The Global Credit Cycle*

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Abstract

We document a global credit cycle that generates predictable comovement in corporate bond returns worldwide. Using a large panel of international corporate bonds, we construct a single factor as a nonlinear function of credit spreads, equity market volatility, and their interactions. The global credit factor explains up to 13% of in-sample and up to 8% of out-of-sample variation in bond-level three-month-ahead returns. Unlike broader measures of global financial conditions, the global credit factor simultaneously captures time-series return predictability and cross-sectional differences in risk exposures across ratings, currencies, and countries. Tighter global credit conditions are associated with deteriorations in local credit conditions and outflows from global bond funds. Taken together, our results are consistent with the factor proxying for a common, time-varying global price of credit risk.

JEL codes: F30, F44, G15, G12

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1 Introduction

With \$19 trillion outstanding as of the end of 2024, the global corporate bond market is both a large investment asset class and a vital source of funding for nonfinancial firms.[1] Given the size of this market, a broad portfolio of corporate bonds would be expected to be well diversified. Yet, in 37% of months between 1998 and 2024, more than 80% of bonds in the ICE Global Bond Indices—a global portfolio with over 10,000 constituents spanning diverse industries, credit ratings, and regions—moved in the same direction, suggesting a large degree of synchronization. In this paper, we uncover a global credit cycle in bond risk premia and show that it generates predictable comovement in bond prices globally.

We construct a global credit factor and document that it explains up to 13% of variation in three-month-ahead bond-level returns and up to 40% of variation in portfolio-level returns in a global panel of corporate bonds. Building on Adrian et al. (2019a), we estimate the global credit factor using a nonparametric method that relates expected returns on credit-rating-sorted portfolios of advanced economy corporate bonds to a nonlinear function of U. S. equity market volatility and U. S. credit spreads. 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 a nonlinear factor predicts corporate bond portfolios in both the time series and the cross section. The factor incorporates information from both U. S. equity market volatility (as measured by the VIX), U. S. credit spreads (as measured by the Gilchrist and Zakrajšek, 2012, default-adjusted spread, EBP), and, importantly, their interactions; specifications that use only the VIX *or* U. S. credit spreads are systematically rejected by the data. The global credit factor has low correlation with alternative proxies for the global financial cycle, including the VIX itself, the Miranda-Agrippino et al. (2020) global

[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.

financial cycle factor, and the Goldman Sachs U. S. financial conditions index, indicating that the global *credit* cycle is distinct from the global *financial* cycle.

Several features of the evidence are consistent with the global credit factor proxying for a common, time-varying price of credit risk. The factor forecasts bond-level returns around the world, with exposures increasing in bond and country risk. A one standard deviation increase in the global price of credit risk increases risk premia on high yield bonds by 11.7 percentage points but the risk premia on AAA/AA-rated bonds by only 1.5 percentage points. The global credit factor explains up to 13.3% of overall variation in corporate bond returns, with 11.7% of that due to time-series variation in the factor and 1.5% due to differential exposures in the cross section. While the latter component is modest in magnitude, it confirms that the factor is not merely capturing aggregate market conditions: bonds with different characteristics load differently on the same global factor, consistent with heterogeneous exposures to credit risk. Furthermore, the R^2s obtained in an out-of-sample exercise, while smaller, remain substantial, confirming that the global credit factor provides reasonable return forecasts in real time.

We document that the credit factor is truly global. The factor predicts returns across different regions of the world, bonds denominated in different currencies, and individual countries. Furthermore, the time series of the factor as well as the factor's ability to predict bond returns globally is robust to either targeting alternative portfolios that exclude the U. S. or using non-U. S. predictors. Factors constructed to target only emerging market portfolios or portfolios of bonds in advanced economies excluding the U. S. or relying on European proxies for volatility and credit spreads are highly correlated with our baseline factor.

Three key features of the factor contribute to its predictive power: nonlinearities, information from both the EBP and the VIX, and interactions between the two. First, both the linear EBP and the linear VIX substantially underperform their nonlinear counterparts in predicting corporate bond returns, highlighting the role of nonlinearities. Second, univariate nonlinear functions of either the EBP or the VIX underperform the global credit factor, suggesting that information from both the EBP and the VIX is important for overall performance. Finally, a bivariate factor specification with no interactions between the EBP and the VIX still underperforms the global credit factor. Particularly during periods of loose credit conditions, a factor that allows for interactions between the EBP and the VIX 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 et al. (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 has information that is simultaneously relevant for both the time-series and the cross-sectional variation in the panel of corporate bond returns. That is, among the set of metrics of global financial conditions considered, the global credit factor is the only one that captures both the systematic variation in corporate bond returns and the cross-sectional differential exposure to that systematic risk. Consistent with studies that document a diminishing role for global factors (as proxied by the VIX) in the post-Global Financial Crisis (GFC) period, we also find a diminishing role of the VIX. In contrast, our factor maintains its predictive power, especially in terms of the cross-sectional R^2.

Importantly, we also provide initial evidence of the real costs of the global credit cycle. Large tightenings in the factor predict a prolonged widening of credit spreads and a substantial increase in default probabilities, especially for riskier firms. We further explore the relationship between the global credit factor constructed in this paper and real (local) costs 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' investments flow out of global funds and expected returns increase. Moreover, funds with riskier investment mandates are more sensitive to changes in the global price of credit risk. Thus, institutional investors with broad investment portfolios are exposed to the same fluctuations in the global price of credit risk as individual bonds, suggesting that the return patterns we document are not fully diversifiable.

This paper is related to several strands of literature. First, a number of papers have studied the factor structure of corporate bond returns in the U. S. (Israel et al., 2018; Chung et al., 2019; Bali et al., 2021; He et al., 2022; Dang et al., 2023; Kelly et al., 2023; Dickerson et al., 2023; Elkamhi et al., 2024; Ghaderi et al., 2024; Bartram et al., 2025; Dickerson et al., forthcoming), arguing that corporate bond returns can be described by a small number of aggregate factors. In the cross section, bonds exposed to either more credit (Gebhardt et al., 2005; Van Binsbergen et al., 2025) or liquidity (Lin et al., 2011) risk have higher average returns.[2]

In the international context, Bekaert and De Santis (2021) and Bekaert et al. (2024) study the role of global and local factors in corporate bond returns around the world. Similar to the results for the U. S., Valenzuela (2016) and Li et al. (2022) document a role for illiquidity premia in the cross section of international corporate bond returns, especially in emerging markets. We contribute to the literature on bond returns in both the U. S. and the international context by documenting that global corporate bond returns are predictable—even at the bond level and at short horizons—by a global factor proxying for the global price of risk. We further show that there is heterogeneity in exposures to the factor along a number of dimensions including bond currency, bond duration, bond return volatility, and country type.

[2] Early papers include Blume et al. (1991), Fama and French (1993), and Elton et al. (1995).

Second, we contribute to the literature studying nonlinearities in risk prices. Adrian et al. (2019a) show that a price of risk constructed as a nonlinear function of the VIX captures “flight-to-safety” between U. S. equities and Treasuries, while Adrian et al. (2019b) extend the flight-to-safety intuition to global equity and sovereign bond markets. Our paper contributes to this literature by documenting that, in the global corporate bond market, the VIX alone is not sufficient to describe the global price of credit risk. Instead, information from credit spreads is crucial to look through temporary VIX volatility during periods of calm credit markets. Our results thus point to different types of financial intermediaries playing a role in the global pricing of credit risk.

Relatedly, Bali et al. (2022) and Bell et al. (2024) use machine learning techniques to forecast U. S. corporate bond returns from a large set of bond and firm characteristics. Our approach is complementary but distinct: rather than maximizing predictive accuracy from a high-dimensional feature set, we focus on identifying a low-dimensional, economically motivated factor—rooted in the interaction of equity volatility and credit spreads—that has a structural interpretation through the lens of intermediary-based asset pricing. The parsimony of our factor is a feature, not a limitation: it generates interpretable variation that can be linked to fund flows, real credit conditions, and the broader global financial cycle.

Third, our paper contributes to the literature documenting a large degree of comovement in asset prices around the globe. Rey (2013) and Miranda-Agrippino and Rey (2015, 2020) document the existence of a global financial cycle in asset prices, capital flows, and credit growth, the role of U. S. monetary policy as the driver of the cycle, and its implications for other countries' monetary policy independence. These studies, as well as the large subsequent literature,[3] document a tight relationship between the global financial cycle and measures of global risk aversion such as the VIX. We contribute to this literature by documenting that corporate bond returns can be *forecasted* by a common factor, expanding our understanding of the global financial cycle beyond contemporaneous comovements. We also show that our

[3] Miranda-Agrippino and Rey (2022) provide a comprehensive review of this literature.

proxy for the global price of risk substantially outperforms other measures of global financial conditions in pricing corporate bonds globally.

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 explore risk premia at the individual bond level. 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 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).[4] The underlying constituents' data include the effective option-adjusted spread and duration of 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,

[4] 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.

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 (see Warga, 1991, for details). As with the ICE global data, the Lehman-Warga Fixed Income Database includes returns, yield-to-maturity, and duration of each bond-month, as well as bond and issuer characteristics, such as issuer industry, coupon type and rate, bond seniority, and call and put provisions.

We follow Boyarchenko and Elias (2023) in merging the secondary market corporate bond quotes with bond characteristics from consolidated SDC Platinum–Mergent FISD, ultimate parent's balance sheet information from consolidated Compustat–Worldscope, 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, for example, financing arms of nonfinancial ultimate parents but exclude bonds issued by nonfinancial subsidiaries of financial ultimate parents.[5] 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+.[6] 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.

[5] We define an ultimate parent as being a nonfinancial corporation if the balance sheet data assign 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 than the financing conditions in the issuer's country.

[6] There are only 120 bonds in the underlying sample issued by firms in emerging markets that are rated above A+, including 55 issued by firms in China and 46 issued by firms in the UAE. These bonds are outliers in the universe of emerging market bonds.

Our final sample includes more than 2.3 million bond-month return observations for over 40,000 unique bonds across 50 countries, from January 1986 to December 2024. The number of bonds and bond-issuing ultimate parents increases over time, with the largest number of bonds issued in USD, by both domestic and foreign ultimate parents.[7]

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 $rx_{i,t+1}$ is computed as:

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

where S^c_t is the spot exchange rate of currency c with respect to the USD at date t and $r^{tsy}_{\mathrm{3m},t+1}$ 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 rate risk and exchange rate 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 a duration risk component:

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

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

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. For the period 1986–1990, when the VIX is not available, we use the VXO instead, adjusted (from a linear regression in the overlapping sample between VIX and VXO) to match the level of the VIX in 1990. 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.[8]

Finally, we rely on Emerging Portfolio Fund Research (EPFR) for data on returns and 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 the geographical location of funds' investments. Our sample covers monthly observations for over 10,000 unique funds in the period 2002–2024.

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 use the insights from these

[8] Figure A.2 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.

models to parametrize the global credit factor as a nonlinear function of the VIX and U.S. credit spreads, relying on reduced-rank regressions to identify the nonlinear function that maximizes out-of-sample return predictability.

3.1 Motivation

We are interested in measuring risk premia reflected in international corporate bond returns, and, in particular, the risk prices associated with the exposures for which corporate bond investors demand compensation. While risk premia are not directly observable, a large literature (e.g., Ferson and Harvey, 1991; Lettau and Ludvigson, 2001; Duffee, 2002; Adrian et al., 2015) has used return predictability regressions to measure time variation in risk premia.

The starting point for this approach is the assumption of no arbitrage and the existence of an equilibrium pricing kernel, with a corresponding vector of prices of risk λ_t and (potentially) time-varying exposures $b_{i,t}$ of bond i to the risks priced by λ_t. With these assumptions, the equilibrium expected excess return on bond i is given by:

$$\mathbb{E}_t \left[rx_{i,t+1} \right] = b_{i,t} \lambda_t.$$

While *expected* excess returns are not directly observable, excess returns are, which we can decompose into an expected and an unexpected component:

$$rx_{i,t+1} = \mathbb{E}_t \left[rx_{i,t+1} \right] + \underbrace{\left(rx_{i,t+1} - \mathbb{E}_t \left[rx_{i,t+1} \right] \right)}_{\equiv \epsilon_{i,t+1}} = b_{i,t} \lambda_t + \epsilon_{i,t+1}. \tag{2}$$

Equation (2) thus relates future return realizations to information observable at time t.

The nonparametric approach we pursue in this paper allows us to estimate λ_t under general assumptions, without specifying the time-series properties of the factors driving variation in λ_t over time or assuming a specific maximization problem underlying the equilibrium pricing kernel. Instead, we represent the equilibrium price(s) of risk as a potentially nonlinear function of observable proxies for aggregate risk. While disentangling the precise mechanisms that link the equilibrium price of risk to the marginal utilities of particular investors in global credit markets is beyond the scope of this paper, it is nonetheless instructive to consider how a nonlinear relationship between risks and risk aversion may arise.

Recent literature has advocated for an intermediary-based view of asset prices. That literature argues that intermediaries, not households, are the marginal investors in financial markets, so that equilibrium asset prices are determined by the pricing kernel of the marginal financial intermediary.[9] Unlike households, whose equilibrium pricing kernel is determined by preferences, the effective risk aversion of financial intermediaries is determined by balance sheet constraints, which may be imposed by the regulatory environment, risk management considerations, or the preferences of end investors. The occasionally binding nature of such constraints generates nonlinearities in the relationship between aggregate risk and aggregate effective risk aversion and, thus, aggregate prices of risk. To the extent that more than one type of financial intermediary is active in the global credit market at the same time, we would further expect the equilibrium price of risk to reflect the marginal cost of balance sheet constraints of more than one intermediary.[10]

Which aggregate measures of risk best capture expected excess returns in corporate bond markets? We assume that the nonlinear relationship between equilibrium risk prices 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; in other words, the

[9] 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).

[10] Models with more than one intermediary include Vayanos and Vila (2009), Adrian and Boyarchenko (2013), Vayanos and Vila (2021), and Coimbra and Rey (2024).

expected excess returns on corporate bonds are related to the level of credit spreads (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 risky assets, measured either using the VIX or realized volatility. To capture these different facets of risk aversion (or constraints of different types of intermediaries), our empirical procedure allows expected excess returns to load on both the U. S. EBP and the VIX.

3.2 The global credit factor

We estimate nonparametrically the common component of expected excess returns as a function of credit spreads and volatility, $\varphi\left(cs_t, \mathrm{VIX}_t\right) \propto \lambda_t$, 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 highly flexible and allows for a flexible nonlinear relationship between proxies for global risk aversion and expected excess returns. We estimate the global credit factor—which proxies for the global price of credit risk—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 among 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

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

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]

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 in September 2008. In the run-up to the global financial crisis, the level of the global credit factor is historically low, predicting very 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—a high price of credit risk—around the world.

Is the estimate of the global credit factor 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 keeping the predictors the same.[13] Figure 2a shows that the estimated time series of the global credit factor 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 bonds of firms in emerging markets. The results in Figure 2a thus show that the relationship between the global credit factor and predictors is stable across different sets of target portfolios used for the estimation.

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

[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.

In our second exercise, we examine instead how the choice of predictors affects the estimated time series of the global credit factor. To do so, we replace our U. S.-based predictors with their European counterparts. In particular, we replace the VIX with the Eurex option-implied volatility index (VSTOXX), and the U. S. EBP with the weighted average default-adjusted spread on corporate bonds issued by firms in the same eight countries as represented in the VSTOXX.[14] We then use the out-of-sample mean-squared error criterion to select the optimal factor specification for these alternative European predictors, targeting predictability of the baseline advanced economy portfolios. Figure 2b shows that the factor estimated using European predictors is very similar to the global credit factor estimated using 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 our baseline factor.

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 credit factor that are remarkably similar to our baseline factor.

We illustrate the relationship between the global credit factor, the VIX, and credit spreads in Figure 3. Starting with Figure 3a, 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 (8) 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

We conclude this section with two cross-sectional asset pricing exercises that justify our interpretation of $\varphi\left(cs_t, \mathrm{VIX}_t\right)$ as the global price of risk in global corporate bond markets. We use the implications of asset pricing theory, which links the exposures $b_{i,t}$ in equation (2) to factor loadings. For example, if the equilibrium pricing kernel has prices of risk that are affine in the global credit factor (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, λ_1 is the coefficient that determines how prices of risk vary as a function of the global credit factor, and $\alpha_{i,h}$ captures deviations from no arbitrage. 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 $b_i = \beta_i \lambda_1$.

In our first test, for the four advanced economy portfolios used to construct the global credit factor, we estimate the unrestricted panel forecasting relationship $rx_{i,t+h} = a_i + b_i \varphi\left(cs_t, \mathrm{VIX}_t\right) + \epsilon_{i,t+h}$ by SRR regression. We then jointly estimate the prices of risk and risk factor exposures for these portfolios using $rx_{i,t+h} = \alpha_i + \beta_i\left(\lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)\right) + \beta_i u_{t+h} + \epsilon_{i,t+h}$, where $\varphi\left(cs_t, \mathrm{VIX}_t\right)$ is taken as given and u_{t+h} is the error from the projection of

$\varphi(cs_{t+h}, \mathrm{VIX}_{t+h})$ on $\varphi(cs_t, \mathrm{VIX}_t)$ and a constant. 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 (four U. S. portfolios, four portfolios of advanced economies 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 model that restricts loadings on the global credit factor to $\beta_i \lambda_1$ result 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 risk premia over the global credit cycle

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 use the full richness of our bond-level data to explore further the relationship between expected returns—risk premia—and the estimated GCC. Throughout this section, we maintain the assumption of a pricing kernel affine in the factor as given by equation (3), so that the realized excess return process is given by:

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

For parsimony, we further assume that the loadings $\beta_{i,t}$ on the price of risk $\lambda_0+\lambda_1\varphi\left(cs_t, \mathrm{VIX}_t\right)$ are constant within a credit rating category, so that we can simplify the above to:

$$rx_{i,t+h} = \beta\left(\lambda_0 + \lambda_1\varphi\left(cs_t, \mathrm{VIX}_t\right)\right) + \beta_r\left(\lambda_0 + \lambda_1\varphi\left(cs_t, \mathrm{VIX}_t\right)\right) \times \mathbb{1}_{r,i,t} + \epsilon_{i,t+h}, \tag{4}$$

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

Throughout this section, we focus on the population R^2 as our measure of model 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 population 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 population R^2 as:

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

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 (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 in column 1. In order to further explore the global nature of the factor, we also split the sample by region, in columns 2–4, and currency, in columns 5–6.

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 0.68 on average for high yield bonds (the omitted category), to 0.35 and 0.20 for BBB-rated and A-rated bonds, respectively, and further to 0.09 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 11.7 percentage point (p.p.) increase in annualized three-month-ahead expected excess returns on high yield bonds, a 6 p.p. increase in expected excess returns on BBB-rated bonds, a 3.4 p.p. increase in expected excess returns on A-rated bonds, and a 1.5 p.p. increase in expected excess returns on AAA/AA-rated bonds. These represent meaningful changes relative to unconditional average excess returns of 7.96%, 2.79%, 1.25%, and 0.71% across high yield, BBB-rated, A-rated, and AAA/AA-rated bonds, respectively.[15]

[15] Throughout, we use standard errors clustered at the bond level to test for statistical significance. In Appendix Table A.5, we show that our baseline results—both in terms of the statistical significance of the estimated coefficients and the decomposition of the R^2—are unaffected by alternative standard error choices, such as two-way clustering, Driscoll and Kraay (1998) standard errors, or Cameron et al. (2008) wild bootstrap.

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 (column 3) have lower average estimated β with respect to the global credit factor than bonds issued by firms in emerging markets (column 4). 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.[16]

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 9.2% for bonds issued by U. S. firms to 13.3% for bonds issued by firms in emerging markets. 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 70% higher than that of advanced economies. This outperformance is particularly remarkable given that the global credit factor is constructed targeting returns on portfolios of advanced economy bonds only, and reinforces the interpretation of the factor

[16] 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 (see Appendix Table A.7).

as a truly global price of risk.[17]

The final two columns in Table 1 study risk premia across currencies. Comparing columns 5 and 6, we see that USD-denominated bonds have a greater overall exposure to the global credit cycle than bonds denominated in other currencies (0.68 vs. 0.60 point estimate). The cross-rating exposure differential, however, is greater for bonds in non-USD currencies, driven by a greater differential in risk premia around the investment grade cutoff. Indeed, the cross-sectional R^2 is larger for bonds denominated in other currencies (0.7% for USD-denominated vs. 1% for non-USD-denominated), while the time-series R^2 is greater for USD-denominated bonds (7.6% for USD-denominated vs. 6.5% for non-USD-denominated). That is, the global credit factor explains more of the overall variation in returns for USD-denominated bonds, but non-USD bonds have greater differentials in exposures to the global credit factor across credit ratings.[18]

One potential concern with these in-sample results is that they are an artifact of overfitting arising from the flexibility of our approach. We now evaluate the out-of-sample performance of the global credit factor as a predictor of returns. In particular, we construct factor vintages using an expanding out-of-sample approach, with the first vintage constructed using data through December 2008 and each subsequent vintage adding one additional month of data at a time. Each factor vintage is estimated using the same bivariate basis, but with the parameters of the SRR regression reestimated in each sample. We then reestimate the bond-level return predictability regression for each factor vintage using the same subsample as used in constructing the factor vintage and predict the next realization of three-month-

[17] Appendix Table A.10 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.11 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.

[18] We further explore how exposure to the global credit cycle varies across currencies in the context of Appendix Table A.12, discussed in Appendix A.7.

ahead returns. For example, for the original factor vintage, we estimate the bond-level return predictability regression using data through December 2008 and predict bond-level returns as of January 2009 (returns from January to April 2009). We then repeat this exercise, adding one month of observations at a time (and updating to the corresponding factor vintage), and predicting future three-month returns for the first month not used in the estimation.

The out-of-sample R^2 row of Table 1 reports the out-of-sample R^2, computed as the fraction of return variance explained by the predicted returns from the out-of-sample exercise described above. Although lower than the in-sample R^2, the out-of-sample R^2 remains substantial, ranging from around 6% for advanced economies to over 8% for emerging markets. We further illustrate the out-of-sample performance of the global credit factor as a predictor of returns by examining how the estimated coefficients β_r change across different factor vintages. Figure 5 plots the time series of the estimated coefficients from the out-of-sample exercise. Except for the initial few months, the coefficients are remarkably stable over time.

Overall, the out-of-sample R^2 in Table 1 and the coefficient time series in Figure 5 suggest that our estimated global credit factor provides reasonable forecasts in real time and that the relationship between the global credit factor and future realized returns is stable over time. This should alleviate concerns about the risks of overfitting from our bivariate, nonparametric model. In the remainder of the paper, we therefore focus on the full-sample results in which we have more power to discriminate between competing hypotheses.

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 in equation (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 in equation (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* with credit quality (i.e., is higher for higher-rated bonds), 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 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 forecast the cross-section of *credit risk*.[19]

4.2 Contributions to predictability from the EBP and the VIX

The previous section shows that the global credit factor predicts the return due to credit risk for a large panel of corporate bonds. In this subsection, we explore how the 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

[19] In Appendix Table A.13, we further explore whether the global credit factor predicts returns on sovereign bonds and equity indices. The table shows that equity indices have a similar exposure to the global credit factor as high yield bonds, while sovereign bonds have exposures similar to investment grade bonds. For the U. S., the sovereign bond (Treasuries) has the lowest exposure to the global credit factor out of the asset classes considered. For both other advanced economies and emerging markets, the sovereign bond return exposure to the global credit factor is, on average, somewhere between the exposures of BBB and A-rated corporate bonds, likely reflecting the sovereign rating distributions for the countries in the sovereign bond sample. See the discussion in Appendix A.8 for further details.

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,[20] and column 6 uses the optimal *additive* bivariate factor (that is, the bivariate factor that does not allow for interactions between EBP and the VIX). Table 3 shows that the global credit factor outperforms the alternative specifications in terms of overall R^2.

Evaluating each of the three main features of the factor construction in turn,[21] 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 types 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-sectional differences in risk exposures. In contrast, the time-series and cross-sectional 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 expected returns 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

[20] We construct an EBP factor and a VIX factor following the same approach as detailed in Section 3 but with one predictor instead of two.

[21] 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.

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 expected returns tilts the VIX factor toward capturing time-series variation in returns.

Finally, column 6 shows that, when we allow the global credit factor to be nonlinear in both the EBP and the VIX but without interactions between the two, the overall R^2 is still lower than 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 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 by exploring predictive performance 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 additive bivariate factor across periods of tight and loose credit conditions. When credit conditions are tight (columns 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 substantially outperforms both the nonlinear VIX and the additive bivariate factor, with the R^2 more than double for the global credit factor than for either of these alternative specifications. Decomposing the overall R^2 into its components, we see that the time-series R^2 of the global credit factor is substantially higher than those of the alternative specifications. Indeed, the time-series R^2 of the additive bivariate factor during periods of loose credit conditions is negative. While the additive factor has a larger cross-sectional R^2 than the global credit factor, its market-timing R^2 is also negative. 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 or the bivariate factor with no interactions between EBP and the VIX. 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 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 (updated GFCy from Miranda-Agrippino et al., 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 has 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 et al. (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 predict 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.[22] 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 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 15.8% 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 been broadly stable. That is, the lower

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

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 sum of the two R^2 components that rely on cross-sectional differences in exposure—the cross-sectional and the market-timing R^2s—has also halved for the VIX 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 predicts 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, this section demonstrates 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 The global credit cycle and local credit conditions

Are periods of tight credit conditions costly for firms that borrow through the corporate bond market? Existing theories suggest that fluctuations in aggregate conditions can affect both the willingness and the ability of firms to issue (or refinance) debt. As aggregate credit conditions tighten, firms may face greater financing needs but, if credit spreads rise, may be less willing to raise new debt at higher coupon rates. At the same time, tighter credit conditions may induce a "flight-to-quality" (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 a tightening of global credit conditions. 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 in primary market credit spreads and thus dampen firms' willingness to issue new debt.[23] 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. This specification thus compares the evolution of credit conditions following the start of a period of tight credit conditions to the evolution of conditions following a 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 6 plots the estimated dynamics of credit spreads (Figure 6a) and default probabilities

[23] See, for example, White (1974), Taggart (1977), Barry et al. (2008), Barry et al. (2009), Erel et al. (2012), and Hotchkiss et al. (2025).

(Figure 6b) by rating category around a tightening in the global credit factor, with $h = 0$ marking the first month of a period when the global credit factor is in its top tercile and reaches the top quintile at least once during the episode. For example, during the COVID-19 pandemic, the first month of tight global credit conditions is March 2020.

Figure 6a 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 1 p.p. higher than prior to the start of the tightening episode, episode, while spreads on A and BBB bonds are 25 to 40 bps higher. A persistent increase in credit spreads leads to lower investment, especially for firms with higher financing needs, as documented by Almeida et al. (2011) in the context of firms with high debt rollover needs during the Global Financial Crisis and Elias (2021) in the context of episodes of sudden stops in international capital flows.

Figure 6b confirms this intuition. EDFs for all rating categories increase at the onset of the crisis and remain elevated six 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 6 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 firms, 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 6a 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 increase 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%. In cross-horizon results in Table 8b, we see that the persistent (and continuing) increase in EDFs across rating categories we observed in Figure 6b 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 above, by the six-month 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, Boyarchenko and Elias (2024) 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 credit factor 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 on, 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 the geographical location of funds' investments (geofocus).

6.1 Global fund returns

We start by examining whether the global credit factor predicts returns not just at the 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's excess return in month $t+1$, α captures a set of fixed effects that includes 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 includes lags of the flows variable as well as fund size. β then captures the overall level of comovement between the global credit factor and future fund returns, while β_r captures 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.

Turning to the comparison to other FCIs, Table 10 shows that, except for 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:

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

where $\frac{flows_{i,t}}{AUM_{i,t-1}}$ is the percentage flows into fund i in month t, α captures a set of fixed effects that includes 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 includes three lags of fund returns in excess of peer funds and lagged log total assets. β then captures the overall level of comovement between the global credit factor and fund flows, while β_r captures the differential sensitivity across types of funds.

The results in Table 11 show that, overall, tightenings in the global credit factor are associated with fund outflows. Starting with the results in column 1 (funds investing in any geography except dedicated U. S. funds), high yield funds (the omitted category) experience outflows 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 regression (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 in 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 in 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 in 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 in short-term funds are more sensitive to changes in global credit conditions than investors in intermediate-term funds. Inflows into high yield short-term funds are particularly affected 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 returns and flows suggest that the risks to individual corporate bond returns due to exposure to the global credit factor are not fully diversifiable. This again highlights that the global credit factor captures systematic risks in the global market for corporate fixed income.

7 Conclusion

We construct a proxy for 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 resulting global credit factor thus forecasts 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. Large tightenings of the global credit factor predict a prolonged widening 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 provides 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 comovement between the global credit factor and flows into global funds. This comovement 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 large 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 global risk premia. This table reports the estimated coefficients from the regression of three-month-ahead bond-level excess holding period returns on the global credit factor (GCC), constructed using the nonlinear sieve estimator described in Section 3. Columns report the full sample results, as well as splits of the bond universe by parent company region of domicile (U. S., other advanced economies, emerging markets) and by denomination currency (USD, non-USD). For the out-of-sample exercise, we first estimate different vintages of the factor, indexed by a sample cutoff t^*, using data up to date $t^* - 1$. Given a factor vintage, we then 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}. The out-of-sample R^2 is then the covariance between the predicted returns from this out-of-sample exercise using different factor vintages and the realized returns. We start our out-of-sample evaluation in January 2009 (predicting returns up to April 2009). Sample: monthly observations, January 1986–December 2024. High yield bonds are the omitted category. Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. 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.

		Regions			Currencies	
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
GCC	0.68	0.64	0.75	0.87	0.68	0.60
	(0.01)***	(0.01)***	(0.03)***	(0.04)***	(0.01)***	(0.03)***
BBB × GCC	-0.32	-0.28	-0.43	-0.35	-0.30	-0.36
	(0.01)***	(0.01)***	(0.03)***	(0.05)***	(0.01)***	(0.03)***
A × GCC	-0.48	-0.43	-0.58	-0.55	-0.46	-0.46
	(0.01)***	(0.01)***	(0.03)***	(0.05)***	(0.01)***	(0.03)***
AAA/AA × GCC	-0.58	-0.48	-0.70		-0.53	-0.55
	(0.01)***	(0.01)***	(0.03)***		(0.01)***	(0.03)***
In-sample R^2	9.4	9.2	9.4	13.3	9.6	8.8
Time-series R^2	7.1	7.1	6.8	11.7	7.6	6.5
Cross-sectional R^2	0.8	0.7	1.1	0.6	0.7	1.0
Market-timing R^2	1.5	1.4	1.6	0.9	1.3	1.3
Out-of-sample R^2	5.9	5.8	5.8	8.1	6.0	5.7
N. of obs	2,376,804	1,449,575	800,004	127,225	1,807,898	568,906
N. bonds	40,103	24,630	14,252	2,434	30,144	9,959

Table 2: Decomposing returns into sources of risk. This table reports the estimated coefficients from the regression of three-month-ahead bond-level excess holding period returns on the global credit factor (GCC), decomposing excess returns into the contribution of credit risk, the differential duration risk due to foreign (non-USD) currency sovereign curves ("currency diff"), and duration risk from the perspective of a U. S. investor. Sample: monthly observations, January 1986–December 2024. Column 3 omits bonds denominated in USD as the differential duration risk for those bonds is 0. 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	0.79	0.68	0.20	0.09
	(0.01)***	(0.01)***	(0.01)***	(0.00)***
BBB × GCC	-0.29	-0.32	-0.01	0.01
	(0.01)***	(0.01)***	(0.01)	(0.00)***
A × GCC	-0.43	-0.48	-0.03	0.02
	(0.01)***	(0.01)***	(0.01)***	(0.00)***
AAA/AA × GCC	-0.52	-0.58	-0.11	0.04
	(0.01)***	(0.01)***	(0.01)***	(0.00)***
Total R^2	9.0	9.4	3.3	0.0
Time-series R^2	7.9	7.1	3.4	-0.0
Cross-sectional R^2	0.3	0.8	-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: Contributions of VIX and EBP to the global credit factor. This table reports the estimated coefficients from the regression of three-month-ahead bond-level excess holding period returns on alternative proxies for the price of risk. "EBP" is the excess bond premium of Gilchrist and Zakrajšek (2012); VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. $\varphi(\cdot)$ denotes the nonlinear sieve transformation that maps predictors into a return-forecasting factor, with $GCC \equiv \varphi(EBP, VIX)$ the global credit factor and $\varphi_1(EBP) + \varphi_2(VIX)$ the optimal additive bivariate factor (with no interactions between EBP and VIX). Sample: monthly observations, January 1986–December 2024. 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) $\varphi_1(EBP) + \varphi_2(VIX)$
FCI	0.68	10.47	0.51	0.64	0.82	0.70
	(0.01)***	(0.21)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
BBB × FCI	-0.32	-3.90	-0.30	-0.32	-0.40	-0.34
	(0.01)***	(0.23)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
A × FCI	-0.48	-6.63	-0.40	-0.48	-0.58	-0.49
	(0.01)***	(0.22)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
AAA/AA × FCI	-0.58	-8.54	-0.45	-0.56	-0.71	-0.59
	(0.01)***	(0.23)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***
Total R^2	9.4	4.7	4.2	6.9	8.6	9.0
Time-series R^2	7.1	4.0	1.9	4.6	6.6	6.7
Cross-sectional R^2	0.8	-0.1	1.8	1.1	0.6	0.8
Market-timing R^2	1.5	0.8	0.5	1.2	1.4	1.5
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 bond risk premia. This table reports the estimated coefficients from the regression of three-month-ahead 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. 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. $\varphi(\cdot)$ denotes the nonlinear sieve transformation that maps predictors into a return-forecasting factor, with $GCC \equiv \varphi(EBP, VIX)$ the global credit factor and $\varphi_1(EBP) + \varphi_2(VIX)$ the optimal additive bivariate factor (with no interactions between EBP and VIX). Sample: monthly observations, January 1986–December 2024. 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.

	Tight			Loose		
	(1)	(2)	(3)	(4)	(5)	(6)
	GCC	$\varphi(VIX)$	$\varphi_1(EBP)+$ $\varphi_2(VIX)$	GCC	$\varphi(VIX)$	$\varphi_1(EBP)+$ $\varphi_2(VIX)$
FCI	0.66	0.85	0.72	2.86	-0.92	-0.52
	(0.01)***	(0.01)***	(0.01)***	(0.07)***	(0.05)***	(0.02)***
BBB × FCI	-0.31	-0.41	-0.35	-1.53	0.13	0.48
	(0.01)***	(0.02)***	(0.01)***	(0.07)***	(0.05)**	(0.02)***
A × FCI	-0.46	-0.60	-0.52	-2.18	0.45	0.56
	(0.01)***	(0.01)***	(0.01)***	(0.07)***	(0.05)***	(0.02)***
AAA/AA × FCI	-0.56	-0.74	-0.62	-2.41	0.65	0.63
	(0.01)***	(0.01)***	(0.01)***	(0.07)***	(0.06)***	(0.02)***
Total R^2	10.6	10.2	10.0	1.9	0.8	0.7
Time-series R^2	7.0	6.6	6.1	1.2	0.7	-0.2
Cross-sectional R^2	2.1	2.1	2.4	0.5	0.1	1.1
Market-timing R^2	1.5	1.5	1.4	0.2	-0.0	-0.2
Corr. with GCC	1.00	0.86	0.95	1.00	-0.42	0.68
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 risk premia with alternative FCIs. This table reports the estimated coefficients from the regression of three-month-ahead bond-level excess holding period returns on common alternative financial condition indices. GCC is the global credit factor, as described in Section 3. VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. "GFCy" is the global financial cycle from Miranda-Agrippino et al. (2020) (which updates the original Miranda-Agrippino and Rey, 2015, factor). ΔTWI 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 (available starting in 1990). Sample: monthly observations, January 1986–December 2024. 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) ΔTWI	(5) GS FCI
FCI	0.68	0.51	-7.27	0.82	0.08
	(0.01)***	(0.01)***	(0.14)***	(0.02)***	(0.00)***
BBB × FCI	-0.32	-0.30	1.32	-0.32	-0.05
	(0.01)***	(0.01)***	(0.16)***	(0.02)***	(0.00)***
A × FCI	-0.48	-0.40	4.01	-0.54	-0.07
	(0.01)***	(0.01)***	(0.15)***	(0.02)***	(0.00)***
AAA/AA × FCI	-0.58	-0.45	5.59	-0.69	-0.07
	(0.01)***	(0.01)***	(0.15)***	(0.02)***	(0.00)***
Total R^2	9.4	4.2	5.4	1.6	1.6
Time-series R^2	7.1	1.9	4.7	1.2	0.0
Cross-sectional R^2	0.8	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 risk premia across subperiods. This table reports the estimated coefficients from the regression of three-month-ahead bond-level excess holding period returns on the global credit factor (GCC, odd columns) and the VIX (even columns). Each pair of columns corresponds to a time-series subsample, with columns 3 and 4 corresponding to observations during the Global Financial Crisis, columns 7 and 8 to observations during the COVID-19 pandemic, and the remaining columns to periods outside those stress episodes (1998–2006; 2010–2019; 2021–2024). VIX is the CBOE option-implied volatility index. Sample: monthly observations, January 1998–December 2024. 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	0.60	0.45	0.52	0.61	1.03	0.44	0.98	1.01	1.57	0.31
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.00)***	(0.03)***	(0.03)***	(0.03)***	(0.00)***
BBB × FCI	-0.40	-0.36	-0.22	-0.24	-0.65	-0.30	-0.42	-0.45	-0.83	-0.19
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.02)***	(0.01)***	(0.03)***	(0.03)***	(0.03)***	(0.01)***
A × FCI	-0.50	-0.42	-0.35	-0.39	-0.86	-0.39	-0.66	-0.69	-1.04	-0.22
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.03)***	(0.03)***	(0.03)***	(0.00)***
AAA/AA × FCI	-0.52	-0.43	-0.46	-0.52	-0.89	-0.40	-0.72	-0.73	-1.07	-0.23
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.02)***	(0.01)***	(0.03)***	(0.03)***	(0.03)***	(0.01)***
Total R^2	5.6	4.1	15.7	5.8	3.8	2.8	15.8	9.6	3.5	1.9
Time-series R^2	3.2	0.7	12.4	4.1	1.7	0.6	12.3	6.3	2.2	0.1
Cross-sectional R^2	1.3	3.1	0.9	0.9	1.3	1.9	1.7	2.4	1.0	1.8
Market-timing R^2	1.1	0.3	2.3	0.8	0.8	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 spread changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions. Panel 7a reports the contemporaneous response of credit spreads for both the full sample and by parent company region of domicile (U. S., other advanced economies, emerging markets). Panel 7b reports the cumulative full-sample response up to 6 months after the start of tight episode. 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. Sample: monthly observations, January 1986–December 2024. Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. 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) U. S.	(3) AE, ex U. S.	(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 expected default frequency (EDF) changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions. Panel 8a reports the contemporaneous response of firm EDFs for both the full sample and by parent company region of domicile (U. S., other advanced economies, emerging markets). Panel 8b reports the cumulative full-sample response up to 6 months after the start of tight episode. 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. Sample: monthly observations, January 1986–December 2024. Due to lack of observations, AAA/AA-rated firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. All regressions include country and rating fixed effects. High yield firms are the omitted category. Standard errors clustered at the firm 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) 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 (GCC) and interactions with fund type dummies. Columns correspond to the geographical focus of the fund's investments, as reported in EPFR. Sample: monthly observations, January 2002–December 2024. High yield funds are the omitted category. All regressions 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	0.48	0.67	0.32	0.72	0.36	0.40
	(0.02)***	(0.05)***	(0.44)	(0.07)***	(0.01)***	(0.02)***
All quality × GCC	-0.03	-0.25	-0.04	-0.34	-0.07	0.05
	(0.03)	(0.07)***	(0.45)	(0.08)***	(0.03)**	(0.03)**
Investment grade × GCC	-0.12	-0.20	0.12	-0.53	-0.15	-0.06
	(0.02)***	(0.05)***	(0.45)	(0.07)***	(0.02)***	(0.03)**
Government × GCC	-0.21	-0.42	-0.02	-0.44	-0.32	-0.19
	(0.02)***	(0.05)***	(0.45)	(0.08)***	(0.01)***	(0.03)***
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 the global credit factor (GCC; odd columns) and the VIX (even columns) and interactions with fund type dummies. VIX is the CBOE option-implied volatility index. Pairs of columns correspond to the geographical focus of the fund's investments, as reported in EPFR. Sample: monthly observations, January 2002–December 2024. High yield funds are the omitted category. All regressions 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	0.48	0.63	0.67	0.89	0.32	0.60	0.72	0.76	0.36	0.54	0.40	0.61
	(0.02)***	(0.02)***	(0.05)***	(0.04)***	(0.44)	(0.32)*	(0.07)***	(0.09)***	(0.01)***	(0.02)***	(0.02)***	(0.03)***
All quality × FCI	-0.03	-0.08	-0.25	-0.28	-0.04	0.11	-0.34	-0.22	-0.07	-0.27	0.05	-0.01
	(0.03)	(0.03)***	(0.07)***	(0.05)***	(0.45)	(0.34)	(0.08)***	(0.09)**	(0.03)**	(0.03)***	(0.03)**	(0.03)
Investment grade × FCI	-0.12	-0.27	-0.20	-0.41	0.12	0.19	-0.53	-0.45	-0.15	-0.32	-0.06	-0.19
	(0.02)***	(0.02)***	(0.05)***	(0.04)***	(0.45)	(0.33)	(0.07)***	(0.09)***	(0.02)***	(0.02)***	(0.03)**	(0.03)***
Government × FCI	-0.21	-0.45	-0.42	-0.67	-0.02	-0.06	-0.44	-0.45	-0.32	-0.52	-0.19	-0.37
	(0.02)***	(0.03)***	(0.05)***	(0.04)***	(0.45)	(0.32)	(0.08)***	(0.09)***	(0.01)***	(0.02)***	(0.03)***	(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 lagged total assets) on the global credit factor (GCC) and interactions with fund type dummies. Columns correspond to the geographical focus of the fund's investments, as reported in EPFR. Sample: monthly observations, January 2002–December 2024. High yield funds are the omitted category. All regressions 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, the global credit cycle, and fund type. This table reports the estimated coefficients from the regression of flows into global funds (normalized by lagged total assets) on the global credit factor and interactions with fund type dummies. Columns correspond to fund sample splits by domicile (U. S. and other advanced economies), type (mutual funds, MF, and exchange traded funds, ETF), and target maturity of investments as reported in EPFR (short term, 1–4 years, and intermediate term, 4–6 years). Sample: global funds investing in any geography except dedicated U. S. funds, monthly observations, January 2002–December 2024. High yield funds are the omitted category. All regressions 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 global credit factor. This figure plots the time series of the global credit factor (GCC) estimated by sieve reduced-rank regression, as described in Section 3. The factor is scaled to have a coefficient of one in the predictive regression for three-month-ahead excess return on the advanced economy high yield bond portfolio. Sample: monthly observations, January 1986–December 2024. Arrows and text identify selected periods of stress.

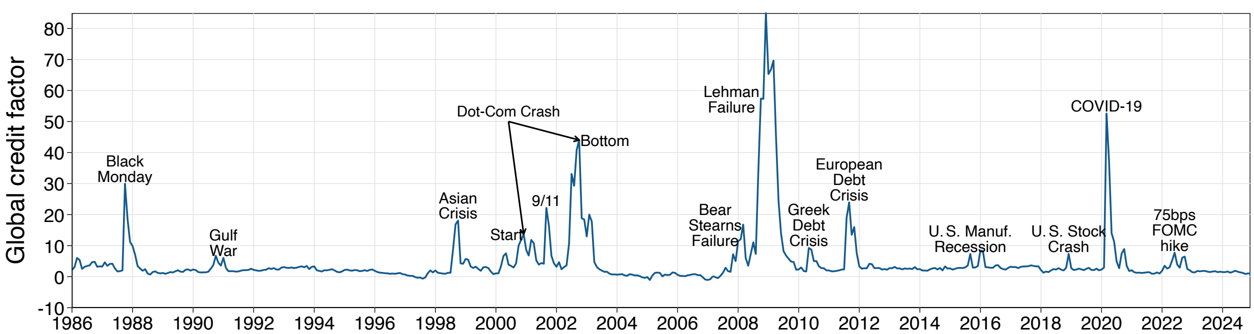
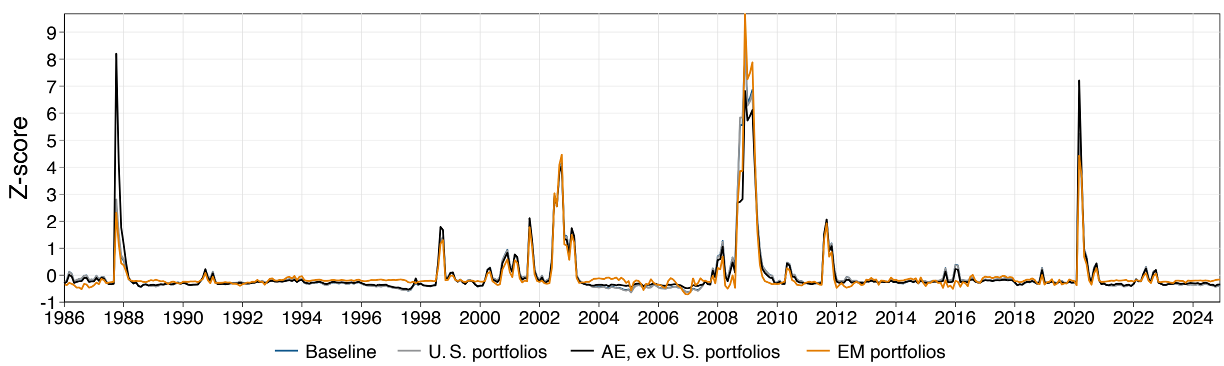


Figure 2. Comparing the global credit factor to alternative estimation procedures. This figure plots the comparison between the global credit factor constructed to price advanced economy bond return portfolios, and those constructed to price U. S. portfolios, advanced economies excluding U. S. portfolios, and emerging market portfolios (Figure 2a), and between the global credit factor constructed using U. S. and European predictors (Figure 2b). Factor time series in Figure 2a have been standardized to have mean 0 and standard deviation 1 to make factor comparisons easier. "EBP" is the excess bond premium of Gilchrist and Zakrajšek (2012); VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. In Figure 2b, volatility is measured using the Eurex option-implied volatility index (VSTOXX) and credit spreads using the "European EBP", constructed as the amount-outstanding-weighted average of bond-level default-adjusted spreads on bonds issued by parent companies domiciled in the eight countries covered by VSTOXX (Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, and Spain).

(a) Comparison to global credit factors constructed to target alternative portfolios (standardized)



(b) Comparison to global credit factor constructed using European predictors

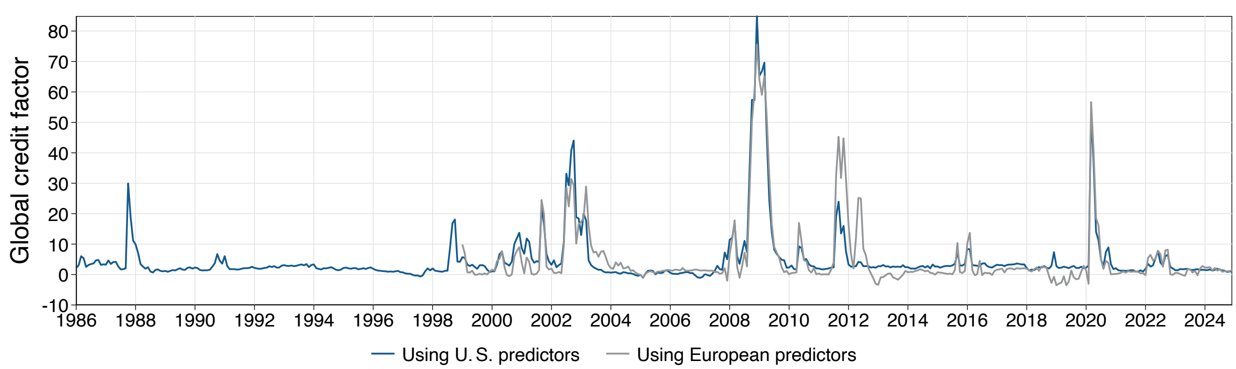
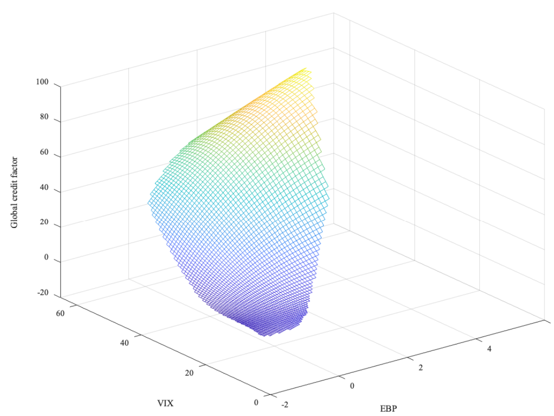
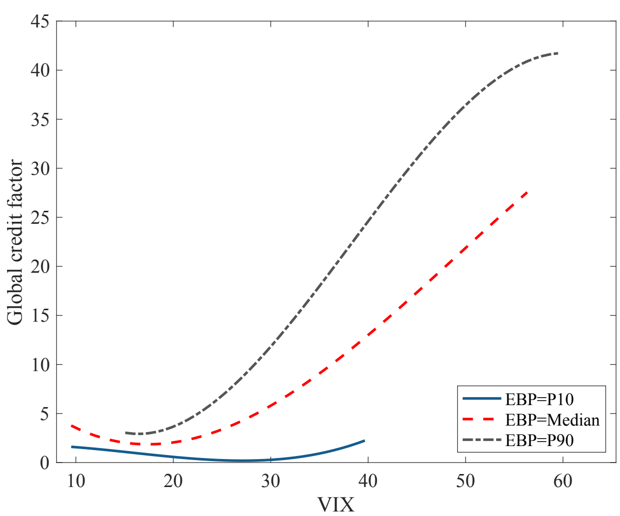


Figure 3. Relationship between the global credit factor and underlying predictors. This figure plots the estimated global credit factor $\varphi\,(EBP, VIX)$ as a function of its two underlying predictors: EBP (the excess bond premium of Gilchrist and Zakrajšek, 2012) and VIX (the CBOE option-implied volatility index, supplemented with VXO data prior to 1990). Figure 3a shows the joint surface $\varphi\,(EBP, VIX)$ over the (EBP, VIX) plane. Figure 3b shows the marginal relationship between $\varphi\,(EBP, VIX)$ and the VIX, fixing EBP at its sample 10th percentile, median, and 90th percentile. Figure 3c shows the marginal relationship between $\varphi\,(EBP, VIX)$ and EBP, fixing the VIX at its sample 10th percentile, median, and 90th percentile. Sample: monthly observations, January 1986–December 2024.

(a) Global credit factor



(b) Global credit factor vs VIX



(c) Global credit factor vs EBP

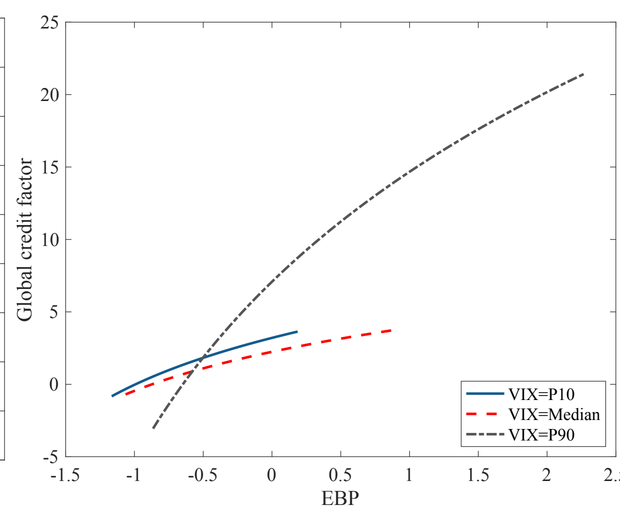


Figure 4. Cross-sectional asset pricing. This figure plots average three-month-ahead excess returns against the restricted joint forecasting regressions $rx_{i,t+h} = (\alpha_i + \beta_i\lambda_0) + \beta_i\lambda_1\varphi\left(\mathrm{EBP}_t, \mathrm{VIX}_t\right) + \beta_i u_{t+h} + \epsilon_{i,t+h}$ 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. "EBP" is the excess bond premium of Gilchrist and Zakrajšek (2012); VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. Sample: monthly observations, January 1986 (January 1998 for 4b) to December 2024.

(a) Baseline advanced economy portfolios

(b) Cross-country portfolios

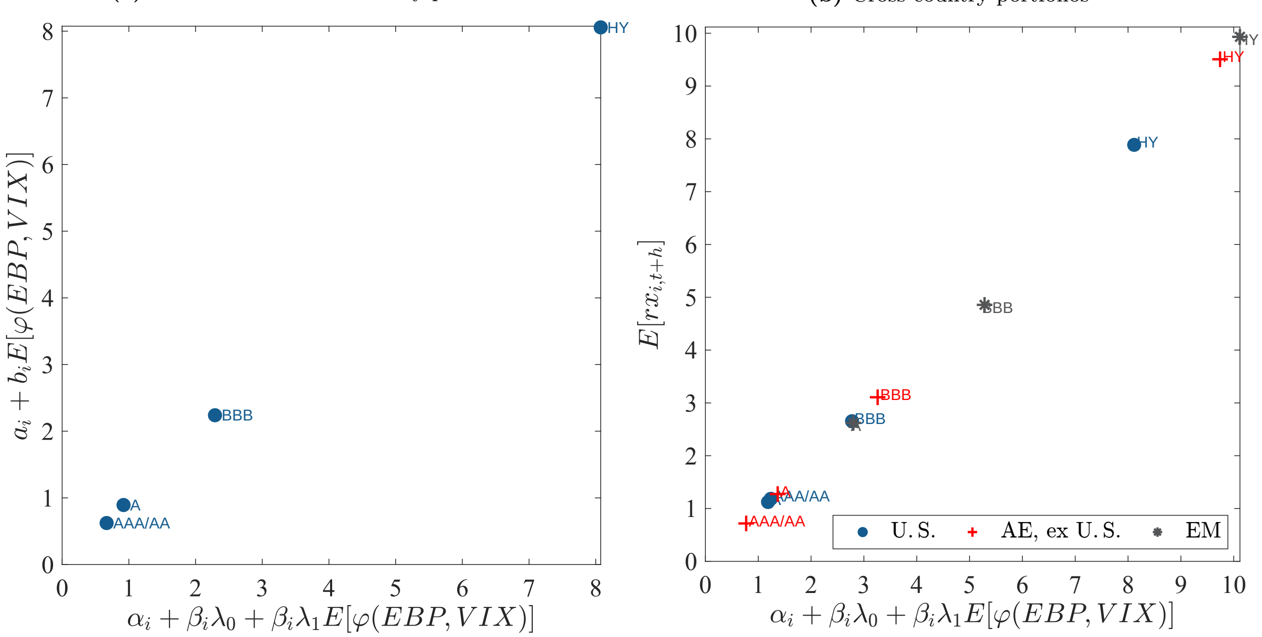


Figure 5. Estimated predictive coefficients across factor vintages. This figure plots the time series of estimated coefficients from bond-level return predictability regressions on different vintages of the global credit factor. Each factor vintage is estimated using data up to date t^*. Given a global factor vintage, each point of the coefficient time series estimates the regression of three-month bond-level excess holding period returns on the global credit factor using data up to date t^*. "EBP" is the excess bond premium of Gilchrist and Zakrajšek (2012); VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. Sample: monthly observations, January 1986–December 2024.

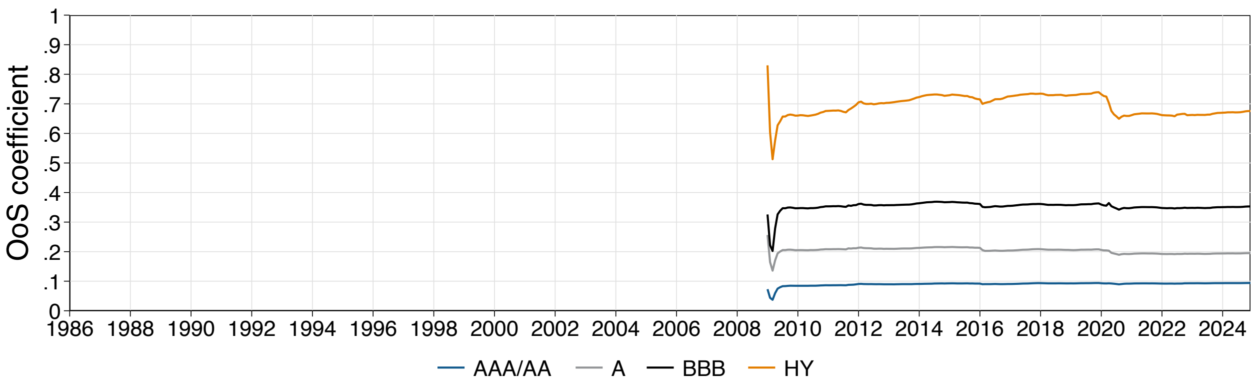
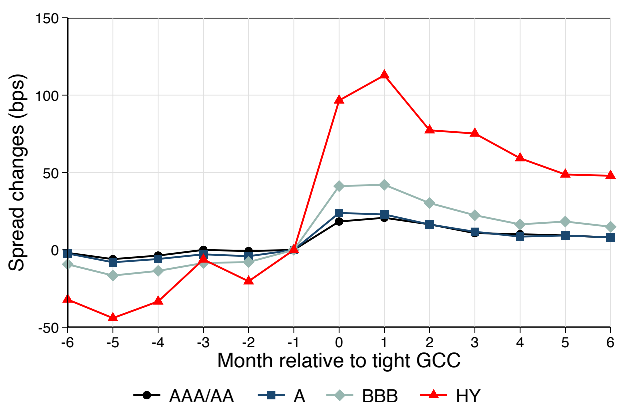
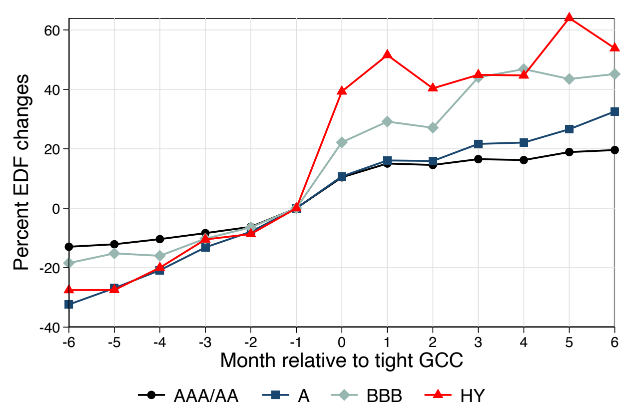


Figure 6. Effect of extreme tightenings. This figure reports the estimated coefficients from the regression of spread and percent expected default frequency (EDF) changes relative to the month before the start of a spell of tight global credit conditions on an indicator for tight credit conditions (tight GCC). Figure 6a plots the estimated coefficients from the regression of changes in credit spreads on the tight credit conditions dummy, with the sample split by bond rating (AAA/AA, A, BBB, high yield). Figure 6b plots the estimated coefficients from the regression of percent changes in EDFs on the tight credit conditions dummy, with the sample split by firm rating (AAA/AA, A, BBB, high yield). 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. Sample: monthly observations, January 1986–December 2024. All regressions include country and rating fixed effects.

(a) Bond-level spread changes



(b) Firm-level EDF changes



Internet Appendix

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 follow Adrian et al. (2019a,b) in using a reduced-rank, sieve-based procedure to estimate nonparametrically the common component of expected returns as a function of credit spreads and volatility, $\varphi\left(cs_t, \mathrm{VIX}_t\right) \propto \lambda_t$, 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 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 $\hat{b}_h$ and $\hat{\gamma}_h$ 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 four advanced economy portfolios: AAA/AA, A, BBB, and high yield (below BBB-) corporate bonds.[24] We use the (log) U. S. EBP as our measure of credit spreads.[25] 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 $\varphi\left(cs_t, \text{VIX}_t\right)$. 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).[26] 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 for up to three factors ($r = 3$), spline bases of order up to four (corresponding to piecewise cubic polynomials), and up to six 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 $2,058 = 14 \times 3 \times 7 \times 7$ possible bivariate specifications (seven versions of a bivariate basis $\times$ (additive or multiplicative) $\times$ up to three factors $\times$ between 0 and 6 interior credit spread knots $\times$ between 0 and 6 interior VIX knots). We discern amongst these 2,058 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.[27] We then iterate, adding one month of observations at a

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

[25] 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 subsamples.

[26] 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.

[27] 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.

time. The out-of-sample MSE for a given specification is then given by:

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

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.3 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.4 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) "GZ" 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.4 shows that while the 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.4 and Table A.3 suggest that our estimated global credit factor contains 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).[28] First, we focus on extracting factors that predict risky asset returns while the factor construction in Miranda-Agrippino and Rey (2015) targets 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.

A.4 Portfolio-level risk premia

Table A.4 reports the estimated coefficients from the return predictability regression at the portfolio level, for rating-level portfolios constructed from all available bonds (column 1, "world"); bonds issued by firms in the U. S. (column 2); bonds issued by firms in advanced economies excluding the U. S. (column 3); and bonds issued by firms in emerging market economies (column 4). The table shows that, at the portfolio level, the overall R^2 increases substantially relative to the bond-level R^2 in Table 1, with the portfolio-level R^2 ranging from around 25% for portfolios of emerging market bonds to almost 40% for bonds of firms in advanced economies outside of the U. S. Relative to the bond-level return predictability, Table A.4 also shows that all three sources of R^2 increase when moving from bond-level to portfolio-level returns, suggesting the improvement is not only due to reduced idiosyncratic volatility in returns when moving to the portfolio level.

A.5 Additional results on bond-level risk premia

In this subsection, we discuss briefly additional results using the baseline global credit factor and exploring additional dimensions of bond-level returns.

Table A.6 examines how rating-level exposures differ across countries. Columns 1–3 show that, for investment grade bonds, bonds issued by firms in advanced economies outside of the U. S. have a lower exposure to the global credit factor than bonds issued by firms in the U. S. For high yield bonds, this relationship reverses, and bonds issued by firms in advanced economies outside of the U. S. have a larger exposure to the global credit factor than bonds issued by firms in the U. S. Across all credit ratings, bonds issued by firms in emerging

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

markets have the greatest exposure to the global credit factor. The table also shows that the overall R^2 is lowest for the safest bonds (bonds rated AAA or AA). Turning to the three components of the overall R^2, we see that the cross-country differences do not contribute meaningfully to the overall R^2. This is intuitive: bonds do not switch countries, so that, at the bond level, there is no variation in the estimated exposures.

Table A.7 parametrizes the variation in bond-level exposures to the global credit factor as a function of three bond-level characteristics—duration-matched, currency-adjusted spread; bond duration; and bond return volatility over the previous 24 months—instead of as a function of bond-level ratings. The table shows that riskier bonds are more exposed to variation in the global credit factor, so that riskier bonds have a higher credit risk premium. With these alternative characteristics, the overall R^2 increases to 16.5%–21.6%. The market timing R^2 contributes the most to the overall R^2, highlighting that the overall predictive ability of the global credit factor is driven by the factor capturing increases in risk premia for riskier bonds during periods of stress. As with the baseline results in Table 1, Table A.7 shows that these results hold across regions (columns 2–4), and for both USD-denominated bonds and bonds denominated in other currencies (columns 5–6).

Table A.8 reports the estimated relationship between returns and the global credit factor across different return horizons. The table shows that the global credit factor predicts returns at up to a year horizon, with all three components of the overall R^2 increasing across horizons. The table also shows that, although the exposure of longer horizon returns to the global credit factor is lower, even at the 12-month horizon there are substantial differences in the exposure of riskier and safer bonds. Table A.8b further explores how return predictability changes across horizons when we estimate factors targeting the same (longer) horizon. Table A.8b shows that the results are similar to those from Table A.8a, suggesting a relatively flat term structure of expected excess returns.

Table A.9 explores the relationship between the global credit factor and returns at the country level. The table shows that, across both advanced and emerging market economies, the global credit factor predicts bond-level returns, with high yield bonds systematically the most exposed to variation in the global credit factor and AAA/AA bonds the least exposed. Comparing the results for advanced and emerging market economies, we see that returns in emerging markets have a higher R^2. Finally, the table also shows that, for bonds issued by firms in emerging market economies, the time-series R^2 is a larger fraction of the overall R^2.

A.6 Bond-level risk premia with alternative proxies for the global price of credit risk

In this subsection, we examine how alternative proxies for the global price of credit risk—constructed either targeting alternative portfolios or using alternative predictors—perform in predicting global bond returns.

Table A.10 shows that the global credit factors constructed targeting either the baseline portfolios of bonds of firms in advanced economies (column 1), bonds of firms in the U. S. only (column 2), bonds of firms in other advanced economies (column 3), or bonds of firms in emerging markets (column 4) predict bond returns similarly well. The global credit factor targeting portfolios of bonds of firms in other advanced economies has the highest overall R^2 (9.6%) while the global credit factor targeting portfolios of bonds of firms in emerging markets has the lowest overall R^2 (8.6%). The baseline factor, however, has the highest cross-sectional R^2 across all four alternatives.

Table A.11 then examines return predictability using the global credit factor constructed using the VSTOXX instead of the VIX and the weighted average default adjusted spread on corporate bonds issued by firms in the same 8 countries as represented in the VSTOXX instead of the U. S. EBP. The table shows that the risk premia on bonds around the world are once again captured by the global credit factor constructed using European predictors. High yield bonds have the highest exposure to the global credit factor while AAA/AA-rated bonds have the lowest exposure to the global credit factor. Comparing the return predictability across regions, we see that, as with the baseline results in Table 1, returns on bonds issued by firms in emerging markets are most predictable, and are exposed the most to variation in the global price of credit risk. The table also shows that returns on bonds denominated in USD are more exposed to the global credit factor than returns on bonds denominated in other currencies. Thus, the higher exposure of USD-denominated bonds to the global credit cycle that we saw in Table 1 is not driven by using U. S. predictors.

A.7 Cross-currency differentials in exposures to the global price of credit risk

The richness of our international bond-level data allows us to explore cross-currency differentials in exposures to the global credit cycle in greater detail. In particular, we now restrict our sample to firms that have bonds in more than one currency and study whether bonds of the same firm but issued in different currencies are differentially exposed to the global credit cycle. We are interested in two particular comparisons: bonds denominated in USD relative to bonds denominated in other currencies, and bonds denominated in the currency local to the ultimate parent of the issuing firm relative to bonds denominated in foreign currency. While the first exercise focuses on the global role of the dollar in transmitting global credit shocks, the second exercise evaluates whether foreign currency bonds amplify firms' exposures to the global credit cycle.

In both cases, we modify our baseline bond return predictability regression to include month, firm, and firm-month fixed effects:

$$rx_{i,t+h} = \alpha_f + \alpha_t + \alpha_{f,t} + \beta_{\text{Currency}} \mathbb{1}_{\text{Currency}} + \beta_r \left(\lambda_0 + \lambda_1 \varphi \left(cs_t, \text{VIX}_t\right)\right) \times \mathbb{1}_{\text{Currency}} + \epsilon_{i,t+h},$$

where α_f is an ultimate parent fixed effect, α_t is a month fixed effect, $\alpha_{f,t}$ is an ultimate parent-month fixed effect, and $\mathbb{1}_{\text{Currency}}$ is an indicator equal to 1 for USD-denominated bonds in the first exercise and an indicator equal to 1 for local currency bonds in the second exercise.

Table A.12a shows that, while USD-denominated bonds earn a lower return on average, they also have a greater exposure to the global credit cycle. Thus, the cross-currency differentials we saw overall in Table 1 persist even at the firm level, suggesting a special role of dollar-denominated assets in transmitting global credit shocks. Turning to the currency-level comparisons in columns 2–6, we see that these exposure differentials are present for all currencies except the British pound. The greatest exposure differential is between USD- and JPY-denominated bonds, while the smallest exposure differential is between USD- and EUR-denominated bonds.

Turning to the difference in exposure between local and foreign denominated bonds, in Table A.12b we see that the exposure differentials relative to USD-denominated bonds we saw in Table A.12a translate into different exposures for local and foreign bonds. For firms with USD domestic currency (column 1), bonds in local currency are more exposed to the global credit cycle, so that issuing bonds in foreign currency dampens the effect of the global credit cycle for these firms. In contrast, for firms whose domestic currency is either EUR, CAD, or JPY (columns 2, 4, and 5), issuing in foreign currency increases exposure to fluctuations in the global price of credit risk.

A.8 Other asset classes

In this subsection, we examine briefly how the global credit factor performs in predicting returns on other asset classes, namely equity indices and sovereign bonds. To keep returns comparable across corporate bonds and these additional assets, we compute portfolio-level returns on corporate bonds at the country-rating bucket level. We use MSCI total return unhedged indices for a given country to measure equity returns. We compute sovereign returns by interpolating each country's zero coupon yield curve to the 10-year point at month t and to the 9-year 9-month point at time $t + 3$, reflecting the returns to a trading strategy in which every month a 10-year bond is purchased and resold three months later as a 9-year 9-month bond.

Table A.13 examines how exposures of these alternative asset classes differ from the exposures of the rating-level portfolios. The table shows that equity returns have exposures to the global credit factor similar to those of the high yield bond portfolios. In contrast, the estimated exposures of the sovereign bond returns to the global credit factor are similar to the exposures of the investment grade portfolios. In particular, U. S. Treasuries have the lowest exposure to the global credit factor out of all the U. S. portfolios. For other advanced economies and emerging markets, instead, the sovereign bonds have exposures in-between the exposures of BBB and A-rated corporate bond portfolios.

B Additional data details

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

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 from consolidated Compustat–Worldscope, 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 yield-to-maturity for security b of firm f on date t issued in currency c with duration $d^c_{b(f),t}$, we first compute the duration-matched credit spread as:

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

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

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

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

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

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

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:

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

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.1: Sample summary statistics. This table reports the sample summary statistics for the bond characteristics by currency, averaged over monthly observations in the sample period, January 1986–December 2024. Bond excess returns and currency-adjusted, duration-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 $t = 1, \dots, (t^* - 1)$ and an out-of-sample period $t = t^*, \dots, T$. 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 minimum and the 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%. Sample: monthly observations, January 1986–December 2024.

(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 monthly sample (January 1986–December 2024), Column 2 for the pre-crisis sample (January 1986–July 2007), Column 3 for the post-crisis sample (January 2010–December 2019). "TWI" is the 12-month change in the broad dollar index. "EBP" is the excess bond premium of Gilchrist and Zakrajšek (2012); VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. $\varphi(\cdot)$ denotes the nonlinear sieve transformation that maps predictors into a return-forecasting factor. "GFCy" is the global financial cycle from Miranda-Agrippino et al. (2020) (which updates the original Miranda-Agrippino and Rey, 2015, factor). "U. S." (available starting January 1990) and "Global" (available starting March 2007) GS FCI are the U. S. and global Goldman-Sachs financial conditions indices, respectively. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	(1) Full sample	(2) Pre-crisis	(3) Post-crisis
VIX	0.76***	0.74***	0.74***
GZ 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 GZ spread	0.22***	0.13**	0.34***
USD TWI	0.20***	-0.07	-0.01
GFCy	-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 risk premia. This table reports the estimated coefficients from the regression of three-month-ahead excess holding period returns on the global credit factor (GCC) at the portfolio level. Each portfolio is the amount-outstanding-weighted average of bonds in a given region–credit rating pairing. Column 1 reports the results for portfolio constructed using all bonds in the sample ("world"); column 2 the results for portfolios constructed using bonds of parents domiciled in the U. S.; column 3 the results for portfolios constructed using bonds of parents domiciled in other advanced economies; column 4 the results for portfolios constructed using bonds of parents domiciled in emerging markets. Sample: monthly observations, January 1986–December 2024. High yield portfolio is the omitted category in all regressions. Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. R^2 reported in percent. Heteroskedasticity-robust standard errors 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	0.63	0.60	0.72	0.63
	(0.07)***	(0.07)***	(0.10)***	(0.10)***
BBB × GCC	-0.30	-0.27	-0.43	-0.12
	(0.09)***	(0.10)***	(0.11)***	(0.12)
A × GCC	-0.45	-0.42	-0.56	-0.25
	(0.08)***	(0.08)***	(0.10)***	(0.14)*
AAA/AA × GCC	-0.52	-0.45	-0.65	
	(0.08)***	(0.09)***	(0.10)***	
Total R^2	30.1	27.7	39.7	25.2
Time-series R^2	19.9	20.0	22.1	23.9
Cross-sectional R^2	3.3	2.7	4.3	0.7
Market-timing R^2	7.0	5.1	13.2	0.6
N. of obs	1,872	1,872	1,296	967

Table A.5: Alternative standard error choices. This table reports the estimated coefficients from the regression of three-month-ahead bond-level excess holding period returns on the global credit factor (GCC) for different standard error specifications. Driscoll and Kraay (1998) and Newey and West (1987) use 12 lags. Cameron et al. (2008) wild bootstrap conducted with 1,000 simulations, with blocks of 1,000 observations. R^2 reported in percent. Sample: monthly observations, January 1986–December 2024. High yield bonds are the omitted category. Standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	Single cluster			Two-way cluster			Other		
	(1) Bond	(2) Firm	(3) Country	(4) Bond× Time	(5) Firm× Time	(6) Ctry× Time	(7) Driscoll-Kraay	(8) Newey-West	(9) Wild BS
GCC	0.68	0.70	0.68	0.66	0.68	0.66	0.68	0.68	0.68
	(0.01)***	(0.03)***	(0.03)***	(0.08)***	(0.08)***	(0.05)***	(0.11)***	(0.00)***	(0.03)***
BBB × GCC	-0.32	-0.33	-0.32	-0.32	-0.33	-0.32	-0.32	-0.32	-0.32
	(0.01)***	(0.03)***	(0.03)***	(0.03)***	(0.04)***	(0.03)***	(0.05)***	(0.00)***	(0.03)***
A × GCC	-0.48	-0.50	-0.48	-0.48	-0.50	-0.48	-0.48	-0.48	-0.48
	(0.01)***	(0.03)***	(0.04)***	(0.05)***	(0.05)***	(0.04)***	(0.08)***	(0.00)***	(0.04)***
AAA/AA × GCC	-0.58	-0.60	-0.58	-0.58	-0.60	-0.58	-0.58	-0.58	-0.58
	(0.01)***	(0.03)***	(0.06)***	(0.05)***	(0.06)***	(0.06)***	(0.09)***	(0.00)***	(0.06)***
Total R^2	9.4	9.7	9.4	9.0	9.3	9.0	9.4	9.4	9.4
Time-series R^2	7.1	7.3	7.1	6.7	6.9	6.7	7.1	7.1	7.1
Cross-sectional R^2	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Market-timing R^2	1.5	1.6	1.5	1.5	1.6	1.5	1.5	1.5	1.5
N. of obs	2,376,804	2,148,534	2,376,804	2,376,804	2,148,534	2,376,804	2,376,804	2,376,804	2,376,804
N. clusters	40,103	4,965	50	468	468	50			50

Table A.6: Bond-level risk premia by rating. This table reports the estimated coefficients from the regression of three-month-ahead excess holding period returns on the global credit factor (GCC), with exposures parametrized by a country type dummy. Bonds issued by U. S. firms are the omitted category. Each column corresponds to subsamples of observations by bond rating, with column 1 reporting the results for bonds rated either AA or AAA, column 2 the results for bonds rated A, column 3 the results for bonds rated BBB, and column 4 the results for high yield bonds (rated below BBB-). Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. Sample: monthly observations, January 1986–December 2024. 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) AAA/AA	(2) A	(3) BBB	(4) HY
GCC	0.17	0.21	0.36	0.64
	(0.01)***	(0.00)***	(0.01)***	(0.01)***
AE, ex U. S. $\times$ GCC	-0.12	-0.04	-0.05	0.10
	(0.01)***	(0.00)***	(0.01)***	(0.03)***
EM $\times$ GCC		0.11	0.16	0.23
		(0.02)***	(0.02)***	(0.04)***
Total R^2	4.9	9.8	9.8	8.5
Time-series R^2	4.5	9.7	9.6	8.5
Cross-sectional 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 risk premia with other characteristics. This table reports the estimated coefficients from the regression of three-month-ahead 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 24 months. Sample: monthly observations, January 1986–December 2024. 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.

		Regions			Currencies	
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
GCC	-0.31	-0.33	-0.21	-0.27	-0.34	-0.12
	(0.01)***	(0.01)***	(0.02)***	(0.03)***	(0.01)***	(0.01)***
Spread × GCC	0.09	0.09	0.07	0.07	0.09	0.04
	(0.00)***	(0.00)***	(0.01)***	(0.01)***	(0.00)***	(0.00)***
Duration × GCC	0.04	0.04	0.02	0.04	0.04	0.01
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Return vol × GCC	0.01	0.01	0.22	0.25	0.01	0.28
	(0.00)***	(0.00)***	(0.05)***	(0.05)***	(0.00)***	(0.04)***
Total R^2	16.2	16.4	19.0	21.1	16.7	16.5
Time-series R^2	2.4	2.8	1.9	5.9	2.9	2.3
Cross-sectional R^2	2.4	2.2	3.3	2.8	2.3	2.7
Market-timing R^2	11.4	11.4	13.9	12.3	11.4	11.5
N. of obs	2,338,014	1,426,914	786,206	124,894	1,779,044	558,970
N. bonds	40,102	24,618	14,239	2,428	30,143	9,959

Table A.8: Bond-level risk premia across horizons. This table reports the estimated coefficients from the regression of H-month-ahead excess holding period returns on the global credit factor (GCC), with exposures parametrized by a rating dummy. Panel A.8a uses the baseline factor constructed targeting three-month-ahead excess returns on portfolios of advanced economy bonds. Panel A.8b uses global credit factors constructed targeting H-month-ahead excess returns on portfolios of advanced economy bonds. All regressions include overlapping observations of multiple-period returns. Sample: monthly observations, January 1986–December 2024. 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.

(a) Using factor targeting three-month-ahead returns

	(1) 3M	(2) 6M	(3) 9M	(4) 12M
GCC	0.68	0.50	0.42	0.37
	(0.01)***	(0.01)***	(0.01)***	(0.00)***
BBB × GCC	-0.32	-0.21	-0.17	-0.15
	(0.01)***	(0.01)***	(0.01)***	(0.00)***
A × GCC	-0.48	-0.34	-0.28	-0.25
	(0.01)***	(0.01)***	(0.01)***	(0.00)***
AAA/AA × GCC	-0.58	-0.42	-0.35	-0.31
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
Total R^2	9.4	15.8	19.1	20.7
Time-series R^2	7.1	12.5	15.3	16.4
Cross-sectional R^2	0.8	1.2	1.4	1.7
Market-timing R^2	1.5	2.1	2.4	2.6
N. of obs	2,376,804	2,234,794	2,098,780	1,966,114
N. bonds	40,103	40,073	40,039	39,888

(b) Using factor targeting H-month-ahead returns

	(1) 3M	(2) 6M	(3) 9M	(4) 12M
GCC	0.68	0.59	0.55	0.48
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
BBB × GCC	-0.32	-0.25	-0.21	-0.19
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
A × GCC	-0.48	-0.40	-0.35	-0.32
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
AAA/AA × GCC	-0.58	-0.50	-0.45	-0.40
	(0.01)***	(0.01)***	(0.01)***	(0.01)***
Total R^2	9.4	15.0	18.7	21.2
Time-series R^2	7.1	12.0	15.4	17.0
Cross-sectional R^2	0.8	0.8	0.9	1.4
Market-timing R^2	1.5	2.2	2.4	2.8
N. of obs	2,376,804	2,234,794	2,098,780	1,966,114
N. bonds	40,103	40,073	40,039	39,888

Table A.9: Bond-level risk premia by country. This table reports the estimated coefficients from the regression of three-month-ahead excess holding period returns on the global credit factor, with exposures parametrized by a rating dummy. Each column corresponds to bonds issued by firms in the given country. Panel A.9a reports the results for advanced economies (with columns corresponding to bonds issued by firms domiciled in the U. S., Canada, United Kingdom, Germany, France, Spain, Italy, Japan, and Australia, respectively). Panel A.9b reports the results for emerging market economies (with columns corresponding to bonds issued by firms domiciled in China, Malaysia, Thailand, India, Mexico, Brazil, Russia, Chile, and Argentina, respectively). Sample: monthly observations, January 1986–December 2024. High yield bonds are the omitted category. AAA/AA-rated bonds issued by firms in emerging market economies (Panel A.9b) are excluded from the sample due to lack of observations and the corresponding coefficient not estimated in the regressions. 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.

(a) Advanced economies

	(1) US	(2) CA	(3) GB	(4) DE	(5) FR	(6) ES	(7) IT	(8) JP	(9) AU
GCC	0.64	0.78	0.71	0.68	0.74	1.86	0.60	0.86	0.88
	(0.01)***	(0.07)***	(0.06)***	(0.14)***	(0.07)***	(0.44)***	(0.06)***	(0.10)***	(0.10)***
BBB × GCC	-0.28	-0.40	-0.41	-0.46	-0.52	-1.52	-0.22	-0.76	-0.65
	(0.01)***	(0.07)***	(0.06)***	(0.14)***	(0.08)***	(0.45)***	(0.06)***	(0.11)***	(0.10)***
A × GCC	-0.43	-0.58	-0.49	-0.51	-0.58	-1.70	-0.40	-0.82	-0.72
	(0.01)***	(0.07)***	(0.06)***	(0.14)***	(0.08)***	(0.45)***	(0.07)***	(0.10)***	(0.10)***
AAA/AA × GCC	-0.48	-0.71	-0.58	-0.62	-0.67	-1.85	-0.52	-0.85	-0.80
	(0.01)***	(0.07)***	(0.06)***	(0.14)***	(0.08)***	(0.44)***	(0.07)***	(0.10)***	(0.10)***
Total R^2	9.2	9.0	9.0	11.8	11.8	15.4	9.6	12.9	10.2
Time-series R^2	7.1	7.5	7.9	8.9	8.1	10.3	9.3	1.7	6.4
Cross-sectional R^2	0.7	0.7	0.7	1.1	1.4	1.9	0.5	3.2	1.5
Market-timing R^2	1.4	0.8	0.4	1.8	2.2	3.2	-0.3	8.0	2.3
N. of obs	1,449,575	176,641	125,633	73,159	76,958	20,057	25,503	84,988	28,804
N. bonds	24,630	2,527	2,291	1,582	1,457	349	432	1,685	519

(b) Emerging market economies

	(1) CN	(2) MY	(3) TH	(4) IN	(5) MX	(6) BR	(7) RU	(8) CL	(9) AR
GCC	0.62	1.43	1.09	1.23	0.80	0.77	0.94	1.83	2.19
	(0.06)***	(0.13)***	(0.55)*	(0.08)***	(0.08)***	(0.06)***	(0.15)***	(0.51)***	(0.23)***
BBB × GCC	-0.39	-1.11	-0.76	-0.68	-0.15	-0.35	-0.26	-1.41	-0.97
	(0.07)***	(0.14)***	(0.56)	(0.11)***	(0.10)	(0.07)***	(0.17)	(0.52)***	(0.23)***
A × GCC	-0.41	-1.13	-0.94	-1.09	-0.46	-0.56	0.16	-1.45	
	(0.07)***	(0.14)***	(0.57)	(0.09)***	(0.09)***	(0.07)***	(0.18)	(0.51)***	
Total R^2	8.0	17.0	9.8	24.6	12.1	10.7	24.1	17.5	18.2
Time-series R^2	5.3	17.4	8.0	21.7	11.3	9.9	25.3	12.4	18.0
Cross-sectional R^2	0.6	0.7	0.8	0.7	0.4	0.4	0.2	1.6	0.0
Market-timing R^2	2.0	-1.1	1.0	2.2	0.3	0.3	-1.5	3.5	0.2
N. of obs	25,599	3,135	2,294	7,696	19,854	18,705	9,064	9,091	1,928
N. bonds	615	46	35	150	308	342	160	136	50

Table A.10: Bond-level risk premia using GCC constructions targeting alternative portfolios. This table reports the estimated coefficients from the regression of three-month-ahead excess holding period returns on the global credit factor (GCC), with exposures parametrized by a rating dummy. Each column corresponds to the factor targeting an alternative set of portfolios. Sample: monthly observations, January 1986–December 2024. High yield bonds are the omitted category. Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. 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
GCC	0.68	1.37	0.89	5.98
	(0.01)***	(0.02)***	(0.02)***	(0.10)***
BBB × GCC	-0.32	-0.67	-0.43	-2.78
	(0.01)***	(0.02)***	(0.02)***	(0.11)***
A × GCC	-0.48	-0.98	-0.64	-4.23
	(0.01)***	(0.02)***	(0.02)***	(0.11)***
AAA/AA × GCC	-0.58	-1.18	-0.77	-5.17
	(0.01)***	(0.02)***	(0.02)***	(0.11)***
Total R^2	9.4	9.4	9.6	8.6
Time-series R^2	7.1	6.9	7.2	6.5
Cross-sectional R^2	0.8	0.9	0.8	0.7
Market-timing R^2	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.11: Bond-level risk premia using GCC constructed with European predictors. This table reports the estimated coefficients from the regression of three-month-ahead excess holding period returns on the global credit factor (GCC) constructed using VSTOXX and average EBP across France, Germany, Italy, Spain, Belgium, Netherlands, Finland, and Ireland. VSTOXX is the Eurex option-implied volatility index (VSTOXX); EBP constructed as the amount-outstanding-weighted average of bond-level default-adjusted spreads on bonds issued by parent companies domiciled in the specified countries. Sample: monthly observations, January 1999–December 2024. High yield bonds are the omitted category. Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. 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.

		Regions			Currencies	
	(1) Full sample	(2) U.S.	(3) AE, ex U.S.	(4) EM	(5) USD	(6) Non-USD
Global credit	0.50	0.49	0.51	0.62	0.51	0.43
	(0.01)***	(0.01)***	(0.02)***	(0.02)***	(0.01)***	(0.02)***
BBB × Global credit	-0.22	-0.20	-0.27	-0.24	-0.20	-0.24
	(0.01)***	(0.01)***	(0.02)***	(0.03)***	(0.01)***	(0.02)***
A × Global credit	-0.35	-0.32	-0.38	-0.38	-0.33	-0.32
	(0.01)***	(0.01)***	(0.02)***	(0.03)***	(0.01)***	(0.02)***
AAA/AA × Global credit	-0.42	-0.35	-0.47		-0.38	-0.38
	(0.01)***	(0.01)***	(0.02)***		(0.01)***	(0.02)***
Total R^2	10.0	10.1	9.4	13.2	10.3	9.2
Time-series R^2	7.9	8.3	7.1	11.8	8.6	7.0
Cross-sectional R^2	0.6	0.5	0.7	0.4	0.5	0.7
Market-timing R^2	1.5	1.3	1.6	1.0	1.2	1.5
N. of obs	2,119,444	1,201,655	790,840	126,949	1,554,782	564,662
N. bonds	37,119	21,638	14,222	2,432	27,172	9,947

Table A.12: Cross-currency differences in GCC exposure. This table reports the estimated coefficients from the within-firm regression of three-month-ahead excess holding period returns on the global credit factor (GCC) and an indicator equal to 1 if the bond is USD-denominated (Table A.12a) or an indicator equal to 1 if the bond is denominated in the ultimate parent's local currency (Table A.12b). Table A.12a uses observations of returns on bonds issued by multi-currency issuers with at least one USD-denominated bond for the full sample column; and at least one USD-denominated bond and one bond denominated in the currency stated in the column header. Table A.12b uses observations of returns on bonds issued by multi-currency issuers with at least one bond denominated in the currency local to the ultimate parent (columns) and one bond denominated in another currency. Sample: monthly observations, January 1998–December 2024. All regressions include month, firm (ultimate parent), and firm-month fixed effects. R^2 reported in percent. Standard errors clustered at the ultimate parent level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) USD-denominated vs rest

	(1) Full sample	(2) EUR	(3) GBP	(4) CAD	(5) JPY	(6) AUD
USD	-0.27	-0.18	-0.43	-0.52	-0.29	-0.84
	(0.07)***	(0.08)**	(0.17)**	(0.11)***	(0.34)	(0.17)***
USD × GCC	0.10	0.10	0.01	0.13	0.17	0.16
	(0.01)***	(0.01)***	(0.03)	(0.02)***	(0.04)***	(0.03)***
W/in adj. R^2	0.6	0.7	0.0	1.0	3.7	0.7
N. of obs	655,403	452,936	163,391	170,261	42,947	74,854
N. firms	525	398	153	115	46	67

(b) Denominated in local currency vs rest

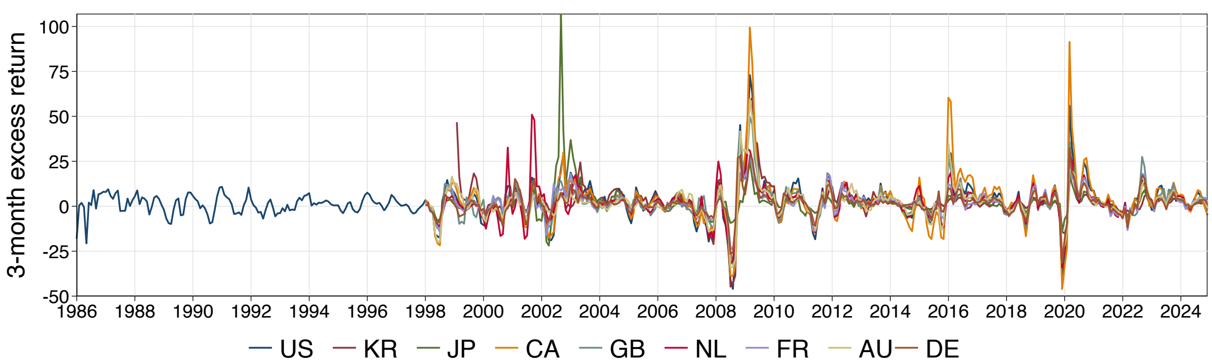
	(1) USD	(2) EUR	(3) GBP	(4) CAD	(5) JPY	(6) AUD
Local	-0.29	0.25	0.60	0.36	-0.48	0.60
	(0.10)***	(0.14)*	(0.25)**	(0.14)**	(0.25)*	(0.16)***
Local × GCC	0.05	-0.16	0.00	-0.12	-0.07	-0.03
	(0.02)***	(0.03)***	(0.02)	(0.03)***	(0.02)***	(0.03)
W/in adj. R^2	0.1	2.0	0.0	0.9	3.2	0.2
N. of obs	267,381	141,993	55,445	73,896	27,338	11,650
N. firms	224	122	77	60	21	25

Table A.13: Risk premia on other asset classes. This table reports the estimated coefficients from the regression of three-month-ahead excess holding period returns on the global credit factor (GCC) at the portfolio level. Each corporate bond portfolio is the amount-outstanding-weighted average of bonds in a given country–credit rating pairing. Equity returns measured using MSCI total return unhedged indices for a given country. Sovereign returns computed by interpolating each country's zero coupon yield curve to the 10-year point at month t and to the 9-year 9-month point at time $t + 3$, reflecting the returns to a trading strategy in which every month a 10-year bond is purchased and resold three months later as a 9-year 9-month bond. Sample: monthly observations, January 1986–December 2024. High yield bond portfolio is the omitted category. Due to lack of observations, AAA/AA-rated bonds issued by firms in emerging market economies are excluded from the sample and the corresponding coefficient is not estimated in the regression in column 4. R^2 reported in percent. Driscoll and Kraay (1998) standard errors with 12 lags reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

		Regions		
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM
GCC	0.71	0.60	0.68	0.78
	(0.12)***	(0.09)***	(0.10)***	(0.18)***
Equity × GCC	0.10	-0.17	-0.04	0.38
	(0.16)	(0.15)	(0.14)	(0.25)
BBB × GCC	-0.42	-0.27	-0.44	-0.39
	(0.07)***	(0.06)***	(0.05)***	(0.13)***
A × GCC	-0.53	-0.42	-0.55	-0.44
	(0.09)***	(0.08)***	(0.08)***	(0.17)***
AAA/AA × GCC	-0.62	-0.45	-0.60	0.00
	(0.10)***	(0.08)***	(0.08)***	(.)
Sovereign × GCC	-0.46	-0.49	-0.44	-0.43
	(0.07)***	(0.08)***	(0.05)***	(0.14)***
Total R^2	6.6	11.3	7.0	6.9
Time-series R^2	4.7	10.2	5.3	4.5
Cross-sectional R^2	0.8	2.1	1.1	0.4
Market-timing R^2	1.2	-1.0	0.5	2.0
N. of obs	59,255	2,808	40,722	15,725

Figure A.1. Three-month-ahead bond excess returns. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) three-month-ahead duration-hedged excess returns for nonfinancial corporate, senior fixed-coupon bonds issued by ultimate parents domiciled within the largest 9 advanced economy and emerging market countries in our sample. Returns reported in annualized percent terms. Sample AE countries (Figure A.1a) are: United States, South Korea, Japan, Canada, United Kingdom, Netherlands, France, Australia, and Germany. Sample EM countries (Figure A.1b) are: China, Malaysia, Thailand, India, Mexico, Brazil, Russia, Chile, and Argentina. Sample: monthly observations, January 1986–December 2024.

(a) Advanced economies



(b) Emerging market economies

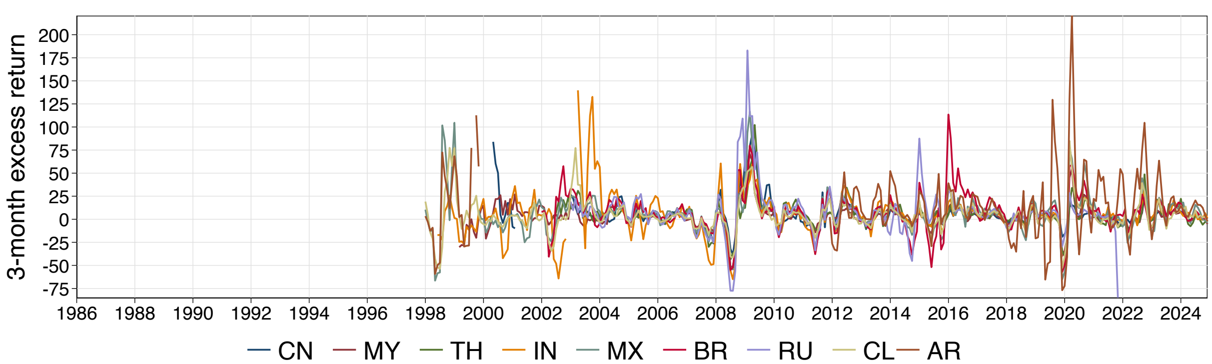
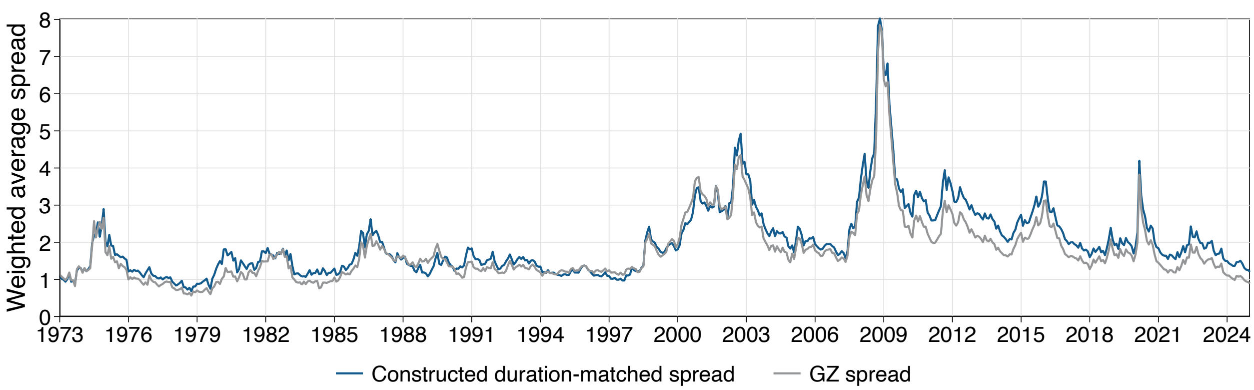


Figure A.2. Comparison to Gilchrist and Zakrajšek (2012) series. This figure plots the time series of U. S. average duration-matched and default-adjusted credit spreads in our sample versus the Gilchrist and Zakrajšek (2012) spreads. Figure A.2a plots the duration-matched spread, measured as the difference between the bond yield and the yield on a U. S. Treasury portfolio with matched duration. Figure A.2b plots the default-adjusted spread, measured as the difference between the duration-matched spread and the spread predicted from the relationship between log spread, log expected default frequencies, and bond and firm characteristics. For both the duration-matched and default-adjusted spread, we average bond-level spreads using amount outstanding weights, for all bonds issued by U. S. firms in the sample. Sample: monthly observations, January 1986–December 2024.

(a) Duration-matched spread



(b) Default-adjusted spread

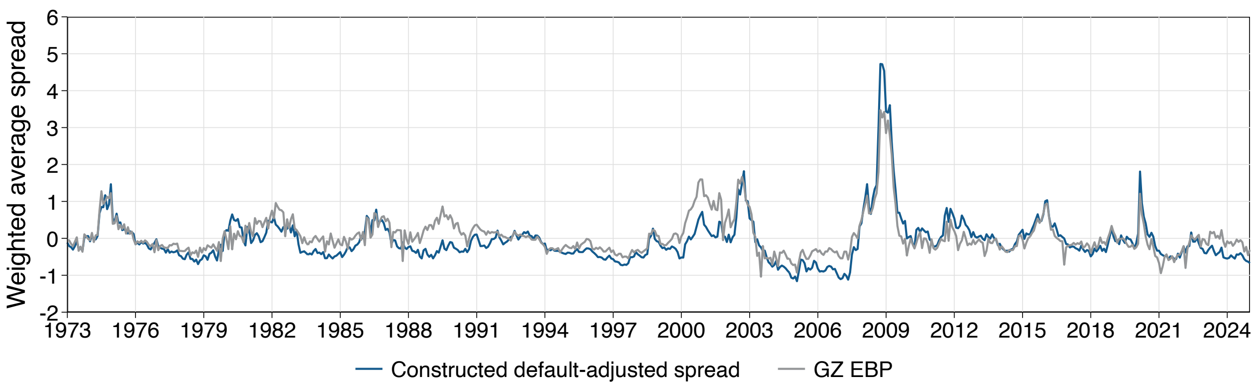


Figure A.3. Comparing the global credit factor to univariate factors. This figure plots the comparison between the global credit factor and the factors extracted from credit spreads, $\varphi\,(EBP)$, and VIX, $\varphi\,(VIX)$, separately. "EBP" is the excess bond premium of Gilchrist and Zakrajšek (2012); VIX is the CBOE option-implied volatility index, supplemented with VXO data prior to 1990. $\varphi\,(\cdot)$ denotes the nonlinear sieve transformation that maps predictors into a return-forecasting factor, with $GCC \equiv \varphi\,(EBP, VIX)$ the global credit factor and $\varphi_1\,(EBP) + \varphi_2\,(VIX)$ the optimal additive bivariate factor (with no interactions between EBP and VIX). Sample: monthly observations, January 1986–December 2024. To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations.

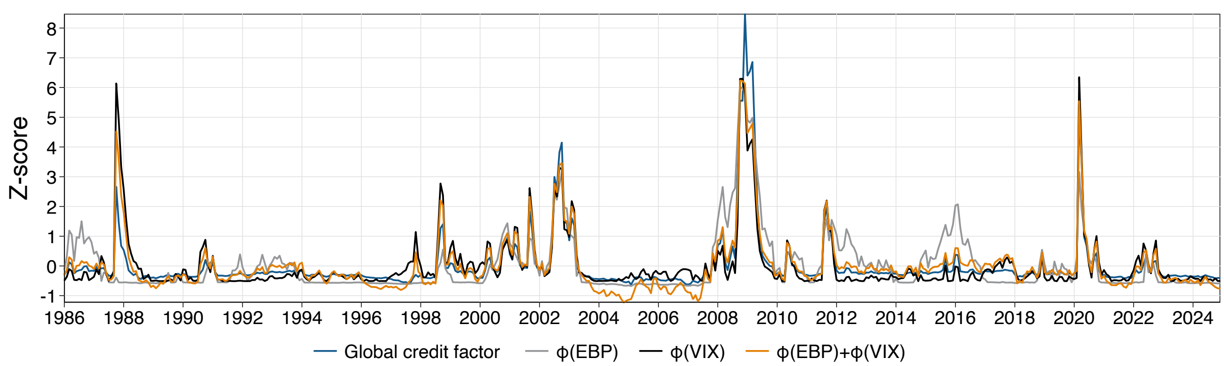
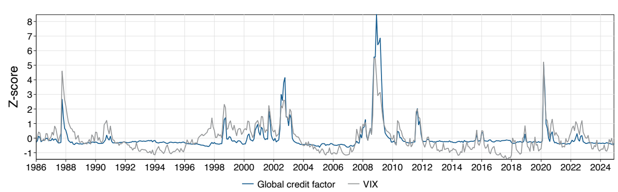
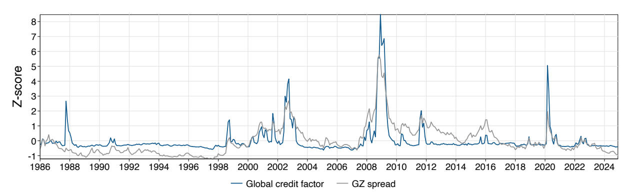


Figure A.4. Comparison to other variables. This figure plots the time series of the global credit factor estimated by reduced-rank regression against commonly used measures of financial conditions: VIX (the CBOE option-implied volatility index, supplemented with VXO data prior to 1990), Gilchrist and Zakrajšek (2012) "GZ" spread and excess bond premium (EBP), the 12-month change in the broad dollar index, the original Miranda-Agrippino and Rey (2015) (January 1990–December 2012) and the updated Miranda-Agrippino et al. (2020) global factor, and the U. S. (available starting January 1990) and global (available starting March 2007) Goldman Sachs financial conditions indices (GS FCI). Sample: monthly observations, January 1986–December 2024. To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations. We further reverse the sign of the original Miranda-Agrippino and Rey (2015) and the updated Miranda-Agrippino et al. (2020) global factors, so that, for each metric, a more positive value indicates tightening.

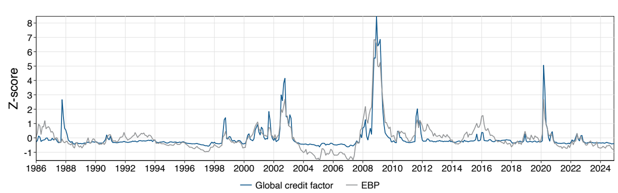
(a) VIX



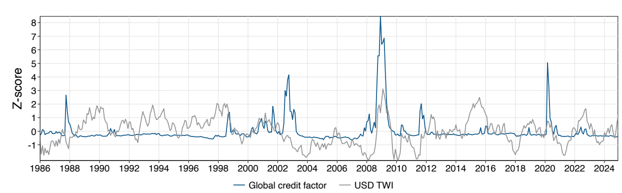
(b) GZ spread



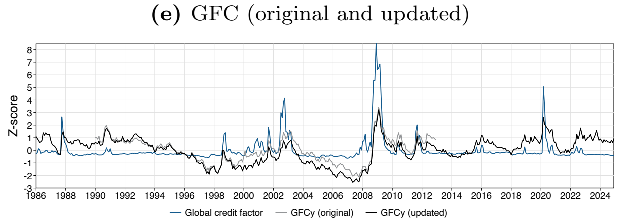
(c) EBP



(d) Broad dollar index



(e) GFC (original and updated)



(f) GS FCI and Global GS FCI