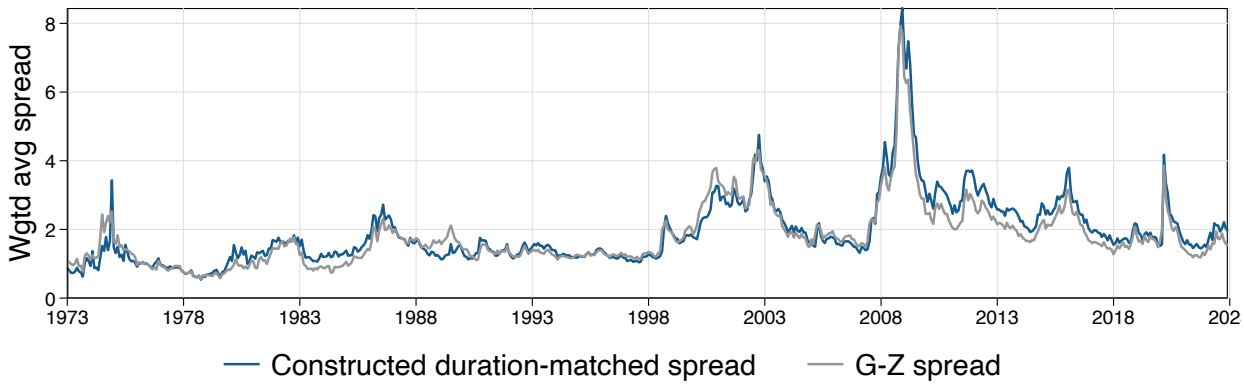


Figure A.8. Comparison to G-Z series. This figure plots the time-series of U. S. average duration-adjusted and default-adjusted credit spreads in our sample versus the Gilchrist and Zakrajšek (2012) spreads..

(a) Duration-matched spread



(b) Default-adjusted spread

