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 U.S. credit spreads and the VIX, and show that incorporating information from nonlinearities and from interactions between the two predictors 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. Large tightenings in the global price of risk correspond to deteriorations in local credit conditions, with persistent increases in both credit spreads and firm default probabilities. Finally, we explore transmission mechanisms and show that flows into bond mutual funds likewise load negatively on the global price of risk, with high yield mutual funds the most affected.

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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 amount 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. We use an out-of-sample criterion to select the optimal sieve reduced-rank specification among a large set of alternatives, including univariate specifications and specifications with more than one factor.

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 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 trade-weighted dollar exchange rate, and the Miranda-Agrippino and Rey (2015) global financial

[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).

cycle factor.

We argue that the global credit factor proxies the global price of credit risk. Using the full richness of our bond-level data, we document that 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. The predictive model that relates future realized returns to current global credit factor realizations and bond risk has a substantial over 9% overall R^2, both in- and out-of-sample.

Furthermore, while time-series variation in the global credit factor represents the largest component of the overall panel R^2 of our predictive regressions at the bond level, the contribution due to the cross-sectional R^2 is also meaningful. Thus, the global credit factor captures systematic risks in the global market for corporate bonds, and bonds in the cross-section have meaningful differential exposure to the systematic risks proxied for by the global credit factor. The contribution of time series variation in the global credit factor to the overall panel predictability is even larger for bonds issued by firms in emerging market economies, reinforcing the interpretation of the factor as a truly global price of credit risk.

What explains the success of the global credit factor as a proxy for the global price of credit risk? To answer this question, we inspect how three main features of the factor construction procedure contribute to bond return predictability. First, we show that, while both raw credit spreads and the VIX predict bond returns, the overall R^2 of such univariate, linear specifications is less than half of that from the global credit factor. Furthermore, while credit spreads perform particularly poorly in capturing the cross-section of exposures, the VIX underperforms in terms of explaining the overall time series variation, providing the first evidence that credit spreads and the VIX contain differential information about the evolution of corporate bond returns. Second, nonlinear functions of credit spreads and the

VIX, although still underperforming the global credit factor, improve relative to their linear counterparts, highlighting the important role that nonlinearities play in the pricing of global credit risk. Third, we show that including the nonlinear credit spread and VIX factors additively in the bond return predictability regression still does not match the performance of the global credit factor, suggesting the importance of including information from the interaction between credit spreads and the VIX.

Indeed, comparing the performance of the global credit factor to the two factor model and the nonlinear VIX model across tight and loose periods, we find that both alternatives perform substantially worse than the global credit factor in explaining returns when global credit conditions are loose. This highlights the key role that the EBP plays as a predictor in factor construction. Sudden and temporary increases in the VIX can occur during periods of loose credit conditions, so a factor that only uses information from the VIX will tighten during those episodes. Instead, when the factor is allowed to use information from both the EBP and the VIX in the factor construction –and, crucially, when the factor allows for interactions between the two– the factor can "look through" temporary volatility in the VIX that is ultimately not reflected in bond returns.

The global credit factor significantly outperforms commonly used measures of global financial conditions, including the VIX, the Miranda-Agrippino and Rey (2020) global financial cycle, the trade-weighted dollar exchange rate, and the Goldman Sachs U.S. financial conditions index. Moreover, none of the alternative proxies for global financial conditions have information that is simultaneously relevant for both the time-series and the cross-sectional variation in the panel of corporate bond returns. That is, the global credit factor is the only metric of global financial conditions that captures both the systematic variation in corporate bond returns and the cross-sectional differential exposure to that systematic risk.

We conclude our examination of the global credit factor as a proxy for the global price of credit risk by examining how its predictive power for corporate bonds returns has changed since the global financial crisis (GFC). While a recent literature has argued for a diminished role of global factors in local financial cycles, those studies have largely focused on changes to the importance of the VIX in explaining variation in capital flows and extreme capital flow episodes. We document that the ability of the VIX to predict "normal period" corporate bond returns has likewise declined since the crisis. The predictive ability of the global credit factor for corporate bond returns has also declined somewhat in the post-GFC period. However, unlike the VIX, this decline in predictability stems from reduced variation in the factor during normal times, rather than from reduced exposure of bond returns to the global credit factor in the post-GFC period.

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 five 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, beyond credit spreads, firms' default probabilities also 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. We leverage the global credit factor constructed in this paper to further explore the real (local) costs of tightening global credit conditions in a series of subsequent papers. In Boyarchenko and Elias (2024), we show that tight global credit conditions impair firms' ability to optimally manage their debt structure. Turning to the aggregate implications, in Boyarchenko and Elias (2026), we show that loose credit conditions predict downturns in real activity in the medium and long run.

Finally, we explore the connection between the global credit factor and global intermediaries.

We show that the returns and flows of global mutual funds and ETFs are likewise exposed to variation in the global credit factor. When the global credit factor tightens, customers flow out of global funds and expected returns increase. Moreover, we show that, even at the fund level, exposure to the global factor varies with the credit risk of a fund's investments with funds investing in high yield bonds displaying the highest exposure and funds investing in investment grade corporate bonds and in government bonds displaying less exposure.

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; Bali et al., 2021; He et al., 2022; Kelly et al., 2023; Bartram et al., 2025), 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 and country risk.

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

[3] See e.g. Bernanke and Gertler (1989), Vayanos (2004), Adrian and Boyarchenko (2012), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Gertler and Kiyotaki (2015), Gabaix and Maggiori (2015).

[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.

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 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 predictability. We provide initial evidence on the real effects of a tightening in global credit conditions in Section 5. Section 6 explores the role of global financial intermediaries in the transmission of global credit conditions. Section 7 concludes.

2 Data description

2.1 Corporate bond data

We rely on the comprehensive international debt market dataset 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. We focus here on secondary market quotes at the bond level, from a dataset that coalesces ICE Global Bond Indices with the Lehman-Warga Fixed Income Database.

The ICE Global Bond Indices dataset starts in January 1998 and ends in December 2024. 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.

We 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.[6] 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.

[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.

[6] See Warga (1991) for details.

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's balance sheet information, and expected default frequency (EDF) data from Moody's KMV CreditEdge. 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.[7] Moreover, we restrict the sample of bonds we use to be senior, unsecured, fixed-coupon bonds. We further exclude bonds with duration less than one quarter, bonds with spreads less than 50 basis points (bps) or more than 2000 bps, and bonds issued by emerging market firms that are rated higher than A+. Finally, we only keep bonds with spells of at least 12 months of consecutive non-missing return observations, and restrict our sample of countries to those that have at least 15 bonds after the previous filters.

Our final sample includes more than 2.3 million bond-month (more than 40,000 unique bonds) return observations, from January 1986 to December 2024, across 50 countries. 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.[8]

We take the perspective of a U.S. investor in computing the excess returns on bond i at date t. Thus, we convert the currency-specific return $r^c_{i,t}$ 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 return,

[7] 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.

[8] Appendix Table A.1 summarizes key properties of our sample by currency. Appendix Figure A.1 plots the time series of weighted-average 12-month ahead corporate bond excess returns for the largest countries in our sample.

$rx_{i,t}$, is computed as

$$rx_{i,t+1} = \left(1 + r^c_{i,t+1}\right) \frac{S^c_{t+1}}{S^c_t} - \left(1 + r^{tsy}_{3\text{m},t+1}\right),$$

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 $t+1$. While $rx_{i,t+1}$ measures the excess return that a U.S.-based investor would earn if they were to leave interest risk and exchange risk unhedged, our focus is on the credit risk component of the overall return. We thus expand the decomposition of returns into sources of risk proposed in recent literature (see e.g. Van Binsbergen et al., 2025) to our setting of a global market for corporate bonds. 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:

$$rx_{i,t+h} = \underbrace{\left(r^c_{i,t+h} - r^c_{DM_i,t+h}\right) \frac{S^c_{t+h}}{S^c_t}}_{\text{Credit risk}} + \underbrace{r^c_{DM_i,t+h} \frac{S^c_{t+h}}{S^c_t} - r^{tsy}_{DM_i,t+h}}_{\text{Currency curve differential}} + \underbrace{r^{tsy}_{DM_i,t+h} - r^{tsy}_{3m,t+h}}_{\text{Duration risk}}. \tag{1}$$

Here, $r^c_{DM_i,t+h}$ is the h-month holding period return on a sovereign bond for currency c with the same duration DM_i as the corporate bond and $r^{tsy}_{DM_i,t+h}$ is the h-month holding period return on the corresponding duration-matched U.S. Treasury. In computing returns, we match the exchange rate, sovereign curve, and risk-free rate observations to the exact date of the corporate bond price (and spread) observation. Finally, we compound monthly corporate bond excess returns to construct multi-period returns, and annualize.

2.2 Additional data

We construct our measure of the global credit cycle using the U.S. excess bond premium (EBP) and the VIX as predictors. We use the VXO instead of the VIX for the period 1986-1990 when the VIX is not available. We build the time series of EBP 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.[9]

Finally, we rely on Emerging Portfolio Fund Research (EPFR) for data on flows into global bond funds. This dataset contains information on mutual funds and ETFs domiciled in a wide range of countries. We use data on returns, client flows into (and out of) global funds, the credit quality of funds' investments, the funds' domicile, and on the geographical location of funds' investments. Our sample covers monthly observations for over 10,000 unique funds in the period 1996-2024.

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.

[9] Figure A.9 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.

3.1 Motivation

Our starting point is an unconditional CAPM of the form

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

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

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

where we have allowed for the asset (market) $\beta_{i,h}$ to be potentially holding horizon specific. Substituting into the above, we can thus represent the h-period ahead excess return as

$$rx_{i,t+h} = b_{i,h} \mathbb{E}_t \left[rx_{M,t+h} \right] + \epsilon_{i,t+h}, \tag{2}$$

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 (2) 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 one 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.[10] 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. While disentangling the precise mechanisms that link the endogenous evolution of aggregate risk aversion to the 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.

Which aggregate measures of risk best capture expected excess returns in corporate bond markets? We assume that the nonlinear relationship between expected excess market returns and aggregate measures of risk can be parametrized as a function of U.S. credit spreads and the VIX. In fixed income markets, Gilchrist and Zakrajšek (2012) and Gilchrist et al. (2022) argue that the EBP is a quantitative proxy of the risk attitude of financial intermediaries. 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. On the other hand, 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

[10] The intermediary-based asset pricing literature argues that financial intermediaries, not households, are the marginal investors in financial markets, so that equilibrium asset prices are determined by the pricing kernel of the marginal intermediary. The effective risk aversion of financial intermediaries is determined by balance sheet constraints —imposed by the regulatory environment, risk management considerations, or ultimate investor preferences— the tightness of which evolves over time. Examples of such models include Bernanke and Gertler (1989), Vayanos (2004), Adrian and Boyarchenko (2012), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), and Gertler and Kiyotaki (2015).

risky assets, measured either using the VIX or realized volatility. 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.

3.2 The global price of credit risk

We estimate nonparametrically the conditional expected excess market return as a function of credit spreads and volatility, $\varphi\left(cs_t, \mathrm{VIX}_t\right) \equiv \mathbb{E}_t\left[rx_{M,t+1}\right]$, under only weak assumptions. The econometric specification, fully laid out in Appendix A.1, extends the sieve reduced rank regression of Adrian et al. (2019a,b) to allow for bivariate predictors. The sieve reduced rank (SRR) regression is very general, and allows for a flexible nonlinear relationship between proxies for global risk aversion and expected excess returns. We estimate the conditional expected excess market return –the global credit factor– using the information in the credit risk component of three-month-ahead excess returns on four advanced economy portfolios: AAA/AA, A, BBB, and high yield (below BBB) corporate bonds.[11] Our procedure uses an out-of-sample mean-squared error criterion to select the optimal factor specification amongst specifications with both univariate and bivariate bases, specifications with and without interaction terms between credit spreads and the VIX, specifications with different degrees of nonlinearities, and specifications with up to three factors to describe the panel of bond portfolio returns. The out-of-sample criterion selects a single factor, bivariate model with interactions between credit spreads and the VIX, which is piecewise linear in log credit spreads and quadratic in the VIX.[12]

[11] 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.

[12] Appendix Table A.2 reports the out-of-sample MSE for the best-performing factor construction alternatives.

Figure 1 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). In the run-up to the global financial crisis, the level of the global credit factor is historically low, predicting extremely low corporate bond returns going forward. Likewise, the global credit factor is historically low in the run-up to the Asian crisis. The chart also shows that the global credit factor increases during episodes of tight credit conditions outside of the U.S., such as during the Asian crisis and the European debt crisis. That is, although we use the VIX and U. S. credit spreads as predictors in constructing the global credit factor, the factor captures episodes of tight credit conditions –high price of credit risk– around the world.

Is the estimate of the global price of credit risk driven by the choice of predictors and the choice of portfolios targeted by our factor construction? To answer this question, we conduct two exercises. In the first exercise, we examine how the estimated time series of the global credit factor changes for alternative target portfolios while the predictors stay the same.[13] Figure 2a shows that the estimated time series of the global price of credit risk are similar regardless of whether we use the baseline portfolios of bonds of firms in advanced economies, bonds of firms in the U.S. only, bonds of firms in other advanced economies, or, indeed, bonds of firms in emerging markets. Furthermore, since our panel of international corporate bond returns only starts in 1998, the relationship between predictors and these alternative portfolios is only estimated in the post-1998 sample and the predicted time series of the factor prior to 1998 is an out-of-sample exercises for these portfolios. The results in Figure 2a thus show that the relationship between the global price of credit risk and predictors is stable even outside of the data sample used for the estimation.

In our second exercise, we examine instead how the choice of predictors affects the estimated

[13] In particular, we use the same optimal bivariate basis as in the baseline specification, selected using the out-of-sample criterion described above, but reestimate the coefficients to target each new set of corporate bond return portfolios.

time series of the global credit factor. We replace our U.S.-based predictors with their European counterparts. In particular, we replace the VIX with the Euro Stoxx 50 Volatility index (VSTOXX), and the U.S. EBP with the weighted average default adjusted spread on corporate bonds issued by firms in the same 8 countries as represented in the VSTOXX.[14] We then use the out-of-sample mean-squared error criterion again to select the optimal factor specification for these alternative European predictors, targeting predictability of the baseline advanced economy portfolios. Figure 2b shows that the global credit factor estimated using the European predictors is very similar to the global credit factor estimated using the U.S. predictors, with a 92% correlation in the full 1999–2024 sample for which the European predictors are available. The starkest difference between the two time series is during the European debt crisis, with the factor using the European predictors signaling greater tightness, especially in early and mid 2012, than the factor using U.S. predictors.

Overall, the results in Figure 2 show that the credit factor is indeed global. Using the same predictors but alternative portfolios of corporate bonds and using the same portfolios of corporate bonds but alternative predictors both lead to estimates of the time series variation in the global price of credit risk that are remarkably similar to our baseline global credit factor.

We illustrate the relationship between the global credit factor, the VIX and credit spreads in Figure 3. 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 3b isolates the theoretical relationship with the VIX for three different levels of the credit spread (historical 10th, 50th, and 90th percentiles). The figure shows how the effective slope changes with the level of credit spreads. For all levels of the credit spread, the factor is to a large extent flat between the historical minimum (10) and median (18) level of the VIX. Above the VIX median, the slope with respect to the VIX increases as the level of the credit spread increases. That is,

[14] France, Germany, Italy, Spain, Belgium, Netherlands, Finland, and Ireland.

the factor is more sensitive to increases in the VIX at higher levels of spreads, confirming the importance of allowing (and accounting) for interactions between spreads and the VIX.

Turning to the relationship between the global credit factor and credit spreads, in Figure 3c, we see that the global credit factor behaves similarly for low and intermediate levels of the VIX. On the other hand, for high levels of the VIX, the factor displays considerably higher sensitivity to changes in credit spreads.

3.3 Initial evidence of cross-sectional asset pricing

Equation (2) argues that expected returns are affine functions of $\varphi\left(cs_t, \mathrm{VIX}_t\right)$. From the perspective of asset pricing theory, the intercepts a_i and slopes b_i in equation (2) are cross-sectionally related to risk factor loadings. 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 in equation (3) implies that, for the portfolios used to construct the global credit factor, we should have $a_i = \alpha_i + \beta_i\lambda_0$ and $b_i = \beta_i\lambda_1$. 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 $rx_{i,t+h} = a_i + b_i\varphi\left(cs_t, \mathrm{VIX}_t\right) + \epsilon_{i,t+1}$ by SRR regression. We then estimate the prices of risk and risk factor exposures for these portfolios by jointly estimating $rx_{i,t+h} = \alpha_i + \beta_i\left(\lambda_0 + \lambda_1\varphi\left(cs_t, \mathrm{VIX}_t\right)\right) + \beta_i u_{t+h} + \epsilon_{i,t+h}$, where

$\varphi(cs_t, \mathrm{VIX}_t)$ is taken as given and $u_{t+h} \equiv \varphi(cs_{t+h}, \mathrm{VIX}_{t+h}) - \mathbb{E}_t[\varphi(cs_{t+h}, \mathrm{VIX}_{t+h})]$ are the AR(1) innovations to $\varphi(cs_t, \mathrm{VIX}_t)$. Figure 4a compares the expected excess returns from the unrestricted SRR regression estimate and the restricted dynamic asset pricing model, showing 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 in equation (3) to the eleven corporate bond portfolios formed based on country and rating (the four U. S. portfolios, four portfolios of advanced economy excluding the U. S., and the three emerging market portfolios discussed above). Figure 4b plots the in-sample average excess return on these portfolios versus $\alpha_i + \beta_i(\lambda_0 + \lambda_1 \mathbb{E}[\varphi(cs, \mathrm{VIX})])$. The figure 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 4 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 credit 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 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):

$$rx_{i,t+h} = \beta_{i,t}(\lambda_0 + \lambda_1 \varphi(cs_t, \mathrm{VIX}_t)) + \epsilon_{i,t+h}.$$

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

$$rx_{i,t+h} = \beta\varphi(cs_t, \text{VIX}_t) + \beta_r\varphi(cs_t, \text{VIX}_t) \times \mathbb{1}_{r,i,t} + \epsilon_{i,t+h}, \tag{4}$$

where 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).

Throughout this section, we focus on the overall R^2 as our measure of performance, which aggregates over both bonds i and time periods t and thus captures how well a model specification explains panel covariation. We further decompose the overall R^2 into the sum of three components, allowing us to explore how much of the overall panel covariation is due to time series variation in the factor, how much is due to panel variation in factor loadings $\beta_{i,t}$, and how much is due to coincident variation in the factor, factor loadings, and returns. More specifically, stacking the estimation equation (4) across bond-months, so that

$$\overrightarrow{rx}^{(h)} = \vec{\beta}^{(h)}\vec{f} + \vec{\epsilon}^{(h)},$$

we can represent the overall R^2 as

$$\begin{aligned} R^2 = \frac{\text{cov}\left(\hat{\beta}^{(h)}\vec{f}, \overrightarrow{rx}^{(h)}\right)}{\mathbb{V}\left(\overrightarrow{rx}^{(h)}\right)} &= \frac{\mathbb{E}\left[\hat{\beta}^{(h)}\right]\text{cov}\left(\vec{f}, \overrightarrow{rx}^{(h)}\right)}{\mathbb{V}\left(\overrightarrow{rx}^{(h)}\right)} + \frac{\mathbb{E}\left[\vec{f}\right]\text{cov}\left(\hat{\beta}^{(h)}, \overrightarrow{rx}^{(h)}\right)}{\mathbb{V}\left(\overrightarrow{rx}^{(h)}\right)} \\ &+ \frac{\mathbb{E}\left[\left(\hat{\beta}^{(h)} - \mathbb{E}\left[\hat{\beta}^{(h)}\right]\right)\left(\vec{f} - \mathbb{E}\left[\vec{f}\right]\right)\left(\overrightarrow{rx}^{(h)} - \mathbb{E}\left[\overrightarrow{rx}^{(h)}\right]\right)\right]}{\mathbb{V}\left(\overrightarrow{rx}^{(h)}\right)}. \end{aligned}$$

The first term above captures the variation that would be explained by time series variation in the factor alone if the exposures were set to the sample average exposure $\mathbb{E}\left[\hat{\beta}^{(h)}\right]$ and is thus closely related to the notion of time-series R^2 in the cross-sectional asset pricing literature (see e.g. Kelly et al., 2023). Closely related to the notion of cross-sectional R^2 instead, the second term measures the variation that would be explained by panel variation in risk exposures alone if the factor were set to its sample average $\mathbb{E}\left[\vec{f}\right]$. The final component captures the extent to which the factor, exposures, and future realized returns experience large deviations at the same time, and can thus be thought of as a "market-timing" R^2.

4.1 Baseline results

Table 1 reports the estimated coefficients from the baseline predictive regression of three-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 1 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 β with respect to the global credit factor decreases from 1.21 on average for high yield bonds (the omitted category), to 0.62 and 0.34 for BBB-rated and A-rated bonds, respectively, and further to 0.17 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 an 11.4 percentage point (p.p.) increase in annualized three-month-ahead expected excess returns on high yield bonds, 5.9 p.p. increase in expected excess returns on BBB-rated bonds, a 3.2 p.p. increase in expected excess returns on A-rated bonds, and a 1.6 p.p. increase in expected excess returns on AAA/AA-rated bonds. These represent meaningful changes relative to unconditional average excess returns of 7.96%, 2.79%, 1.25%, and 0.71% across high yield, BBB-rated, A-rated, and AAA/AA-rated bonds, respectively.

The global nature of the factor is confirmed by the cross-country evidence in columns 2 – 4 of Table 1, where we see that the global credit factor is a consistent predictor of bond excess returns across different economies. Bonds issued by firms in advanced economies have lower average estimated β with respect to the global credit factor than bonds issued by firms in emerging markets. Furthermore, within each region, and even within investment grade bonds (those rated BBB and above) in each region, bonds exhibit the same monotonic loadings discussed in the previous paragraph. That is, riskier bonds exhibit higher exposure to the global credit factor, both by credit risk within each country and across countries with different risk profiles.[15]

Moving beyond the estimated coefficients from the return predictability regression, the table also reports the overall R^2, as well as the decomposition of R^2 into the time-series, cross-sectional, and market timing R^2s, as defined above. Three results are worth noting. First, the overall R^2 is substantial, ranging from 9.1% for bonds issued by U.S. firms to 13.1% for bonds issued by firms in emerging markets.[16] Second, while the time-series R^2 contributes the most to the overall R^2, both the cross-sectional and the market timing R^2s also represent a meaningful portion of the overall R^2. Thus, the global credit factor captures overall variation in global corporate bond returns (as evidenced by the time-series R^2) and bonds in the cross-section have meaningful differential exposure to the global credit factor (as evidenced by the cross-sectional and market timing R^2s). Third, while the cross-sectional R^2 is similar across regions (across columns 2–4), the time-series R^2 for bonds issued by firms in emerging market economies is 75% higher than that for advanced economies. This is particularly remarkable

[15] Appendix Table A.6 tests cross-country differences in exposure to the global credit factor more formally. Across all rating categories, bonds issued by firms in emerging market economies are the most exposed. Within advanced economies, bonds of U.S. firms appear more exposed than bonds of firms in other advanced economies, except for high yield bonds. We also confirm that, when measuring bond risk using alternative metrics to ratings, riskier bonds still have higher exposure to the global credit factor (Appendix Table A.7).

[16] A potential concern with this result is whether the in-sample R^2 reported in Table 1 overstates the model fit. In Appendix Table A.5, we report results from an out-of-sample exercise. Using only data from ICE Global Bond Indices (to make the out-of-sample comparable across regions), we reestimate (4) on expanding windows, adding one month of observations at a time, and predicting the next month's observations of three-month-ahead returns. Table A.5 shows that the in-sample and out-of-sample R^2 are similar, confirming that the predictive performance of the model is not driven by in-sample overfitting.

given that the global credit factor is constructed targeting returns on portfolios of advanced economy bonds only, and reinforces the interpretation of the factor as a truly global price of risk.[17]

While our focus is the credit risk component of corporate bond returns, it is instructive to also consider whether the other components of returns can also be explained by the global credit factor. Table 2 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 1 shows that overall returns display a similar pattern to that discussed in the context of Table 1 (and displayed in column 2 for reference): riskier bonds have higher exposure to the global credit factor, and the overall R^2 has substantial contributions from all three sources of R^2, with the time series R^2 providing the largest contribution.

Turning to column 3 of Table 2, we see that, although statistically significant, the exposure of the currency curve differential component to the global credit factor is relatively low and plays a small role in the overall exposure of returns to the global credit factor. 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, duration risk compensation *increases* in credit rating, although the R^2 is negligible. Going beyond overall R^2, columns 3 and 4 show that the cross-sectional R^2 of the currency differential component and the duration risk component is zero. Thus, while the global credit factor captures some of the time-series variation in the currency risk embedded in international corporate bonds, the cross-section of currency curve

[17] Appendix Table A.8 compares return predictability using alternative measures of the global credit factor. In particular, we construct three alternative global credit factors: targeting U.S. bond portfolios only, targeting portfolios of bonds issued by advanced economy firms excluding U.S. firms, and targeting portfolios of EM firms. For each of these three alternative measures of the global credit factor, the return predictability results are remarkably similar to those using our preferred specification. Furthermore, Appendix Table A.9 shows that the global credit factor constructed with European predictors likewise predicts bond returns around the world. These results are once again consistent with the global credit factor being a proxy for a truly global price of credit risk.

differential returns does not have differential exposure to the global credit factor. In other words, the contribution to overall R^2 of total returns coming from the cross-sectional R^2 is due exclusively to the factor being able to price the cross-section of *credit risk*.

4.2 Contributions to predictability from the EBP and the VIX

The previous section shows that the global credit factor prices the return due to credit risk for a large panel of corporate bonds. In this subsection, we explore how three main features of the factor construction procedure –the role of using information from both credit spreads and the VIX, the role of allowing for nonlinearities in the relationship between predictors and the global price of risk, and the role of interactions between predictors– contribute to the overall performance of the global credit factor as a predictor of returns.

Table 3 compares the predictive power of the global credit factor to that of five alternative specifications. Columns 2 and 3 study predictability with the underlying predictors, columns 4 and 5 display results using the corresponding univariate nonlinear factors,[18] and column 6 using both univariate factors as predictors. Table 3 shows the global credit factor significantly outperforms the alternative specifications in terms of overall R^2.

Evaluating each of the three main features[19] of the factor construction in turn, we first see in columns 2 and 3 that, when included in their linear form both the EBP and the VIX underperform the global credit factor significantly (their R^2 is less than half that of the global credit factor). Furthermore, turning to the decomposition of R^2, Columns 2 and 3 show that EBP and VIX capture different type of information about the panel of bond returns. The time-series R^2 is almost the same as the overall R^2 for the EBP, suggesting that the EBP captures time-series variation in returns but not cross-section differences in

[18] We construct an EBP factor and a VIX factor following the same approach as detailed in Section 2 but with one predictor instead of two.

[19] That is, (1) the inclusion of both the EBP and the VIX as predictors; (2) allowing for nonlinearities; and (3) allowing for interactions between the EBP and the VIX.

risk exposures. In contrast, the time-series and cross-sections R^2s contribute equally to the overall R^2 for the VIX. Indeed, the cross-sectional R^2 for the VIX exceeds that of the global credit factor, suggesting that the VIX does a particularly poor job in capturing the time-series variation in global corporate bond returns. These results provide our first indication of the importance of including information from both the EBP and the VIX in the factor construction.

Second, allowing for the relationship between the global price of risk and each individual predictor to be nonlinear (columns 4 and 5) leads to a substantial improvement in the predictive power of both the EBP and the VIX factors. While the improvement in the EBP factor comes primarily from an increase in the cross-sectional R^2, the improvement in the VIX factor comes predominantly from an increase in the time series R^2. That is, allowing for nonlinearities shapes the EBP factor to capture not only time-series variation in returns but also cross-sectional return differences. In contrast, allowing for nonlinearities in the relationship between the VIX and the global price of credit risk tilts the VIX factor toward capturing time-series variation in returns.

Finally, column 6 shows that, when we include both the EBP and the VIX factors as predictors, around a third of the overall R^2 is due to the EBP factor and two-thirds due to the VIX factor, suggesting that information from both predictors is relevant for predicting returns. However, even when including both non-linear factors as regressors, the overall R^2 does not match that of the global credit factor. This highlights the importance of the interactions between the EBP and the VIX as a key part of the global credit factor construction. Overall, Table 3 shows that both nonlinearities and the interactions between our predictors play a crucial role in improving the fit of our model.

Table 4 further explores the key role played by interactions between our two predictors. While the VIX factor and the additive combination of the VIX and EBP factors perform well in the full sample (as evidenced by the overall R^2 in columns 5 and 6 of Table 3), we now consider how the performance of different factors changes across states of the credit cycle. In particular, we define episodes of tight credit conditions to be those when the global credit factor is in its top tercile and reaches the top quintile at least once during the episode. Similarly, we define episodes of loose credit conditions to be those when the global credit factor is in its bottom tercile and reaches the bottom quintile at least once during the episode.

Table 4 shows significant differences in the relative performance of the VIX factor and the two factor model across periods of tight and loose credit conditions. When credit conditions are tight (column 1–3), these two alternative specifications perform similarly well to the global credit factor in predicting returns. Instead, when credit conditions are loose (columns 4 – 6), the global credit factor significantly outperforms both the nonlinear VIX (R^2 more than doubles) and the two-factor model (R^2 almost doubles). Furthermore, both the time-series and the cross-sectional R^2s of the global credit factor are significantly higher than of these alternative specifications. That is, the global credit factor both captures more of the time series variation and more of the cross-sectional dispersion in returns during loose credit conditions than either the VIX factor alone or in combination with the nonlinear EBP factor. This difference in performance between tight and loose periods is driven by the fact that the correlation between the global credit factor and the VIX factor changes dramatically from 86% during tight periods to -42% during periods of loose credit conditions.

The changing nature of the relationship between the global credit factor and the VIX factor across states of the world highlights the importance of including the EBP as a predictor in the factor construction. As discussed in section 3, periods of loose credit conditions can be affected by sudden and temporary spikes in the VIX and hence, a factor constructed using only the VIX as a predictor will signal tightening during those periods. Instead, including information from the EBP (and allowing for interactions between the EBP and the VIX) allows the factor to "look through" temporary volatility in the VIX that is ultimately not reflected in bond returns. Crucially, as evidenced by the underperformance of the R^2 in column 6, simply adding the EBP factor as an additional predictor is not sufficient and allowing for interactions between the EBP and the VIX is key.

4.3 The global credit factor and other global FCIs

We conclude this section by comparing the predictive performance of the global credit factor to four commonly used measures of global financial conditions: the VIX, the global financial cycle (GFCy as in Miranda-Agrippino and Rey, 2020), the change in the trade-weighted dollar index (as suggested by Bruno et al., 2018, 2022), and the Goldman Sachs U.S. Financial Conditions Index (GS FCI).

Table 5 shows that the global credit factor outperforms the alternative FCIs in terms of overall R^2. Moreover, none of the alternative FCIs have substantial contributions from both the time-series and the cross-sectional R^2s to the overall R^2. For example, relative to the Miranda-Agrippino and Rey (2020) GFCy, the global credit factor performs substantially better in the cross-section. This is intuitive as the GFCy is constructed to pick up overall market movement and not to price the cross-section of bond returns (or assets more generally). On the other hand, the VIX and the GS FCI perform relatively well in the cross-section but underperform drastically in the time series. For the GS FCI in particular, only the cross-sectional R^2 contributes to the overall R^2, so that a model that replaces the time series of the GS FCI with the average level of the GS FCI performs equally well. Finally, the TWI performs particularly poorly in predicting corporate bond returns, underperforming the global credit factor in both the time-series and the cross-section.

Recent studies have argued that the importance of global factors has diminished in the post-GFC period.[20] To a large extent, these studies arrive at this conclusion by showing the declining role of the VIX in explaining variation in a set of outcomes such as capital flows or

[20] See e.g. Avdjiev et al. (2020), Forbes and Warnock (2012, 2021), and Goldberg (2023).

the probability of a sudden stop. Table 6 explores whether the role of the VIX in explaining corporate bond returns has likewise diminished and whether or not the same pattern is true for the predictive ability of the global credit factor.

Table 6 splits the 1998 – 2024 sample into five subperiods: three "normal" periods (1998 – 2006, 2010 – 2019, and 2021 – 2024) and two "stress" periods (2007 – 2009 and 2020). Three results are worth noting. First, both the VIX and the global credit factor perform substantially better during stress episodes, with the overall R^2 of the global credit factor reaching 15.5% in 2020. Second, the R^2 of the VIX has decreased considerably within "normal" periods: the VIX's overall R^2 has more than halved between the pre-GFC period and the post-COVID period. This is consistent with studies that discuss the diminishing role of global factors. Third, while the "normal" period R^2 of the global credit factor has also declined somewhat in the post-GFC period, its cross-sectional R^2 has remained the same. That is, the lower overall R^2 in the post-crisis period for the global credit factor appears to be due to reduced variation in the factor during normal times rather than from reduced exposure. In contrast, similar to the decline in the overall R^2, the cross-sectional R^2 of the VIX has also halved between the pre-GFC period and the post-COVID period, suggesting that the cross-sectional exposure to the VIX has decreased.

Overall, the results in this section show that the global factor consistently prices corporate bond returns around the globe in both the time series and the cross-section. This section also shows that nonlinearities and the interaction between the EBP and the VIX play a key role in the factor's predictive power. Finally, the section shows that the factor outperforms other commonly used proxies of global financial conditions and that its role does not seem to be diminishing in the post-GFC period.

5 Real effects of global credit shocks

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" (Vayanos, 2004; Caballero and Krishnamurthy, 2008), 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.[21] 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.

As discussed above, we identify episodes of tight credit conditions as those when the global credit factor is in its top tercile and reaches the top quintile at least once during the episode. We then construct a dummy variable, Tight GCC_t, that equals one in the first month of a tight episode, is missing during the remaining months of tight periods, and equals 0 otherwise.

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

Tight GCC_t thus compares the evolution of credit conditions following the start of a period of tight credit conditions relative to a normal non-tight month.

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 $h \in \{-6, 6\}$:

$$y_{i,t+h,t-1} = \alpha_{c,h} + \alpha_{r,h} + \beta_h \text{Tight GCC}_t + \beta_{r,h} \text{Tight GCC}_t \times \mathbb{1}_r + \epsilon_{i,t+h},$$

where $\alpha_{c,h}$ and $\alpha_{r,h}$ are country and rating fixed effects, and $y_{i,t+h,t-1}$ is either the change in the currency-adjusted duration-matched spread on bond i in month t or the percent change in 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 5 plots the estimated dynamics of credit spreads (Figure 5a) and default probabilities (Figure 5b) 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 5a shows that the start of a period of tight credit conditions corresponds to a substantial, persistent increase in credit spreads across credit ratings. Credit spreads across all credit ratings remain elevated up to 6 months after the start of a period of tight credit conditions. For high yield bonds, credit spreads are 10% higher than prior to the start of the tightening episode, while for A and BBB bonds credit spread are 5% higher than prior to the start of the episode. To the extent that such tightenings in global credit conditions coincide with firms' refinancing needs, this suggest that firms may be particularly disadvantaged by periods of tight global credit conditions and thus experience large and persistent increases in financial fragility.

Figure 5b confirms this intuition. EDFs for all rating categories increase at the onset of the crisis and remain elevated 6 months after the onset of the crisis. These effects are larger for riskier firms, with the one-year EDFs of high yield firms rising by around 40% at the onset of a period of tight credit conditions. Thus, the start of tight periods corresponds to persistently higher borrowing costs and increased default risk for lower-rated borrowers.

We investigate the statistical significance of the results in Figure 5 in Tables 7 and 8. Table 7a compares the initial increases in credit spreads across countries. The impact of tight credit conditions is larger for bonds issued by emerging market issuers, with credit spreads in advanced economies increasing by around 100 bps in the first month of a period of tight credit conditions and spreads in emerging countries increasing by around 130 bps. Across all economies, increases in credit spreads for safer bonds are significantly lower than those for high yield bonds. Table 7b then confirms that the cross-rating differences in the persistence of credit spread increases discussed in the context of Figure 5a are statistically, as well as economically, significant. On average, spreads on high yield bonds increase by 100 bps at the onset of a period of tight credit conditions and remain 50 bps higher than initial spreads six months after the start of the episode. In contrast, spreads on AAA/AA-rated bonds are just 10 bps higher than initial spreads within six months.

Turning to changes in firm-level EDFs in Table 8, we see that the initial increases in EDFs (in percent terms) for high yield firms is highest in the U.S., with EDFs increasing by around 42% in the U.S. in the first month of a period of tight credit conditions and EDFs in emerging markets increasing by around 30%. Turning to the cross-horizon results in Table 8b, we see that the persistent (and continuing) increase in EDFs across rating categories we saw in Figure 5b is also statistically significant. Furthermore, while the initial increase in EDFs for high yield firms is significantly higher than that for firms rated A and below, by the six months horizon even these relatively safer firms have experienced substantial EDF increases.

Overall, the results in this section provide initial evidence that shocks to the global price of credit risk translate into a persistent deterioration in local credit conditions, which may lead to adverse real outcomes at an aggregate level. We further investigate the interactions between the global credit cycle, credit conditions faced by local firms, and aggregate real outcomes in a series of subsequent papers. In particular, in Boyarchenko and Elias (2024) we show that, beyond translating into higher secondary market spreads as documented here, tight global credit conditions impair firms' ability to manage their debt structure optimally. Turning to the real effects of the global credit cycle, in Boyarchenko and Elias (2026) we show that loose credit conditions predict downturns in real activity in the medium and long run.

6 The global credit cycle and global intermediaries

The results so far highlight a tight relationship between the global price of credit risk — proxied by our global credit factor— and the credit conditions faced by firms around the world, including individual bond returns, credit spreads, and firms' expected default frequencies. In this section, we turn to the relationship between the global price of credit risk and global investors in bond markets. The results in this section are consistent with global intermediaries playing a key role in the global transmission of shocks to the price of credit risk.

More specifically, we study the relationship between the global credit factor and the returns of and flows into global mutual funds and ETFs. We use data provided by Emerging Portfolio Fund Research (EPFR) to measure returns, client flows into (and out of) global funds, the credit quality of funds' investments, the funds' domicile, and on the geographical location of funds' investments.

6.1 Global fund returns

We start by examining whether the global credit factor predicts returns not just at an individual bond level but also for global funds investing in fixed income assets. We estimate:

$$rx_{i,t+1} = \alpha + \beta\varphi\left(cs_t, \text{VIX}_t\right) + \beta_r\varphi\left(cs_t, \text{VIX}_t\right) \times \mathbb{1}_r + X_{i,t} + \epsilon_{i,t},$$

where $rx_{i,t+1}$ is fund i excess return in month $t+1$, α is a set of fixed effects that include fund type, domicile, and investment scope (geofocus) fixed effects, $\mathbb{1}_r$ is an indicator variable that identifies the type of fund, and $X_{i,t}$ is a set of fund level controls that include lags of the flows variable as well as fund size. β then captures the overall level of comovement between the global credit factor and fund flows and β_r capture the differential sensitivity depending on the type of fund.

Table 9 shows that, with the exception of funds investing in Latin America, an increase in the global credit factor predicts higher fund returns in the following month. Moreover, bond funds investing in riskier securities have greater exposure to the global factor while government bond funds have the lowest exposure in most regions.

Finally, Table 10 shows that, for all regions, the global credit factor explains a higher share of variation in fund returns than the VIX can. With the exception of global funds investing in Latin America, the share of variation explained by the global credit factor is substantially higher than that explained by the VIX. This confirms our findings in previous sections which suggest that the global credit factor outperforms other measures of global financial conditions —such as the VIX— in explaining variation in bond returns.

6.2 Global fund flows

Going beyond fund returns, in this section we explore global fund investors' responses to movements in the global credit factor. We estimate:

$$\frac{flows_{i,t}}{AUM_{i,t-1}} = \alpha + \beta\varphi\left(cs_t, \text{VIX}_t\right) + \beta_r\varphi\left(cs_t, \text{VIX}_t\right) \times \mathbb{1}_r + X_{i,t} + \epsilon_{i,t}, \tag{5}$$

where $\frac{flows_{i,t}}{AUM_{i,t-1}}$ is the percentage flows into fund i in month t, α is a set of fixed effects that include fund type, domicile, and investment scope (geofocus) fixed effects, $\mathbb{1}_r$ is an indicator variable that identifies the type of fund, and $X_{i,t}$ is a set of fund level controls that include lags of the flows variable as well as fund size. β then captures the overall level of comovement between the global credit factor and fund flows and β_r capture the differential sensitivity depending on the type of fund.

The results in Table 11 show that, overall, tightenings in the global credit factor are associated with lower fund inflows. Starting with the results in column 1 (funds investing in European bonds), high yield funds (the omitted category) experience lower inflows when the factor is higher. More importantly, the positive point estimates in the rest of the rows indicate that most other types of funds experience relatively lower negative flows. That is, high yield funds –the type of funds with the riskiest investment mandate– experience lower inflows than their safer counterparts. These results are consistent with the patterns of bond returns discussed in the previous section. Turning to columns 2 – 5, we see that the results in column 1 extend to funds investing in most regions, with the one exception being funds investing in Asia.

We conclude this section by evaluating whether particular types of funds amplify the transmission of global credit conditions. Table 12 reports the estimated coefficients from (5), comparing funds domiciled in the U.S. and other advanced economies (columns 1 and 2), mutual funds and ETFs (columns 3 and 4), and funds with different asset duration mandates (columns 5 and 6). Starting with the fund domicile comparison in columns 1 and 2, we see that investors into funds domiciled in the U.S. are overall less sensitive to changes in global credit conditions than investors in funds domiciled in other advanced economies. Furthermore, while U.S.-domiciled funds have lower inflows regardless of the funds' credit rating mandate, inflows into funds domiciled outside of the U.S. are credit risk sensitive. That is, investors into funds domiciled in advanced economies other than the U.S. are more sensitive to changes in the global price of credit risk overall, and are more attentive to the credit risk of those funds' investments.

Comparing inflows into mutual funds and ETFs in columns 3 and 4, we see that investors into ETFs are more sensitive to the global credit factor. This is consistent with the findings in Converse et al. (2023) that ETFs amplify the transmission of global shocks. Finally, columns 5 and 6 show that investors into short-term funds are more sensitive to changes in global credit conditions than investors into intermediate-term funds. Inflows into high yield short-term funds are particularly impacted by the global credit cycle, while inflows into intermediate-term funds decline when the global credit factor tightens regardless of credit rating.

Overall, the results on bond fund return and flows suggest that the risks to individual corporate bond returns associated with exposure to the global credit factor cannot be diversified. This again highlights that that global credit factor captures systematic risks in the global market for corporate fixed income.

7 Conclusion

We construct the price of risk in international corporate bond markets as a nonlinear function of the VIX and U.S. credit spreads. We show that allowing for nonlinearities improves the ability of credit spreads to explain cross-sectional variation in returns and the ability of the

VIX to explain time series variation. Crucially, including information from credit spreads in the factor construction allows the factor to "look through" temporary increases in the VIX that are irrelevant for the corporate bond market.

Our resultant global credit factor thus 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. The global credit factor is unique among commonly used metrics of global financial conditions in capturing both the time-series and cross-sectional variation in returns, leading the global credit factor to significantly outperform these alternative proxies in predicting international corporate bond returns. Furthermore, we show that, unlike the VIX, the cross-sectional exposure of bond returns to the global credit factor has not declined since the global financial crisis, suggesting that the pricing of risks in the corporate bond market remains global.

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 lose 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 intermediary. 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 a tight co-movement between the global credit factor and flows into global funds. This suggests that the global credit cycle transmits not just through a global repricing of risk but also through a rebalancing of global portfolios. 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.

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Table 1: Bond-level return predictability. This table reports the estimated coefficients from the regression of 3-month bond-level excess holding period returns on the global credit factor. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) U.S.	(3) AE, ex U.S.	(4) EM
GCC	1.21	1.15	1.33	1.56
	(0.02)***	(0.02)***	(0.05)***	(0.07)***
BBB × GCC	-0.59	-0.51	-0.78	-0.64
	(0.02)***	(0.02)***	(0.05)***	(0.08)***
A × GCC	-0.87	-0.78	-1.03	-1.00
	(0.02)***	(0.02)***	(0.05)***	(0.08)***
AAA/AA × GCC	-1.04	-0.86	-1.24	
	(0.02)***	(0.02)***	(0.05)***	
Total R^2	9.3	9.1	9.4	13.1
Time series R^2	6.9	6.9	6.6	11.4
Cross section R^2	1.0	0.8	1.2	0.8
Market timing R^2	1.5	1.4	1.5	0.9
N. of obs	2,376,804	1,449,575	800,004	127,225
N. bonds	40,103	24,630	14,252	2,434

Table 2: Decomposing returns into sources of risk. This table reports the estimated coefficients from the regression of 3-month bond-level 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. High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level 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
GCC	1.42	1.21	0.33	0.17
	(0.02)***	(0.02)***	(0.01)***	(0.00)***
BBB × GCC	-0.53	-0.59	-0.01	0.02
	(0.02)***	(0.02)***	(0.01)	(0.00)***
A × GCC	-0.78	-0.87	-0.05	0.04
	(0.02)***	(0.02)***	(0.01)***	(0.00)***
AAA/AA × GCC	-0.92	-1.04	-0.17	0.08
	(0.02)***	(0.02)***	(0.01)***	(0.01)***
Total R^2	9.0	9.3	3.1	0.0
Time series R^2	7.8	6.9	3.1	-0.0
Cross section R^2	0.4	1.0	-0.0	0.0
Market timing R^2	0.8	1.5	-0.0	-0.0
N. of obs	2,376,804	2,376,804	568,906	2,376,804
N. bonds	40,103	40,103	9,959	40,103

Table 3: Understanding contributions of VIX and EBP to bond-level return predictability. This table reports the estimated coefficients from the regression of 3-month bond-level excess holding period returns on alternative proxies for the price of risk. High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) GCC	(2) EBP	(3) VIX	(4) $\varphi(EBP)$	(5) $\varphi(VIX)$	(6) $\varphi(EBP)$, $\varphi(VIX)$
FCI	1.21	10.47	0.51	1.20	1.32	0.57
	(0.02)***	(0.21)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***
BBB × FCI	-0.59	-3.90	-0.30	-0.60	-0.66	-0.37
	(0.02)***	(0.23)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***
A × FCI	-0.87	-6.63	-0.40	-0.89	-0.95	-0.50
	(0.02)***	(0.22)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***
AAA/AA × FCI	-1.04	-8.54	-0.45	-1.04	-1.14	-0.50
	(0.02)***	(0.23)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***
FCI: VIX						0.87
						(0.03)***
BBB × FCI: VIX						-0.37
						(0.03)***
A × FCI: VIX						-0.55
						(0.03)***
AAA/AA × FCI: VIX						-0.74
						(0.03)***
Total R^2	9.3	4.7	4.2	7.0	8.7	9.1
Time series R^2	6.9	4.0	1.9	4.8	6.3	6.5
Cross section R^2	1.0	-0.1	1.8	1.0	1.0	1.1
Market timing R^2	1.5	0.8	0.5	1.3	1.4	1.5
Due to $\beta_r \varphi(EBP)$						3.0
Due to $\beta_r \varphi(VIX)$						6.2
N. of obs	2,376,804	2,376,804	2,376,804	2,376,804	2,376,804	2,376,804
N. bonds	40,103	40,103	40,103	40,103	40,103	40,103

Table 4: Tight credit conditions and return predictability. This table reports the estimated coefficients from the regression of 3-month bond-level excess holding period returns on alternative proxies for the price of risk, conditional on tight (columns 1–3) and loose (columns 4–6) credit conditions. High yield bonds are the omitted category. Episodes of tight credit conditions are those when the global credit factor is in its top tercile and reaches the top quintile at least once during the episode. Episodes of loose credit conditions are those when the global credit factor is in its bottom tercile and reaches the bottom quintile at least once during the episode. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	Tight			Loose		
	(1)	(2)	(3)	(4)	(5)	(6)
	GCC	$\varphi(VIX)$	$\varphi(EBP)$, $\varphi(VIX)$	GCC	$\varphi(VIX)$	$\varphi(EBP)$, $\varphi(VIX)$
FCI	1.17	1.33	0.40	4.95	2.11	6.55
	(0.02)***	(0.02)***	(0.03)***	(0.09)***	(0.05)***	(0.38)***
BBB × FCI	-0.55	-0.65	-0.24	-3.84	-2.21	-3.48
	(0.02)***	(0.02)***	(0.03)***	(0.09)***	(0.06)***	(0.41)***
A × FCI	-0.83	-0.94	-0.36	-4.56	-2.45	-5.16
	(0.02)***	(0.02)***	(0.03)***	(0.09)***	(0.06)***	(0.40)***
AAA/AA × FCI	-1.01	-1.15	-0.32	-4.91	-2.49	-5.68
	(0.02)***	(0.02)***	(0.03)***	(0.09)***	(0.06)***	(0.42)***
FCI: VIX			1.01			2.78
			(0.03)***			(0.08)***
BBB × FCI: VIX			-0.44			-2.66
			(0.04)***			(0.08)***
A × FCI: VIX			-0.65			-3.02
			(0.03)***			(0.08)***
AAA/AA × FCI: VIX			-0.88			-3.10
			(0.03)***			(0.08)***
Total R^2	10.5	10.0	9.9	3.4	1.5	2.0
Time series R^2	6.9	6.3	6.0	0.8	-0.2	0.0
Cross section R^2	2.1	2.3	2.5	2.4	1.5	1.6
Market timing R^2	1.5	1.4	1.4	0.2	0.2	0.3
Corr. with GCC	1.00	0.86	0.83	1.00	-0.42	0.89
N. of obs	571,046	571,046	571,046	604,677	604,677	604,677
N. bonds	34,970	34,970	34,970	31,740	31,740	31,740

Table 5: Bond-level return predictability with alternative FCIs. This table reports the estimated coefficients from the regression of 3-month bond-level excess holding period returns on common alternative financial condition indices. "GFCy" is the global financial cycle from Miranda-Agrippino and Rey (2020). Δ TWI is the monthly change in the Federal Reserve Board trade-weighted nominal dollar index. "GS FCI" is the Goldman Sachs U.S. financial conditions index. High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) GCC	(2) VIX	(3) GFCy	(4) Δ TWI	(5) GS FCI
FCI	1.21	0.51	-7.27	0.82	0.08
	(0.02)***	(0.01)***	(0.14)***	(0.02)***	(0.00)***
BBB × FCI	-0.59	-0.30	1.32	-0.32	-0.05
	(0.02)***	(0.01)***	(0.16)***	(0.02)***	(0.00)***
A × FCI	-0.87	-0.40	4.01	-0.54	-0.07
	(0.02)***	(0.01)***	(0.15)***	(0.02)***	(0.00)***
AAA/AA × FCI	-1.04	-0.45	5.59	-0.69	-0.07
	(0.02)***	(0.01)***	(0.15)***	(0.02)***	(0.00)***
Total R^2	9.3	4.2	5.4	1.6	1.6
Time series R^2	6.9	1.9	4.7	1.2	0.0
Cross section R^2	1.0	1.8	0.0	0.2	1.5
Market timing R^2	1.5	0.5	0.7	0.2	0.0
N. of obs	2,376,804	2,376,804	2,376,804	2,376,804	2,305,623
N. bonds	40,103	40,103	40,103	40,103	39,708

Table 6: Bond-level return predictability across subperiods. This table reports the estimated coefficients from the regression of 3-month bond-level excess holding period returns on the global credit factor. High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	1998–2006		2007-2009		2010–2019		2020		2021–2024	
	(1) GCC	(2) VIX	(3) GCC	(4) VIX	(5) GCC	(6) VIX	(7) GCC	(8) VIX	(9) GCC	(10) VIX
FCI	1.10	0.45	0.93	0.61	1.69	0.44	1.74	1.01	2.44	0.31
	(0.04)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.00)***	(0.06)***	(0.03)***	(0.04)***	(0.00)***
BBB × FCI	-0.74	-0.36	-0.40	-0.24	-1.09	-0.30	-0.74	-0.45	-1.35	-0.19
	(0.04)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.01)***	(0.06)***	(0.03)***	(0.04)***	(0.01)***
A × FCI	-0.91	-0.42	-0.62	-0.39	-1.43	-0.39	-1.18	-0.69	-1.68	-0.22
	(0.04)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.01)***	(0.06)***	(0.03)***	(0.04)***	(0.00)***
AAA/AA × FCI	-0.95	-0.43	-0.81	-0.52	-1.48	-0.40	-1.28	-0.73	-1.73	-0.23
	(0.04)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.01)***	(0.06)***	(0.03)***	(0.05)***	(0.01)***
Total R^2	5.8	4.1	15.4	5.8	3.7	2.8	15.5	9.6	3.5	1.9
Time series R^2	3.1	0.7	12.2	4.1	1.5	0.6	12.0	6.3	1.8	0.1
Cross section R^2	1.6	3.1	0.9	0.9	1.5	1.9	1.8	2.4	1.5	1.8
Market timing R^2	1.1	0.3	2.3	0.8	0.7	0.3	1.8	0.9	0.2	-0.0
N. of obs	370,867	370,867	155,757	155,757	959,617	959,617	121,120	121,120	549,477	549,477
N. bonds	9,358	9,358	7,009	7,009	21,880	21,880	12,548	12,548	16,656	16,656

Table 7: 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. Standard errors clustered at the bond level 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
Tight GCC	96.56	93.52	93.13	126.42
	(1.02)***	(1.23)***	(2.01)***	(3.91)***
BBB × Tight GCC	-55.34	-53.95	-53.40	-61.14
	(1.10)***	(1.33)***	(2.09)***	(4.47)***
A × Tight GCC	-72.70	-71.06	-67.58	-100.29
	(1.04)***	(1.25)***	(2.03)***	(4.02)***
AAA/AA × Tight GCC	-78.21	-75.92	-73.72	
	(1.06)***	(1.27)***	(2.05)***	
Adj. R^2	0.09	0.08	0.10	0.10
N. of obs	1,872,818	1,137,315	628,533	106,970

(b) Average increase across horizons

	(1) $\Delta S_{t-3,t-1}$	(2) $\Delta S_{t-2,t-1}$	(3) $\Delta S_{t-1,t}$	(4) $\Delta S_{t-1,t+3}$	(5) $\Delta S_{t-1,t+6}$
Tight GCC	-6.22	-20.30	96.56	75.28	47.99
	(0.72)***	(0.56)***	(1.02)***	(1.33)***	(1.60)***
BBB × Tight GCC	-2.25	12.42	-55.34	-52.90	-33.04
	(0.75)***	(0.57)***	(1.10)***	(1.40)***	(1.67)***
A × Tight GCC	3.36	16.22	-72.70	-63.55	-39.94
	(0.73)***	(0.57)***	(1.04)***	(1.35)***	(1.63)***
AAA/AA × Tight GCC	6.19	19.50	-78.21	-64.25	-39.62
	(0.76)***	(0.60)***	(1.06)***	(1.38)***	(1.66)***
Adj. R^2	0.01	0.01	0.09	0.01	0.00
N. of obs	1,800,082	1,835,589	1,872,818	1,757,593	1,651,811

Table 8: 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. Standard errors clustered at the firm level ported 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) U.S.	(3) AE, ex U.S.	(4) EM
Tight GCC	39.24	42.27	36.45	29.18
	(2.58)***	(3.73)***	(3.59)***	(4.54)***
BBB × Tight GCC	-17.02	-21.85	-10.71	-12.39
	(3.08)***	(4.20)***	(5.04)**	(5.29)**
A × Tight GCC	-28.56	-29.65	-27.49	-23.61
	(2.79)***	(4.11)***	(3.78)***	(5.71)***
AAA/AA × Tight GCC	-28.95	-34.46	-23.67	
	(3.79)***	(4.47)***	(5.99)***	
Adj. R^2	0.00	0.00	0.01	0.01
N. of obs	150,506	81,721	53,698	15,087

(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) $\frac{\Delta EDF_{t-1,t+6}}{EDF_{t-1}}$
Tight GCC	-10.60	-8.73	39.24	44.80	53.59
	(1.15)***	(0.68)***	(2.58)***	(4.61)***	(11.71)***
BBB × Tight GCC	0.40	2.31	-17.02	-0.67	-8.33
	(1.39)	(1.01)**	(3.08)***	(10.71)	(16.97)
A × Tight GCC	-2.57	0.83	-28.56	-22.98	-20.94
	(7.46)	(3.69)	(2.79)***	(5.63)***	(13.56)
AAA/AA × Tight GCC	2.39	2.57	-28.95	-28.59	-34.26
	(1.82)	(1.25)**	(3.79)***	(6.05)***	(13.53)**
Adj. R^2	0.00	0.00	0.00	0.00	0.00
N. of obs	150,105	150,338	150,506	149,840	148,450

Table 9: One month ahead global fund returns and the global credit cycle. This table reports the estimated coefficients from the regression of one-month-ahead returns of global funds on the global credit factor and interactions with fund type dummies. High yield funds are the omitted category. All regression include geography, domicile, and fund fixed effects, as well as three lags of fund flows and lagged log total assets. Standard errors clustered at the fund level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) All ex U.S.	(2) Europe	(3) LATAM	(4) Asia	(5) U.S.	(6) Global
GCC	0.87	1.23	0.58	1.32	0.66	0.74
	(0.04)***	(0.10)***	(0.81)	(0.12)***	(0.02)***	(0.04)***
All quality × GCC	-0.05	-0.45	-0.07	-0.62	-0.12	0.10
	(0.05)	(0.13)***	(0.82)	(0.14)***	(0.05)**	(0.05)**
Investment grade × GCC	-0.21	-0.36	0.22	-0.97	-0.27	-0.12
	(0.04)***	(0.10)***	(0.82)	(0.12)***	(0.03)***	(0.05)**
Government × GCC	-0.38	-0.76	-0.04	-0.80	-0.59	-0.34
	(0.04)***	(0.10)***	(0.81)	(0.14)***	(0.03)***	(0.05)***
Adj. R^2	2.5	1.8	1.0	2.3	4.0	3.2
N. of obs	641,520	205,545	7,129	101,849	221,891	290,122
N. of funds	10,585	3,366	93	2,587	2,729	4,313

Table 10: One month ahead global fund returns and alternative FCIs. This table reports the estimated coefficients from the regression of one-month-ahead returns of global funds on alternative global FCIs and interactions with fund type dummies. High yield funds are the omitted category. All regression include geography, domicile, and fund fixed effects, as well as three lags of fund flows and lagged log total assets. Standard errors clustered at the fund level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	All ex U.S.		Europe		LATAM		Asia		U.S.		Global	
	(1) GCC	(2) VIX	(3) GCC	(4) VIX	(5) GCC	(6) VIX	(7) GCC	(8) VIX	(9) GCC	(10) VIX	(11) GCC	(12) VIX
FCI	0.87	0.63	1.23	0.89	0.58	0.60	1.32	0.76	0.66	0.54	0.74	0.61
	(0.04)***	(0.02)***	(0.10)***	(0.04)***	(0.81)	(0.32)*	(0.12)***	(0.09)***	(0.02)***	(0.02)***	(0.04)***	(0.03)***
All quality × FCI	-0.05	-0.08	-0.45	-0.28	-0.07	0.11	-0.62	-0.22	-0.12	-0.27	0.10	-0.01
	(0.05)	(0.03)***	(0.13)***	(0.05)***	(0.82)	(0.34)	(0.14)***	(0.09)**	(0.05)**	(0.03)***	(0.05)**	(0.03)
Investment grade × FCI	-0.21	-0.27	-0.36	-0.41	0.22	0.19	-0.97	-0.45	-0.27	-0.32	-0.12	-0.19
	(0.04)***	(0.02)***	(0.10)***	(0.04)***	(0.82)	(0.33)	(0.12)***	(0.09)***	(0.03)***	(0.02)***	(0.05)**	(0.03)***
Government × FCI	-0.38	-0.45	-0.76	-0.67	-0.04	-0.06	-0.80	-0.45	-0.59	-0.52	-0.34	-0.37
	(0.04)***	(0.03)***	(0.10)***	(0.04)***	(0.81)	(0.32)	(0.14)***	(0.09)***	(0.03)***	(0.02)***	(0.05)***	(0.03)***
Adj. R^2	2.5	0.8	1.8	0.4	1.0	1.2	2.3	0.9	4.0	2.3	3.2	1.6
N. of obs	641,520	641,520	205,545	228,670	7,129	7,862	101,849	116,112	221,891	221,891	290,122	290,122
N. of funds	10,585	10,585	3,366	3,372	93	93	2,587	2,588	2,729	2,729	4,313	4,313

Table 11: Global fund flows and the global credit cycle. This table reports the estimated coefficients from the regression of flows into global funds (normalized by size) on the global credit factor and interactions with fund type dummies. High yield funds are the omitted category. All regression include geography, domicile, and fund fixed effects, as well as three lags of fund returns in excess of peer funds and lagged log total assets. Standard errors clustered at the fund level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) All ex U.S.	(2) Europe	(3) LATAM	(4) Asia	(5) U.S.	(6) Global
GCC	-0.05	-0.09	-0.19	-0.04	-0.01	-0.04
	(0.01)***	(0.01)***	(0.05)***	(0.04)	(0.01)	(0.01)***
All quality × GCC	-0.00	0.03	0.11	0.00	-0.03	-0.01
	(0.01)	(0.01)*	(0.06)*	(0.04)	(0.01)**	(0.01)
Investment grade × GCC	0.02	0.07	0.12	0.01	-0.01	0.00
	(0.01)***	(0.01)***	(0.06)**	(0.04)	(0.01)	(0.01)
Government × GCC	0.03	0.07	0.17	0.10	0.03	0.01
	(0.01)***	(0.01)***	(0.05)***	(0.05)**	(0.01)***	(0.01)*
Adj. R^2	5.9	5.8	3.4	2.6	9.2	7.0
N. of obs	665,724	214,171	7,279	105,911	230,222	299,844
N. of funds	10,593	3,369	93	2,587	2,733	4,319

Table 12: Global fund flows and the global credit cycle. This table reports the estimated coefficients from the regression of flows into global funds (normalized by size) on the global credit factor and interactions with fund type dummies. High yield funds are the omitted category. All regression include geography, domicile, and fund fixed effects, as well as three lags of fund returns in excess of peer funds and lagged log total assets. Standard errors clustered at the fund level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	Domicile		Type		Duration	
	(1) U.S.	(2) AE, ex U.S.	(3) MF	(4) ETF	(5) Short term	(6) Intermediate term
GCC	-0.03	-0.05	-0.04	-0.17	-0.09	-0.07
	(0.01)***	(0.01)***	(0.01)***	(0.03)***	(0.02)***	(0.03)**
All quality × GCC	-0.02	0.00	-0.00	0.05	0.02	0.04
	(0.01)*	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Investment grade × GCC	-0.02	0.02	0.02	0.11	0.05	0.05
	(0.02)	(0.01)***	(0.01)***	(0.03)***	(0.02)**	(0.03)
Government × GCC	-0.01	0.03	0.02	0.16	0.08	0.04
	(0.02)	(0.01)***	(0.01)***	(0.03)***	(0.03)***	(0.03)
Adj. R^2	7.0	6.3	5.7	5.2	5.3	7.6
N. of obs	56,014	522,550	597,836	67,887	180,093	239,722
N. of funds	601	7,519	9,575	1,022	4,071	3,730

Figure 1. 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 three-months-ahead excess return on the advanced economy high yield bond portfolio.

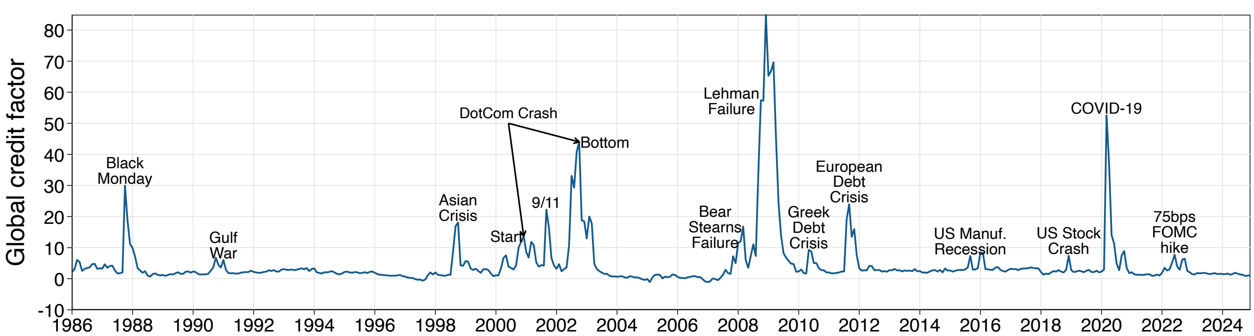
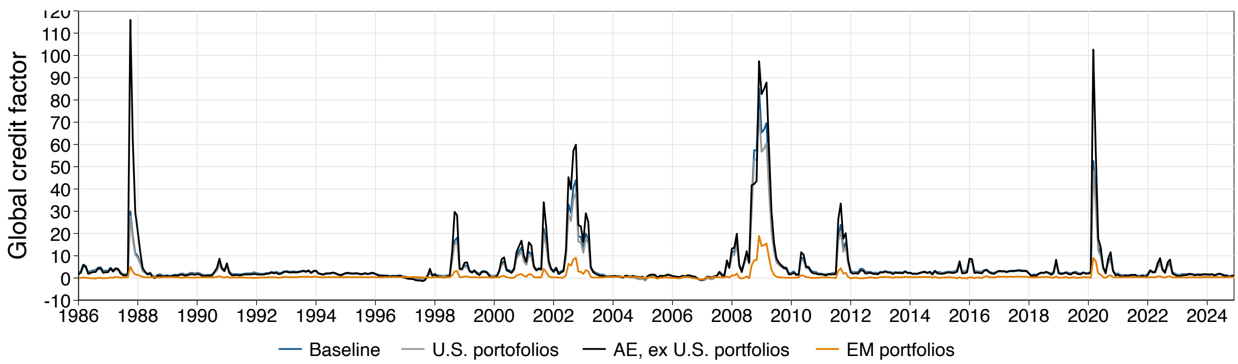


Figure 2. Comparing the global credit factor to alternative estimation procedures. This figure plots the comparison between the global credit factor constructed to price advanced economy bond return portfolios, and those constructed to price U. S. portfolios, advance economies excluding U. S. portfolios, and emerging market portfolios (Figure 2a), and between the global credit factor constructed using U.S. and European predictors.

(a) Comparison to $\varphi\,(\mathrm{EBP}, \mathrm{VIX})$ constructed to target alternative portfolios



(b) Comparison to $\varphi\,(\mathrm{EBP}, \mathrm{VIX})$ constructed using European predictors.

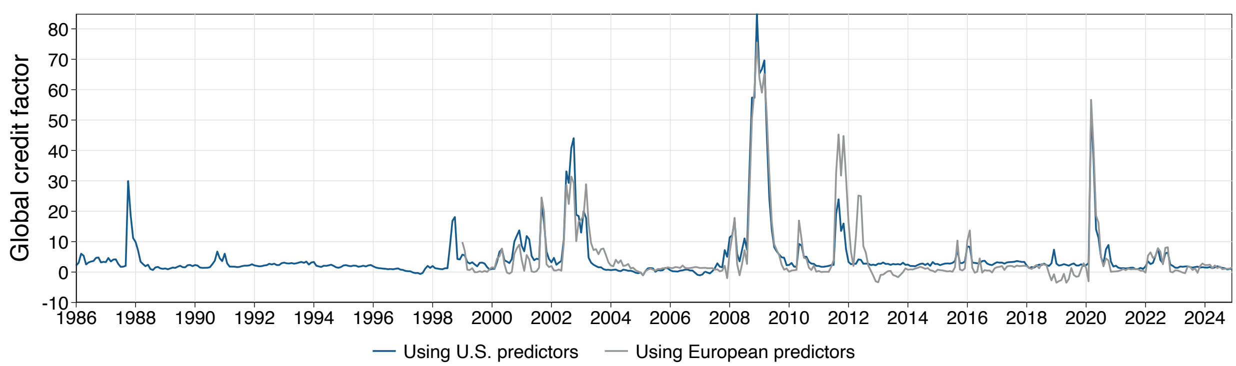
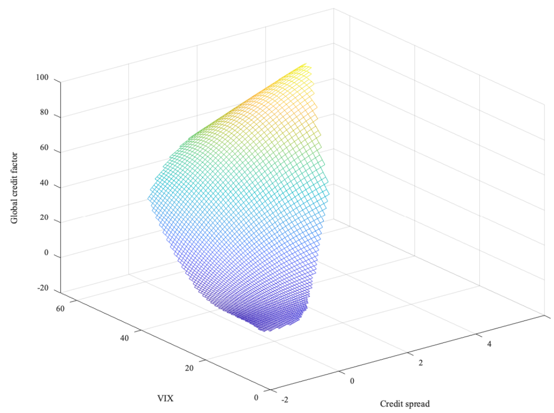
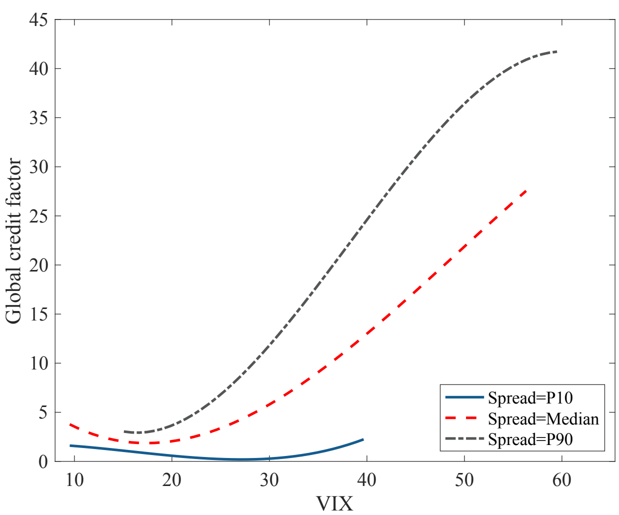


Figure 3. Estimated factor. This figure plots the estimated global credit factor as a function of realizations of the VIX and U. S. credit spreads, measured using the EBP.

(a) Global credit factor



(b) Global credit factor vs VIX



(c) Global credit factor vs EBP

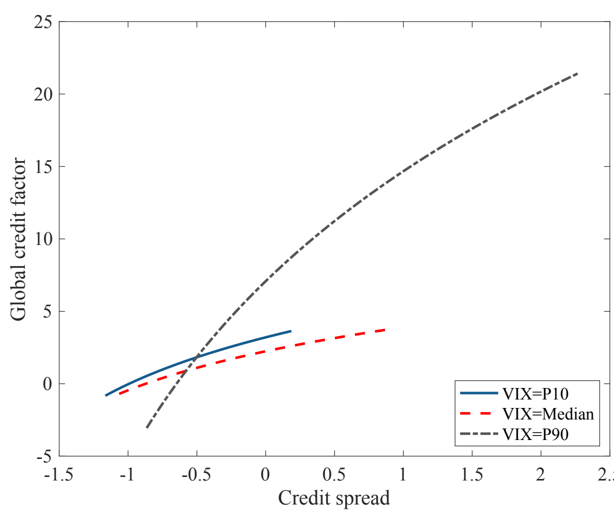


Figure 4. Cross-sectional asset pricing. This figure plots average three-month-ahead excess returns against the restricted joint forecasting regressions $Rx_{i,t+h} = (\alpha_i + \beta_i\lambda_0) + \beta_i\lambda_1\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right) + \beta_i u_{t+h} + \epsilon_{i,t+h}$ obtained from a dynamic asset pricing model with affine prices of risk. The innovations are given by $u_{t+h} = \varphi\left(\mathrm{EBP}_{t+h}, \mathrm{VIX}_{t+h}\right) - E_t\left[\varphi\left(\mathrm{EBP}_{t+h}, \mathrm{VIX}_{t+h}\right)\right]$, 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 4a 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 4b, three 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 4b) to December 2024.

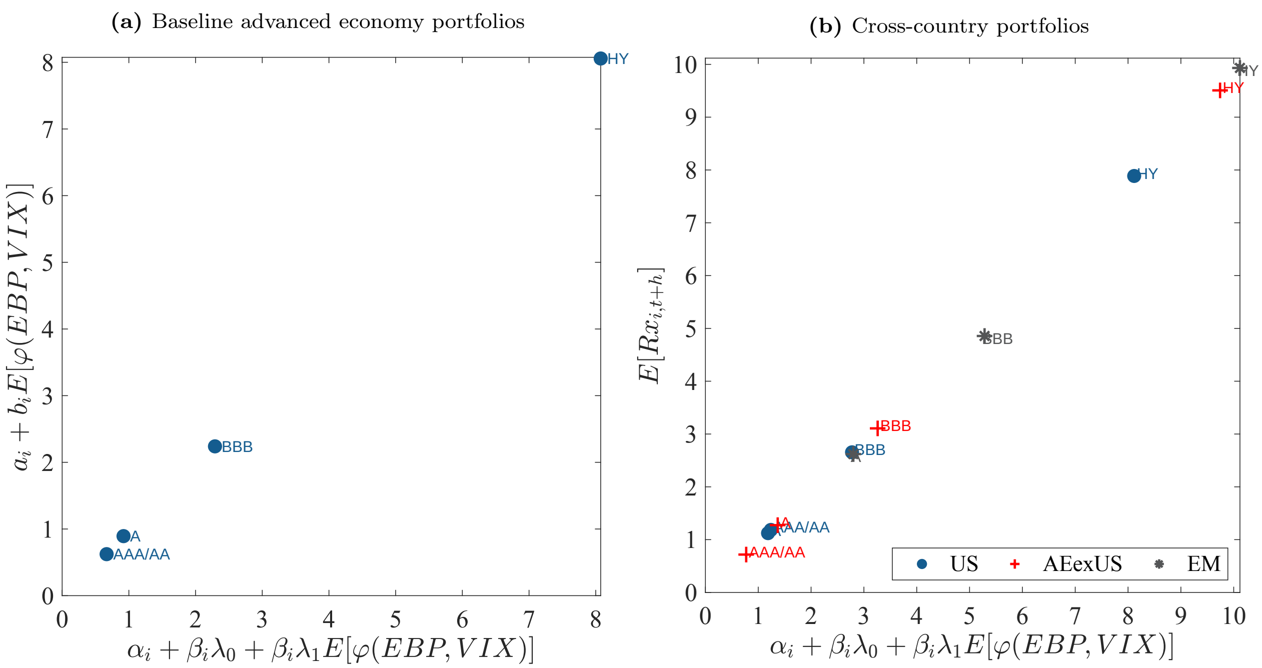
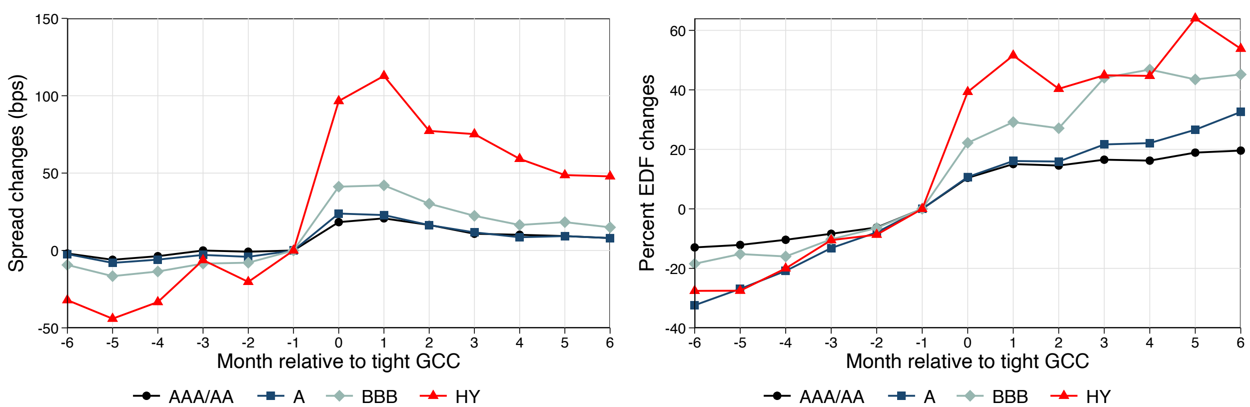


Figure 5. Effect of extreme tightenings. This table reports the estimated coefficients from the regression of spread and percent EDF changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions. Tight global credit conditions measured as a global credit factor realization in the top 25th percentile. All regressions include country and rating fixed effects.

(a) Bond-level spread changes

(b) Firm-level EDF changes



A Additional results

A.1 A reduced rank regression approach to return predictability

In this Appendix, we describe the details of our reduced rank regression approach to constructing the global credit factor. 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 (2). 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, $\varphi\left(cs_t, \mathrm{VIX}_t\right) \equiv \mathbb{E}_t\left[rx_{M,t+1}\right]$, under only weak assumptions. The sieve reduced-rank regression (SRR) replaces the true evolution of excess returns (2) with

$$rx_{i,t+h} = b_{i,h}\left(\gamma_h' X_{m,t}\right) + u_{i,t+h}, \quad u_{i,t+h} = \epsilon_{i,t+h} + b_{i,h}\left(\varphi\left(cs_t, \mathrm{VIX}_t\right) - \gamma_h' X_{m,t}\right), \tag{A.1}$$

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 $\left(\varphi\left(cs_t, \mathrm{VIX}_t\right) - \gamma_h' X_{m,t}\right)$ 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 (A.1) across n assets to obtain

$$\vec{rx}_{t+h} = \vec{b}_h\left(\gamma_h' X_{m,t}\right) + \vec{u}_{t+h}.$$

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 $\vec{b}_h$ and γ_h may all be estimated in closed form, up to a rotation matrix R. We thus 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

$$\hat{b}_h = W^{\frac{1}{2}} L; \quad \hat{\gamma}_h = \hat{A}_{h,OLS}' W^{-\frac{1}{2}} L, \tag{A.2}$$

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

We implement the procedure described above to construct the optimal approximation to $\varphi\left(cs_t, \mathrm{VIX}_t\right)$ based on the information in the three-month-ahead excess returns on 4 advanced economy portfolios: AAA/AA, A, BBB, and high yield (below BBB) corporate bonds.[22] We use the (log) U. S. EBP as our measure of credit spreads.[23] We set W to a diagonal matrix that scales excess returns by the inverse of their standard deviations, 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 $\varphi(cs_t, \mathrm{VIX}_t)$. 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 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).[24] 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 ($r = 3$), spline bases of order up to 4 (corresponding to piecewise cubic polynomials), and up to 6 interior knots, with the two extreme knots placed at the minimum and 90th percentile of the distribution of the corresponding variable and any additional knots spaced evenly in that range. 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 $1,512 = 14 \times 3 \times 6 \times 6$ 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 discern amongst these 1,512 alternatives using an out-of-sample mean-squared error (MSE) criterion. More specifically, for a given specification, we estimate the reduced rank specification (A.1) using data through December 2008 (roughly 60% of our time series). Using the estimated $\left(\hat{b}, \hat{\gamma}_{m_c+m_v}\right)$ and the realized credit spreads and VIX in January 2009, we then predict expected excess returns through April 2009, forming our first (pseudo) out-of-sample forecast.[25] We then iterate,

[22] 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.

[23] 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.

[24] 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.

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

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 linear credit spread basis with no interior knots and piecewise quadratic VIX basis with no interior knots ($X_{m,t} = \mathcal{C}_{2,t} \otimes \mathcal{V}_{3,t}$). 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. Table A.2 reports the out-of-sample MSE for the best-performing factor construction alternatives.

A.2 Univariate factors

Figure A.2 plots the time series of the global credit factor together with $\varphi\left(\text{EBP}\right)$ and $\varphi\left(\text{VIX}\right)$. The figure shows that periods of tightness in the global credit factor are somewhat different than periods of tightness in each of $\varphi\left(\text{EBP}\right)$ and $\varphi\left(\text{VIX}\right)$. For example, the tightening of $\varphi\left(\text{EBP}\right)$ during the global financial crisis occurs earlier than the tightening of either $\varphi\left(\text{EBP}, \text{VIX}\right)$ or $\varphi\left(\text{VIX}\right)$. Likewise, $\varphi\left(\text{EBP}\right)$ tightens earlier than $\varphi\left(\text{EBP}, \text{VIX}\right)$ does in the aftermath of Third Avenue Fund liquidation in December 2015. $\varphi\left(\text{VIX}\right)$ tightens in October 1987 but quickly reverts to more normal levels, while $\varphi\left(\text{EBP}, \text{VIX}\right)$ peaks in November 1987 and remains elevated until February 1988. Overall, these episodes suggest that while a simultaneous tightening of both $\varphi\left(\text{EBP}\right)$ and $\varphi\left(\text{VIX}\right)$ 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.

A.3 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.3 we plot 8 commonly used broad measures of global financial conditions together 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.3 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.3 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.3 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.3 and Table A.3 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 of Miranda-Agrippino and Rey (2015).[26] 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.4 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

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

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 $b\,(f)$.

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

Figure A.4 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.5). 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's 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

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

Figure A.6 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.6 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.4 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.7 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

$$\log s^{\$}_{b(f),t} = \alpha_I + \alpha_{CR} + \gamma \log \mathrm{EDF}_{f,t-1} + \vec{\beta}'_{\mathrm{bond}} X_{bond,t} + \vec{\beta}'_{\mathrm{firm}} X_{firm,t-1} + \epsilon_{b(f),t}, \tag{A.3}$$

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.10 reports the estimated coefficients from regression (A.3) 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.8 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.

Table A.1: Sample summary statistics. This table reports the sample summary statistics for the bond characteristics by currency, averaged over the sample period, January 1986 – 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 1986 – 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	3,979	446	126	4.4	1.4	6.5	3.2	0.24
Dom. USD, ICE	20,571	2,557	608	10.5	2.5	6.8	4.1	0.74
Fgn USD	7,875	1,622	718	9.0	2.6	5.9	4.0	0.70
EUR	5,564	961	830	4.1	1.6	5.3	3.7	0.25
GBP	907	324	554	8.5	1.8	7.6	3.7	0.22
JPY	1,097	95	312	0.3	1.0	5.5	2.7	0.18
CAD	1,715	237	261	3.4	1.6	7.6	3.5	0.17
AUD	482	119	214	2.0	1.2	3.9	3.1	0.14

Table A.2: Out-of-sample MSE for best-performing factor construction alternatives. This table compares the out-of-sample forecast errors of the outlier-robust 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 out-of-sample MSE 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 $\mathbb{E}_{t^*}[Rx_{i,t^*+3}]$ and compare it against the realized return $Rx_{i,t*+3}$, 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 up to April 2009). For each basis function construction approach, we allow up to 6 interior knots, with the two extreme knots placed at the 10th and 90th percentile of the distribution of the corresponding variable and any additional knots spaced evenly in that range, and reduced rank up to 3, but require that the MSE improvement from each additional factor is at least 5%.

(a) Full bivariate bases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RMSE	121.50	130.28	118.35	126.18	117.38	118.45	162.75
Number of factors	1	1	1	1	1	1	1
CS degree	1	2	1	2	1	3	3
Number of CS knots	0	0	0	6	0	6	2
VIX degree	1	1	2	2	3	1	3
Number of VIX knots	1	0	1	0	0	2	5

(b) No interaction bases

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RMSE	121.78	124.24	119.79	126.74	117.80	126.91	124.49
Number of factors	1	1	1	1	1	1	1
CS degree	1	2	1	2	1	3	3
Number of CS knots	0	0	0	0	0	0	0
VIX degree	1	1	2	2	3	1	3
Number of VIX knots	1	1	6	6	0	2	0

(c) Univariate bases

	(A) φ (EBP)			(B) φ (VIX)		
	(1)	(2)	(3)	(4)	(5)	(6)
RMSE	119.82	124.05	131.73	128.78	128.54	125.81
Number of factors	1	1	1	1	1	1
CS degree	1	2	3	0	0	0
Number of CS knots	1	0	0	0	0	0
VIX degree	0	0	0	1	2	3
Number of VIX knots	0	0	0	3	6	0

Table A.3: 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 2 for 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	0.76***	0.74***	0.74***
G-Z spread	0.77***	0.68***	0.53***
φ (VIX)	0.89***	0.85***	0.92***
φ (EBP)	0.84***	0.77***	0.56***
EBP	0.85***	0.73***	0.57***
Predicted G-Z spread	0.22***	0.13**	0.34***
USD TWI	0.20***	-0.07	-0.01
GFC (updated)	-0.36***	-0.27***	-0.37***
U. S. GS FCI	0.50***	0.34***	0.40***
Global GS FCI	0.60***		0.41***

Table A.4: Portfolio-level return predictability. This table reports the estimated coefficients from the regression of 3-month excess holding period returns on the global credit factor. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) World	(2) U.S.	(3) AE, ex U.S.	(4) EM
GCC	1.13	1.08	1.29	1.12
	(0.13)***	(0.12)***	(0.17)***	(0.17)***
BBB × GCC	-0.56	-0.50	-0.77	-0.23
	(0.16)***	(0.17)***	(0.19)***	(0.22)
A × GCC	-0.82	-0.76	-1.00	-0.47
	(0.14)***	(0.14)***	(0.17)***	(0.25)*
AAA/AA × GCC	-0.93	-0.82	-1.15	
	(0.14)***	(0.15)***	(0.17)***	
Total R^2	30.2	27.7	39.4	24.8
Time series R^2	19.4	19.5	21.6	23.4
Cross section R^2	3.9	3.2	4.9	0.8
Market timing R^2	7.0	5.1	13.0	0.6
N. of obs	1,872	1,872	1,296	967

Table A.5: Out-of-sample bond-level return predictability. This table reports the estimated coefficients from the regression of 3-month excess holding period returns on the global credit factor. For the out-of-sample exercise, we split our ICE Global Indices monthly sample from January 1998 to December 2024 into an in-sample period $t = 1, \ldots, (t^* - 1)$ and an out-of-sample period $t = t^*, \ldots, T$. We reestimate the return predictability regression using data through $t^* - 1$, and use the estimated coefficients to predict returns for the next period rx_{i,t^*+3}. We start our out-of-sample evaluation in January 2002 (predicting returns up to April 2002). High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) U.S	(3) AE, ex U.S.	(4) EM
GCC	1.21	1.15	1.33	1.56
	(0.02)***	(0.02)***	(0.05)***	(0.07)***
BBB × GCC	-0.58	-0.51	-0.78	-0.64
	(0.02)***	(0.02)***	(0.05)***	(0.08)***
A × GCC	-0.86	-0.78	-1.03	-1.00
	(0.02)***	(0.02)***	(0.05)***	(0.08)***
AAA/AA × GCC	-1.04	-0.84	-1.24	
	(0.02)***	(0.02)***	(0.05)***	
In-sample R^2	9.7	9.6	9.4	13.1
Out-of-sample R^2	6.9	6.8	6.9	9.2
N. of obs	2,156,838	1,229,609	800,004	127,225
N. bonds	37,373	21,883	14,252	2,434

Table A.6: Bond-level return predictability by rating. This table reports the estimated coefficients from the regression of 3-month excess holding period returns on the global credit factor, with exposures parametrized by a country type dummy. Bonds issued by U.S. firms are the omitted category. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) AAA/AA	(2) A	(3) BBB	(4) HY
GCC	0.29	0.37	0.64	1.15
	(0.01)***	(0.01)***	(0.01)***	(0.02)***
AE, ex U.S. $\times$ GCC	-0.20	-0.07	-0.08	0.18
	(0.01)***	(0.01)***	(0.02)***	(0.05)***
EM $\times$ GCC		0.20	0.29	0.41
		(0.04)***	(0.04)***	(0.08)***
Total R^2	4.6	9.4	9.5	8.3
Time series R^2	4.3	9.4	9.3	8.3
Cross section R^2	-0.0	0.0	0.0	0.0
Market timing R^2	0.3	0.0	0.1	-0.0
N. of obs	222,390	725,570	943,706	485,138
N. bonds	4,739	14,670	18,869	12,181

Table A.7: Bond-level return predictability with other characteristics. This table reports the estimated coefficients from the regression of 3-month excess holding period returns on the global credit factor, with exposures parametrized as a function of spreads, duration, and volatility of returns over the prior 12 months. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) U.S.	(3) AE, ex U.S.	(4) EM
GCC	-0.55	-0.57	-0.36	-0.47
	(0.01)***	(0.02)***	(0.03)***	(0.05)***
Spread × GCC	0.16	0.16	0.12	0.12
	(0.00)***	(0.00)***	(0.01)***	(0.01)***
Duration × GCC	0.06	0.07	0.03	0.07
	(0.00)***	(0.00)***	(0.00)***	(0.01)***
Return vol × GCC	0.01	0.01	0.39	0.45
	(0.01)***	(0.00)***	(0.09)***	(0.08)***
Total R^2	16.5	16.7	19.4	21.6
Time series R^2	2.4	2.7	1.9	5.9
Cross section R^2	2.8	2.7	3.8	3.5
Market timing R^2	11.3	11.3	13.7	12.3
N. of obs	2,338,014	1,426,914	786,206	124,894
N. bonds	40,102	24,618	14,239	2,428

Table A.8: Bond-level return predictability using GCC constructions targeting alternative portfolios. This table reports the estimated coefficients from the regression of 3-month excess holding period returns on the global credit factor, with exposures parametrized by a rating dummy. Each column corresponds to the factor targeting an alternative set of portfolios. High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Baseline	(2) U.S. portfolios	(3) AE ex U.S. portfolios	(4) EM portfolios
FCI	1.21	1.37	0.89	5.98
	(0.02)***	(0.02)***	(0.02)***	(0.10)***
BBB × FCI	-0.59	-0.67	-0.43	-2.78
	(0.02)***	(0.02)***	(0.02)***	(0.11)***
A × FCI	-0.87	-0.98	-0.64	-4.23
	(0.02)***	(0.02)***	(0.02)***	(0.11)***
AAA/AA × FCI	-1.04	-1.18	-0.77	-5.17
	(0.02)***	(0.02)***	(0.02)***	(0.11)***
Total R^2	9.3	9.4	9.6	8.6
Due to FCI var	6.9	6.9	7.2	6.5
Cross section R^2	1.0	0.9	0.8	0.7
Due to cov FCI, chars	1.5	1.5	1.6	1.4
N. of obs	2,376,804	2,376,804	2,376,804	2,376,804
N. bonds	40,103	40,103	40,103	40,103

Table A.9: Bond-level return predictability using GCC constructed with European predictors
This table reports the estimated coefficients from the regression of 3-month excess holding period returns on the global credit factor constructed using VSTOXX and average EBP across France, Germany, Italy, Spain, Belgium, Netherlands, Finland, and Ireland. High yield bonds are the omitted category. R^2 reported in percent. Standard errors clustered at the bond level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) U.S.	(3) AE, ex U.S.	(4) EM
Global credit	1.08	1.05	1.11	1.34
	(0.02)***	(0.02)***	(0.04)***	(0.05)***
BBB × Global credit	-0.49	-0.43	-0.59	-0.54
	(0.02)***	(0.02)***	(0.04)***	(0.06)***
A × Global credit	-0.76	-0.69	-0.83	-0.83
	(0.02)***	(0.02)***	(0.04)***	(0.06)***
AAA/AA × Global credit	-0.91	-0.75	-1.02	
	(0.02)***	(0.02)***	(0.04)***	
Total R^2	10.1	10.1	9.5	13.3
Time series R^2	7.8	8.2	7.0	11.8
Cross section R^2	0.7	0.6	0.9	0.6
Market timing R^2	1.5	1.3	1.6	1.0
N. of obs	2,119,444	1,201,655	790,840	126,949
N. bonds	37,119	21,638	14,222	2,432

Table A.10: 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

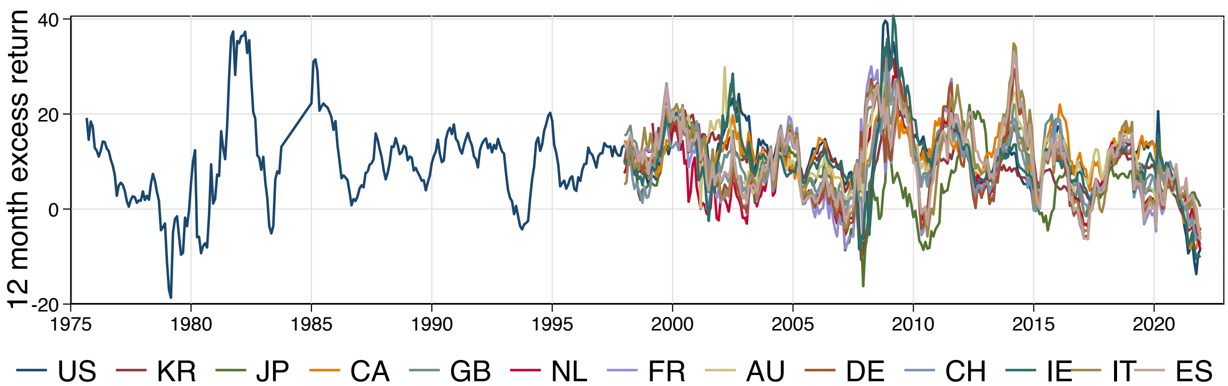
	US	KR	JP	CA	GB	NL	FR	TW	AU	DE	CH	IE	IT	ES
Log EDF	0.13	0.13	0.16	0.13	0.13	0.09	0.16	0.11	0.20	0.13	0.18	0.16	0.11	0.16
	(0.00)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.03)***	(0.02)***	(0.01)***	(0.02)***
Sub in home country	0.04	0.25	0.09	0.02	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. 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 in 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

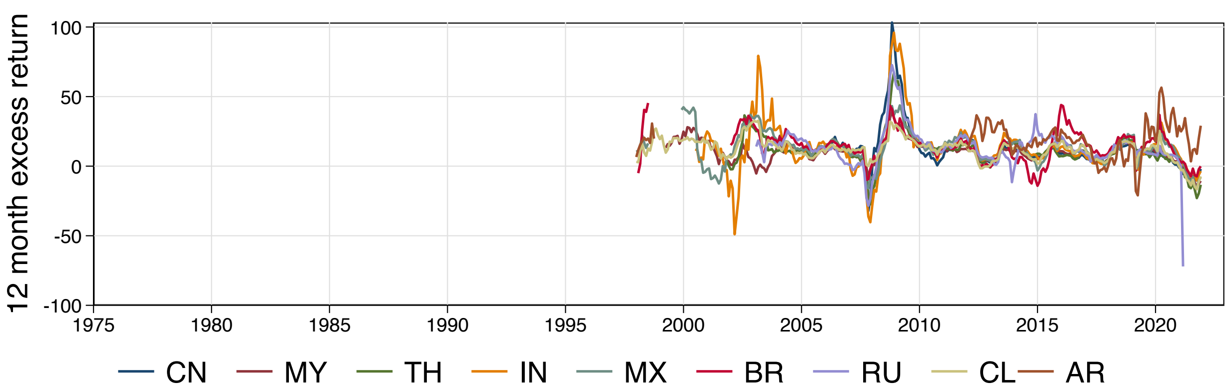


Figure A.2. Comparing the global credit factor to univariate factors. This figure plots the comparison between the global credit factor and the factors extracted from credit spreads and VIX separately. To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations.

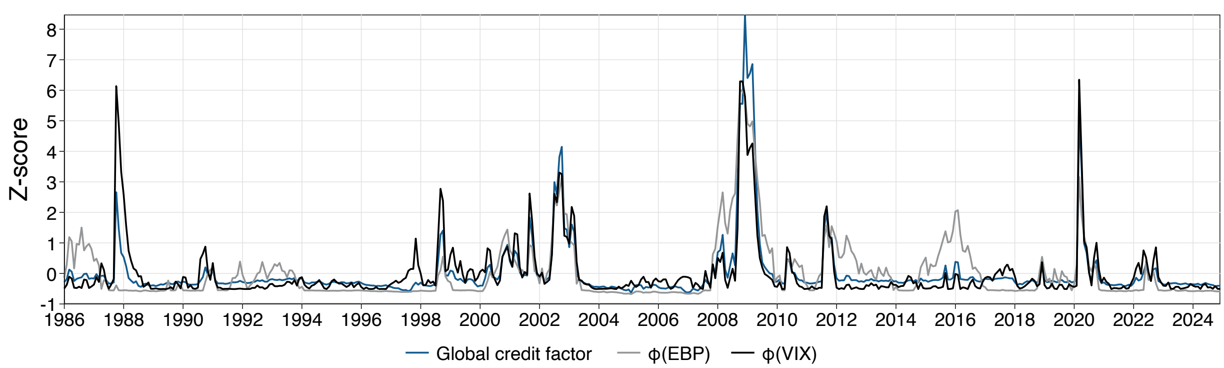
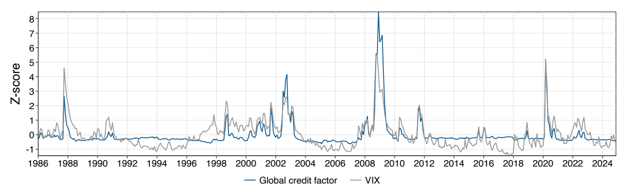
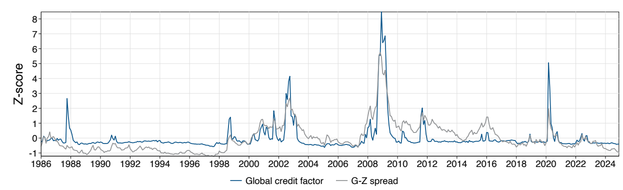


Figure A.3. Comparison to other variables. This figure plots the time series of the global credit factor estimated by reduced-rank regression against commonly used measures of financial conditions: VXO/VIX, Gilchrist and Zakrajšek (2012) "G-Z" spread and excess bond premium (EBP), the 12-month change 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.

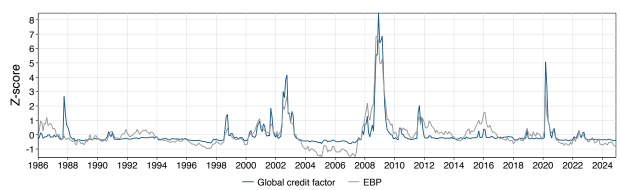
(a) VXO/VIX



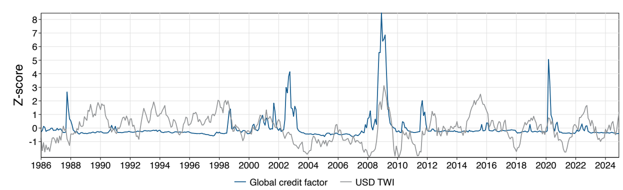
(b) GZ-spread



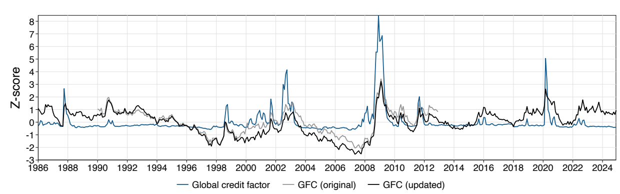
(c) EBP



(d) Broad dollar index



(e) GFC (original and updated)



(f) GS FCI and Global GS FCI

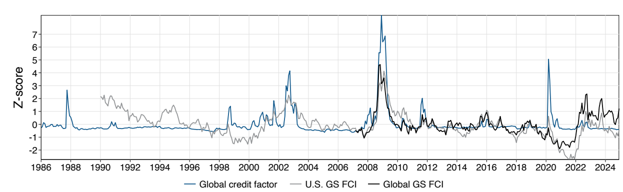
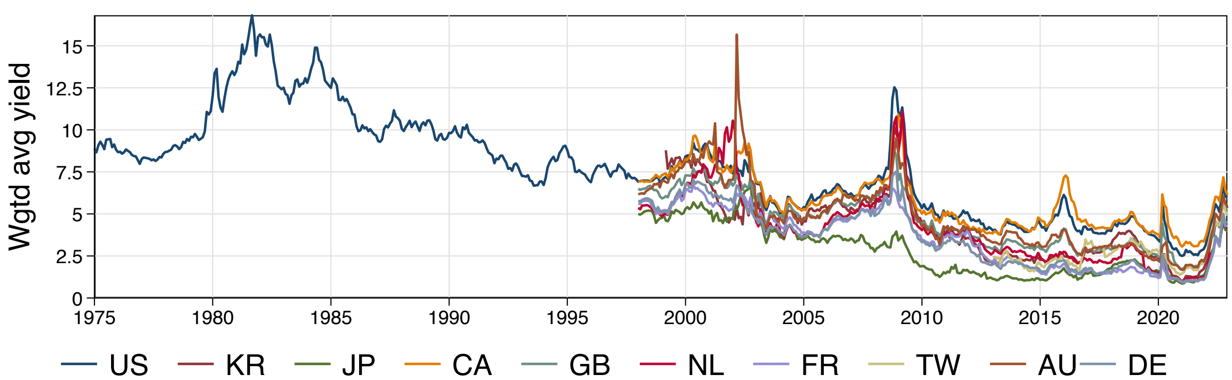


Figure A.4. Raw secondary market quote data. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) yields quoted in ICE for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, 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

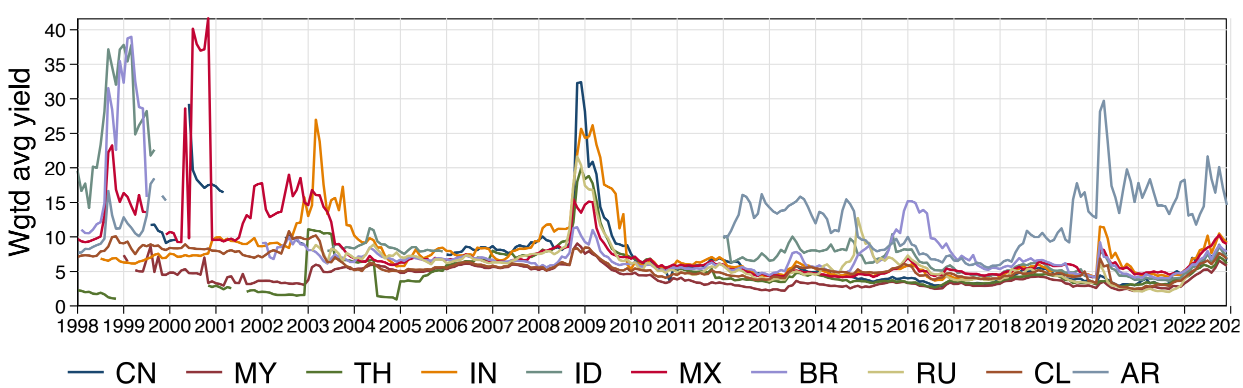
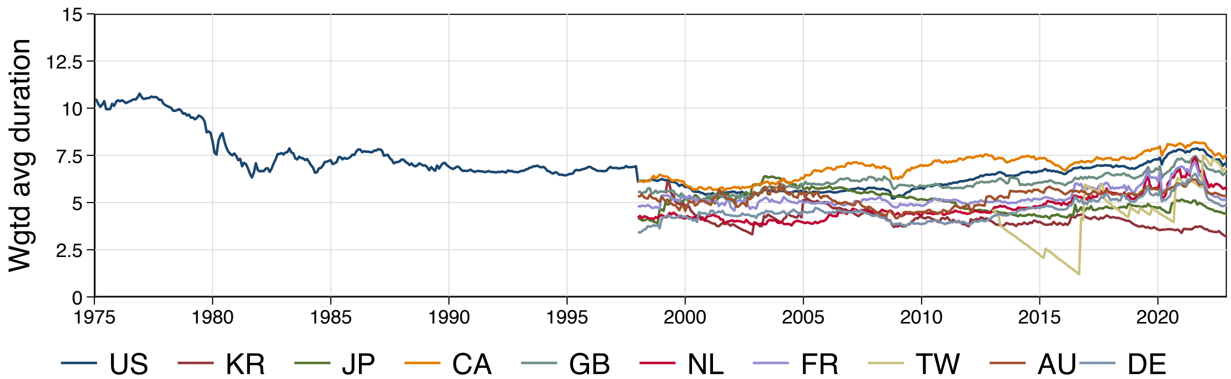


Figure A.5. Secondary market duration data. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) duration for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining 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

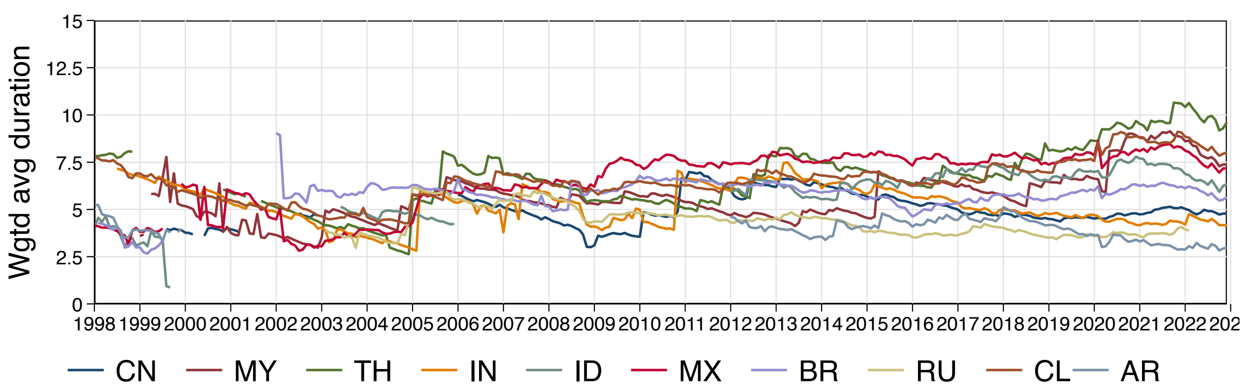


Figure A.6. Average differential to USD credit spreads. This figure plots the time series of the average credit spread between non-USD denominated bonds and USD denominated non-financial corporate, senior fixed-coupon bonds. Average credit spreads estimated from repeated cross-sectional regressions of duration-adjusted credit spreads for firms with bonds outstanding in multiple currencies on currency, firm, and rating fixed effects.

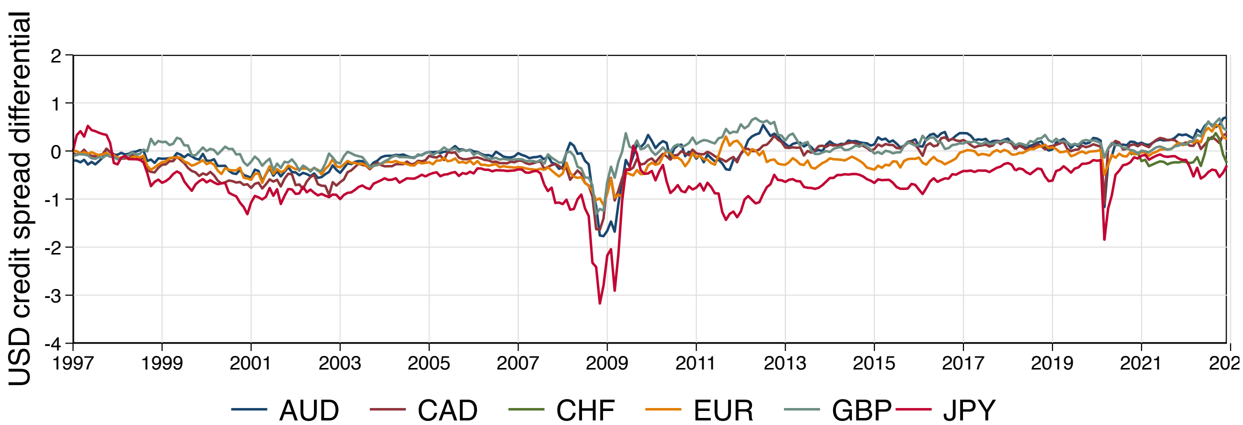
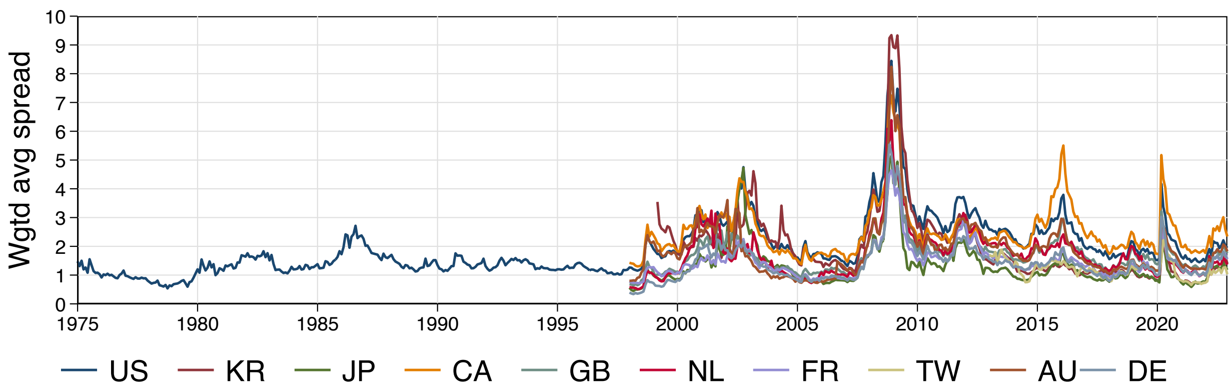


Figure A.7. Secondary market duration-matched, currency-adjusted spreads. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) duration-matched, currency-adjusted spreads for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 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

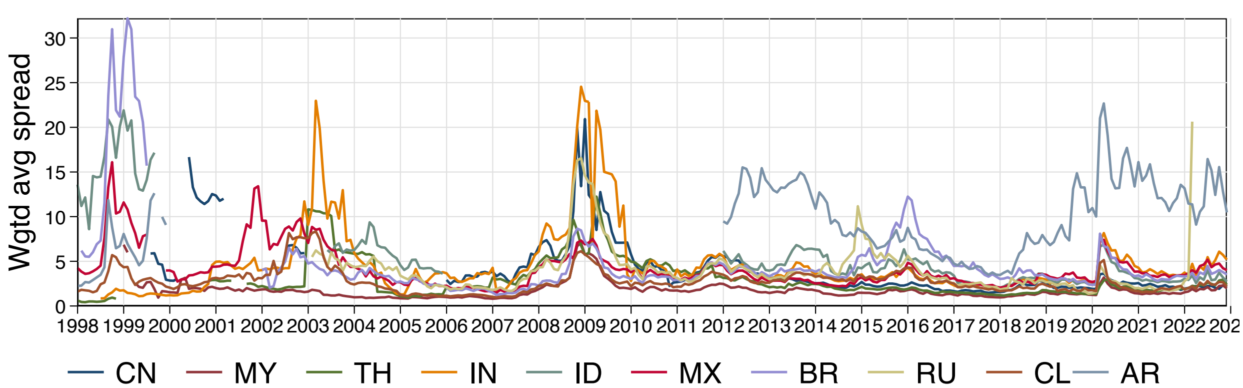
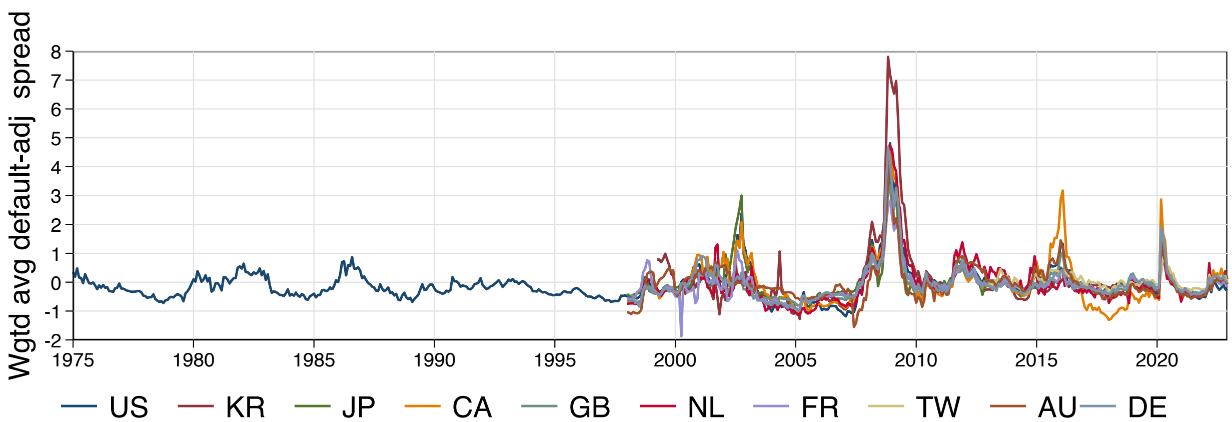


Figure A.8. Estimated default-adjusted spreads. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) default-adjusted credit spreads for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging 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

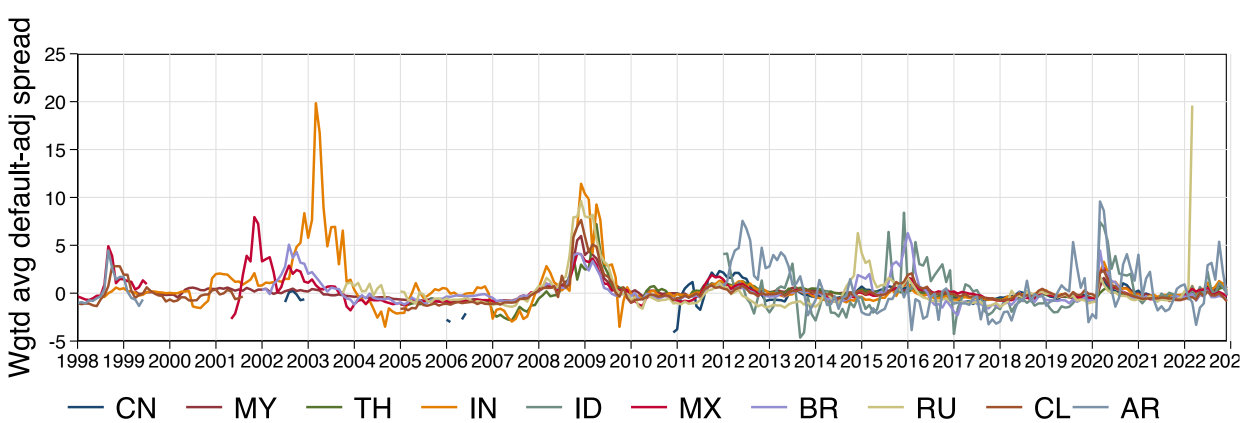
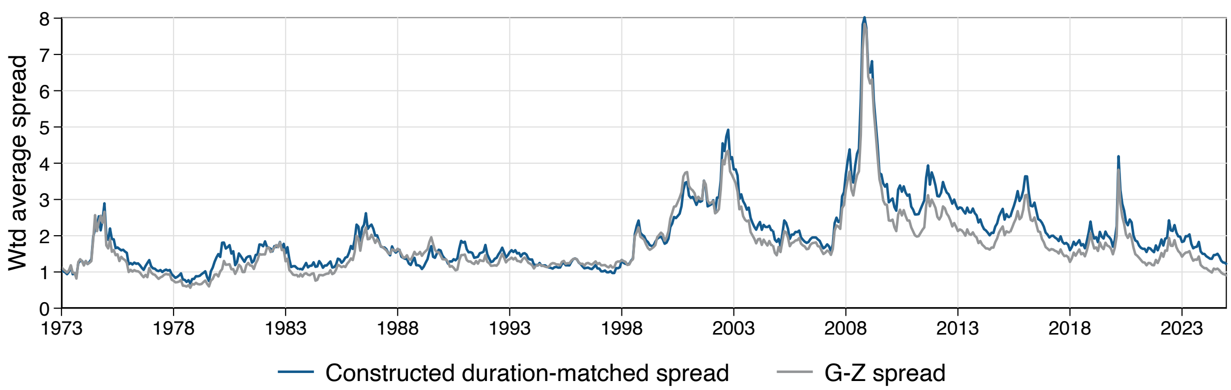


Figure A.9. Comparison to G-Z series. This figure plots the time-series of U. S. average duration-adjusted and default-adjusted credit spreads in our sample versus the Gilchrist and Zakrajšek (2012) spreads..

(a) Duration-matched spread



(b) Default-adjusted spread