The Global Credit Cycle*

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Abstract

Do global credit conditions affect local credit and business cycles? Using a large cross-section of equity and corporate bond market returns around the world, we construct a novel global credit factor and a global risk factor that jointly price the international equity and bond cross-section. We uncover a global credit cycle in risky asset returns, which is distinct from the global risk cycle. We document that the global credit cycle in asset returns translates into a global credit cycle in credit quantities, with a tightening in global credit conditions predicting extreme capital flow episodes and declines in the stock of country-level private debt. Furthermore, global credit conditions predict the mean and left tail of real GDP growth outcomes at the country-level. Thus, the global pricing of corporate credit is a fundamental factor in driving local credit conditions and real outcomes.

JEL codes: F30, F44, G15, G12

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1 Introduction

In the aftermath of the global financial crisis, a growing literature has focused on exploring the global financial cycle (GFCy) in risky asset prices and capital flows, with a focus on the role played by global risk appetite.[1] In parallel, a number of studies have documented the link between local financial cycles and local business cycles, with a focus on the role played by local credit conditions.[2] These two literatures have remained largely disconnected, with the GFCy literature emphasizing the global component of cycles, and the credit literature exploring the local credit-GDP nexus. This paper bridges this gap.

In this paper, we study the role of global credit cycles in driving local credit conditions and local business cycles. Using a measure of the global credit cycle built from international bond-level returns we document three basic facts. First, we show that there is a global credit cycle in risky asset returns and that this cycle is distinct from the global risk cycle. Moreover, there is a global flight-to-safety in risky asset returns. Expected excess returns on high yield bonds increase but expected excess returns on investment grade bonds decrease following tightenings in the global credit factor.

Second, we document that the global credit cycle in asset prices translates into a global credit cycle in credit quantities. We show that tightenings in the factor are associated with large contractions in international capital flows, largely driven by a contraction in the debt portfolio component of capital flows. Moreover, we document that tightenings in the credit factor are also associated with subsequent reductions in the stock of private debt. Both of these findings are consistent with the global credit factor capturing information about the global reallocation of credit.

Third, strained global credit conditions predict lower average growth and a higher probability

[1] See e.g. Rey (2013), Miranda-Agrippino and Rey (2015), and Miranda-Agrippino and Rey (2020).

[2] See e.g. Schularick and Taylor (2012), Gourinchas and Obstfeld (2012), Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), Mian et al. (2017), López-Salido et al. (2017), Krishnamurthy and Muir (2017), and Greenwood et al. (2022).

of a crisis, defined as a large contraction in GDP growth. These results are particularly striking as they hold even after controlling for a number of measures of local and foreign credit conditions that have been shown to predict GDP growth. Furthermore, not only is the global credit factor a statistically significant predictor of a crisis, the predictability is economically meaningful, with magnitudes on par with the predictability from credit quantities established in the literature.

How can a measure of global credit risk premia translate into predictability of local real activity? In Boyarchenko and Elias (2024), we document that the global credit cycle drives firms' capital structure decisions globally – in terms of the instrument, maturity, and currency composition of their debt. Moreover, as we show in Boyarchenko et al. (2023), the composition of firms' liabilities affects the transmission of aggregate shocks, including monetary policy, to the real economy: both firms' willingness to borrow and financial intermediaries' willingness to lend through different types of instruments changes over the local business cycle and the global credit cycle. Put together, these two sets of results suggest a pass-through of global credit conditions to real activity through firms' balance sheets.

Motivated by macrofinance theories,[3] a fundamental aspect of our approach is allowing for non-linearities in the relationship between expected excess returns and the VIX and U. S. credit spreads while restricting the shape of the non-linearity to be the same across countries and asset categories. Non-linearities in expected excess returns capture the intuition of occasionally binding constraints for marginal intermediaries in the markets we consider. Similarly, the existence of global pricing factors accommodates for the presence of global intermediaries – although potentially different between bond and equity markets.

A key element of the analysis in this paper is using the international debt market consolidated data from Boyarchenko and Elias (2023). The consolidated debt market data allow us to supplement secondary corporate bond market quotes from ICE Global Indices for a large

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

cross-country panel of non-financial corporate bonds with balance sheet and expected default frequencies data at the ultimate corporate parent level. Using the ultimate corporate parent information additionally allows us to correctly assign corporate bonds to their country of domicile, even if an individual bond is issued by a financing subsidiary abroad.

This paper is related to several strands of literature. First, the paper contributes to the literature on the Global Financial Cycle (GFCy), which highlights the importance of global factors in driving local credit and business cycles. Rey (2013) discusses the existence of a GFCy in capital flows, asset prices, and credit growth and the effect this has on other countries' monetary policy independence. Miranda-Agrippino and Rey (2020) discuss the importance of U. S. monetary policy as a driver of the GFCy, and Miranda-Agrippino and Rey (2015) study the importance of the GFCy as a driver of world assets returns.

Second, this paper contributes to the literature on the predictive content of credit conditions for future real activity. Gilchrist et al. (2009), Gilchrist and Zakrajšek (2012), López-Salido et al. (2017), Krishnamurthy and Muir (2017), and subsequent literature show that corporate bond credit spreads predict future real activity in the U. S. Corporate bond credit spreads have also been shown to predict real activity across a number of other, primarily advanced, economies (Okimoto and Takaoka, 2017; Gilchrist and Mojon, 2018; Leboeuf and Hyun, 2018; Carabarín Aguirre and Peláez Gómez, 2021). In terms of credit quantities, Schularick and Taylor (2012), Gourinchas and Obstfeld (2012), Mian et al. (2017), and Greenwood et al. (2022), show the connection between credit expansions and financial crises probability and subsequent GDP growth. Finally, Brunnermeier et al. (2021) argue that the nexus between credit conditions and subsequent GDP growth is driven by the endogenous response of monetary policy.

Third, our paper contributes to the literature on global drivers of international capital flows. Avdjiev et al. (2020) explore the sensitivity of both cross-border loan and international bond flows to U. S. monetary policy. Forbes and Warnock (2012, 2021) find that the strong relationship between global risk and the incidence of extreme capital flow events observed in the pre-GFC period is reduced in the post-crisis period. More broadly, Goldberg (2023) discusses changes in the drivers of global liquidity since the crisis.

Finally, our paper contributes to the literature using cross-sectional return predictability to measure common factors in risky asset returns and the economic content of those common factors for future real activity. From an econometric approach perspective, our paper is most closely related to Adrian et al. (2019a), who propose a non-parametric approach to measuring the nonlinear relationship between U. S. equity and Treasury returns and the VIX. Adrian et al. (2019a) show that a non-linear function of the VIX captures "flight-to-safety" between U. S. equity and Treasury markets, while Adrian et al. (2019b) explore the flight-to-safety as a function of the VIX in global equity and sovereign bond markets. We take the intuition of a nonlinear relationship between returns and global risk factors further and show that the risk factors extracted in this way from return predictability regressions predict real activity, an exercise close in spirit to Bryzgalova and Julliard (2020) and the literature within.

The rest of the paper is organized as follows. In Section 2, we describe the data we use. In Section 3, we motivate and describe our factor construction procedure. In Section 4, we present our main results centered around bond return predicability. Section 5 discusses our results on predicting extreme capital flow events and real activity using the global credit cycle. Section 6 concludes.

2 Data description

2.1 Corporate bond data

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

We use secondary bond market quotes from ICE Global Bond Indices. As noted in Kelly et al. (2023), ICE data is considered the "gold standard" for corporate bond data because of the breadth of coverage relative to data on transactions-based prices and the analytics provided as part of the ICE dataset. Our main dataset starts in January 1998 and ends in December 2022, covering both periods of stress such as the global financial crisis and the COVID-19 pandemic, as well as more "normal" periods. We focus in this paper on secondary market pricing information as it captures the potential cost of capital for both companies issuing new debt as well as companies unable/unwilling to issue in a given period.

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 includes effective option-adjusted spread and duration for each bond-day, as well as bond and issuer characteristics, such as issuer domicile, issuer industry, currency of issuance, coupon type and rate, bond seniority, and call and put provisions. We use observations as of the third Wednesday of every month to ensure that the pricing is not affected by month-end index rebalancing activity.

While ICE global data provides us with coverage for the major bond-issuing countries around the world, the time series is somewhat limited –it starts in 1998. We thus supplement the

[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.

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 1975; see Warga (1991) for details.

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

Because we are interested in the real effects of global credit conditions, we restrict our sample of issuer ultimate parents to be nonfinancial corporations. That is, we include bonds issued by e.g. financing arms of nonfinancial ultimate parents but exclude bonds issued by nonfinancial subsidiaries of financial ultimate parents.[5] Moreover, we restrict the sample of bonds we use to be senior, unsecured, fixed-coupon bonds. Finally, we restrict our sample of bonds to bonds issued by ultimate parents in a sample of advanced and emerging economies: United States, South Korea, Japan, Canada, United Kingdom, Netherlands, France, Australia, Germany, Switzerland, Ireland, Italy, Spain, China, Malaysia, Thailand, India, Mexico, Brazil, Russia, Chile, and Argentina. Figure 1 plots the fraction of amount outstanding of bonds included in the Lehman and ICE indices in three broad rating categories: investment grade bonds with rating higher than BBB ("above BBB"), BBB-rated bonds, and speculative grade bonds (rating below BBB). Across advanced economies, the share of BBB-rated bonds has increased over time and now represents a third of the amount outstanding of bonds included

[5] We define an ultimate parent as being a nonfinancial corporation if the balance sheet data assigns a one digit SIC code that is not a 0, 6, or 9. Note that this definition excludes public sector bonds –including supranational organizations– as well as bonds issued by real estate companies.

in ICE Global indices. In emerging market economies, speculative grade bonds remain the most prominent category.

In Appendix B, we describe the procedure for computing duration-matched and default-adjusted bond-level credit spreads in our context of bonds denominated in different currencies, issued by ultimate parent companies domiciled in different countries. We use the bond-level credit spreads in two ways. First, using the panel of ultimate parents domiciled in the U. S., we construct our own time series of U. S. aggregate duration-matched spreads. Constructing our own duration-matched average U. S. credit spread allows us to align the timing of the credit spread observations with the timing of our return observations (the official Gilchrist and Zakrajšek (2012) "G-Z" spread data is end-of-month), as well as to compute the average default-adjusted and the average predicted U. S. credit spread on the same sample of bonds (rather than taking the difference between the G-Z spread and the published EBP series, which represent different sets of bonds).[6] Second, we use bond-level duration-matched spreads as controls in our return predictability regressions.

Our analysis uses a large, cross-country panel of price and spread data on individual non-financial corporate bonds. As is standard in the academic literature (see e.g. Bekaert and De Santis, 2021; Kelly et al., 2023; Dickerson et al., 2023) and in industry practice, we define the one-month return between date t and $t+1$ on bond b issued by firm f in currency c as

$$R^c_{b(f),t+1} = \frac{P^c_{b(f),t+1} + \mathrm{AI}^c_{b(f),t+1} + \mathrm{Coupon}^c_{b(f),t,t+1}}{P^c_{b(f),t} + \mathrm{AI}^c_{b(f),t}} - 1,$$

where $P^c_{b(f),t}$ is the bond's price at date t, $\mathrm{AI}^c_{b(f),t}$ is its accrued interest as of date t, and $\mathrm{Coupon}^c_{b(f),t,t+1}$ are coupons (if any) paid on the bond between date t and $t+1$.

We take the perspective of a U. S. investor in computing the excess returns on bond b at date t. Thus, we convert the currency-specific return $R^c_{b(f),t}$ to implied USD returns using

[6] Figure A.6 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.

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

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

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

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

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

Figure 2 plots the time series of weighted-average 12-month ahead corporate bond excess returns for the countries in our sample. The figure shows that, despite the breadth of coverage of our data in geographic and rating terms, country-level average excess returns are remarkably correlated across countries, motivating our approach to consider a global credit cycle.

2.2 Equity index data

We augment secondary market bond data with data on equity indices from the same sample of countries. We use the MSCI total dollar return index for each country. We construct one-month excess equiity returns as follows:

$$Rx_{e,c,t+1} = \frac{P_{e,c,t+1}}{P_{e,c,t}} - \left(1 + R^{tsy}_{3\mathrm{m},t+1}\right),$$

where $P_{e,c,t}$ is the price of the index for country c at time t and, as before, $R^{tsy}_{3\mathrm{m},t+1}$ is the one-month return on a three-month U. S. Treasury bill rate from date t to $t+1$. We compute h-month returns by cumulating the one-month ahead index returns.

2.3 Country-level data

We complement bond and equity data with standard country-level variables from the BIS, the IMF's International Financial Statistics (IFS), and the World Bank's World Development Indicators (WDI). While we restrict the sample of countries from which we draw bond-level information to the 22 countries with more extensive participation in the international bond market, we use country-level data from 50 countries for our macro-level results. Table 1 summarizes the variables used and their sources.

3 Measuring the global credit cycle

In this section, we provide some motivating evidence that, while global risky asset expected excess returns have a non-linear relationship with common risk proxies, that relationship is different for equity and corporate bond expected excess returns, suggesting a potential role for a distinct global credit cycle. We next use this insight to construct a global credit and a global risk factor as non-linear functions of the VIX and U. S. credit spreads, using reduced rank regressions to identify the two factors that maximize return predictability.

3.1 Motivating evidence

We begin by showing motivating evidence on the non-linearity in excess returns on the U. S. equity and U. S. corporate bond indices, highlighting that the nature of non-linearity is different between equities and corporate bonds. In particular, for both indices, we estimate non-linear regressions of the form

$$Rx_{i,t+h} = a_{i,h} + b_{i,h}vix_t + c_{i,h}vix_t^2 + d_{i,h}vix_t^3 + e_{i,h}cs_t + f_{i,h}cs_t + g_{i,h}cs_t + \epsilon_{i,t+h},$$

where cs_t is the Gilchrist and Zakrajšek (2012) "G-Z" spread. Table 2 reports the estimated coefficients from the above regression for 3-month ahead excess returns. The first two columns show the return predictability regressions for the U. S. equity index. While 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, column 1 shows that the VIX itself does not predict market excess returns linearly.[7] Instead, as documented in Adrian et al. (2019a,b), a non-linear (cubic) polynomial of the VIX does.

When we turn to predicting the excess return on the corporate bond index[8] instead (columns 3 – 7), we see that the relationship with the VIX is somewhat different. Consistent with Ang et al. (2006); Chung et al. (2019); Bao et al. (2023), a linear function of the VIX predicts corporate bond excess returns (column 3). Unlike the U. S. equity returns, column 4 suggests that there is no relationship between corporate bond excess returns and a non-linear function of the VIX.

Asset pricing theory (see e.g. Campello et al., 2008) suggests that returns on corporate bonds should be related to the level of credit spreads. The last three columns of Table 2 investigate that relationship. Consistent with theoretical predictions, a linear function of the aggregate U. S. credit spread predicts excess returns on the corporate bond index (column

[7] See also the evidence in Bekaert and Hoerova (2014), Bollerslev et al. (2013), and Adrian et al. (2019a).
[8] We use the Bloomberg Barclays U. S. Corporate Bond Index.

5). In column 6, we see that non-linear powers of the credit spread are also statistically significant predictors of corporate bond returns, with a doubling of the adjusted R^2. Finally, not surprising given the results in column 4, column 7 shows that the polynomial in credit spreads remains a statistically significant predictor of corporate bond returns after controlling for a polynomial in the VIX, with only the VIX cubic term marginally significant at the 10% level out of the VIX polynomial terms.

To summarize, the motivating evidence in Table 2 suggests that (1) expected excess returns on both equities and corporate bonds are nonlinear functions of aggregate proxies for risk; (2) that the nature of the non-linearity is different between equities and corporate bonds; and (3) that the relevant aggregate risk proxy may be different across equities and corporate bonds. We now use our global corporate bond-level return cross-section and equity index cross-section to explore the "non-linear but distinct" property of global corporate bond and equity returns more fully.

3.2 A reduced rank regression approach to return predictability

The motivating evidence in the previous subsection suggests that, while both global equity and corporate bond expected excess returns have a non-linear relationship with common risk proxies, that relationship is potentially distinct across asset classes. We are thus interested in estimating a more general return predictability regression of the form

$$Rx_{i,t+h} = a_{i,h} + \varphi_{i,h}\left(v_t, c_t\right) + F_{i,h} Z_{i,t} + \epsilon_{i,t+h}, \tag{1}$$

where $\varphi_{i,h}\left(\cdot,\cdot\right)$ is a potentially non-linear, asset- and horizon-specific function of the VIX, v_t, and the U. S. average duration-matched credit spread, c_t, in month t, and $Z_{i,t}$ is a $k \times 1$ vector of asset-specific controls in month t.

Using a Taylor approximation, for a given approximation order p, we can represent

$$\varphi_{i,h}(v_t, c_t) = \sum_{j+k \leq p} c_{i,h}^{(j,k)} v_t^j c_t^k + O_p.$$

Then, stacking the different powers of VIX and credit spreads $v_t^j c_t^k$ into a $m \times 1$ vector X_t, the return predictability regression (1) becomes

$$Rx_{i,t+h} = a_{i,h} + c_{i,h} X_t + F_{i,h} Z_{i,t} + \epsilon_{i,t+h}. \tag{2}$$

We construct our measures of the global risk and global credit cycles by estimating (2) for our global panel of equity and corporate bond excess returns subject to two restrictions on the coefficients $c_{i,h}$.

First, for parsimony, we restrict the loadings $c_{i,h}$ to be constant within a country-asset group so that

$$c_{i,h} = \delta_{i,g} c_{g,h},$$

where $\delta_{i,g}$ is an indicator equal to 1 if asset i is in country-asset group g. In our baseline specification, we group assets into four categories: equities, safest corporate bonds (above BBB rating), BBB-rated corporate bonds, and speculative grade (below BBB rating) corporate bonds. From an economic perspective, the restriction of common coefficients within a country-asset group can be intuitively thought of as estimating the predictive relationship at a portfolio level, while using asset-level characteristics to control for idiosyncratic variation in asset returns. Denote by N_g the total number of country-asset groups, and by c_h the $N_g \times m$ matrix of stacked $c_{g,h}$ coefficients across the N_g country-asset groups.

Second, we are interested in estimating r factors that are *common* across countries and asset categories, so that the rank of the full coefficient matrix c_h is $r < \min(N_g, m)$. To emphasize the intuition that we are interested in how a limited set of r (non-linear) combinations of U. S. equity implied volatility and U. S. credit spreads predict global risky asset returns, we implement the rank restriction on c_h by representing c_h as a product of two matrices

$$c_h \equiv b_h \gamma_m', \tag{3}$$

where γ_m' is an $r \times m$ matrix of loadings that map the m terms of the p-order approximation to the full non-linear function in VIX and credit spreads into r factors, and b_h is an $N_g \times r$ matrix of country-asset group coefficients from the return predictability regression on the factors $\gamma_m' X_t$. Notice that the representation (3) is not unique: for any invertible rotation matrix R, we have

$$c_h = b_h R R^{-1} \gamma_m' \equiv b_{\rho,h} \gamma_{\rho,m}'.$$

That is, the factors $\gamma_m' X_t$ have neither an inherent rotation nor scale. In the estimation procedure we describe below, we use this property to represent, without loss of generality, γ_m as

$$\gamma_m' = \left[I_r \quad \tilde{\gamma}_m' \right],$$

where $\tilde{\gamma}_m'$ is an $r \times (m - r)$ matrix.

With these two restrictions on $c_{i,h}$ in place, we can thus rewrite the return predictability regression (2) as

$$Rx_{i,t+h} = a_{i,h} + \delta_{i,g} b_{g,h} \gamma_m' X_t + F_{i,h} Z_{i,t} + \epsilon_{i,t+h}.$$

Stacking across the N_i observations of returns on asset i, we thus have

$$Rx_{i,h} = \delta_{i,g} X_i' \gamma_m b_{g,h}' + \tilde{Z}_i' \tilde{F}_{i,h}' + \epsilon_{i,h},$$

where X_i is the matrix of observations of X_t during the N_i periods of observations of asset i, $\tilde{Z}_i' = [\mathbb{1}_{N_i} \quad Z_i']$, and $\tilde{F}_{i,h} = [a_{i,h} \quad F_{i,h}]$. Denote by Δ_{N,N_g} the matrix of 0's and 1's assigns N assets into our N_g asset groups. Then, stacking across the N assets (for a total of T panel observations), we have

$$Rx_h = \bar{X}' vec\left(\gamma_m b_h' \Delta_{N,N_g}'\right) + \bar{Z}' vec\left(\tilde{F}_{i,h}'\right) + \epsilon_h,$$

where $\bar{X}' = diag\left(X_1', \ldots, X_N'\right)$ is a $T \times mN$ matrix, and $\bar{Z}$ is defined in a similar manner. Using the representation $\gamma_m' = [I_r \quad \tilde{\gamma}_m']$, we can rewrite the above as

$$Rx_h = \bar{X}_1' vec\left(b_h' \Delta_{N,N_g}'\right) + \bar{X}_2' vec\left(\tilde{\gamma}_m b_h' \Delta_{N,N_g}'\right) + \bar{Z}' vec\left(\tilde{F}_{i,h}'\right) + \epsilon_h, \tag{4}$$

where $\bar{X}_1$ is now a $T \times rN$ matrix of stacked observations of the first r rows of X_t, and $\bar{X}_2$ is a $T \times (m-r)\,N$ matrix of stacked observations of the remaining $m-r$ rows of X_t. Denoting $\tilde{c}_h = b_h \tilde{\gamma}_m'$, we can interpret the reduced-rank restriction implicit in the return predictability regression (4) as an asymptotic least-squares (ALS), with a parametric restriction of the form $g\left(b\left(\theta_0\right), a\left(\theta_0\right)\right) = 0$, where

$$g\left(b, a\right) = \underbrace{\begin{bmatrix} vec\left(b_h\right) \\ vec\left(\tilde{c}_h\right) \end{bmatrix}}_{b(\theta_0)} - \begin{bmatrix} I_{N_g,r} & 0 \\ 0 & I_{m-r} \otimes b_h \end{bmatrix} \underbrace{\begin{bmatrix} vec\left(b_h\right) \\ vec\left(\tilde{\gamma}_h\right) \end{bmatrix}}_{a(\theta_0)}. \tag{5}$$

The ALS estimator of $\tilde{\gamma}$ and b_h thus solves

$$\hat{a}_h = \underset{\tilde{\gamma}_m, b_h}{\operatorname{argmax}} \quad g\left(\hat{b}, a\right)' \hat{W} g\left(\hat{b}, a\right),$$

where $\hat{W}$ is a weighting matrix and

$$g\left(\hat{b}, a\right) = \begin{bmatrix} vec\left(b_h^{ols}\right) \\ vec\left(\tilde{c}_h^{ols}\right) \end{bmatrix} - \begin{bmatrix} I_{N_g,r} & 0 \\ 0 & I_{m-r} \otimes b_h^{ols} \end{bmatrix} \begin{bmatrix} vec\left(b_h\right) \\ vec\left(\tilde{\gamma}_h\right) \end{bmatrix}.$$

Before we describe the estimation strategy we pursue in this paper, it is worth emphasizing the specifics of our setting that make the standard reduced rank regression estimators unsuitable. First, a large number of our assets are bonds. Thus, we are working with an unbalanced panel of returns due to the natural attrition in time series observations of returns on fixed income, defaultable bonds. Moreover, since we are interested in understanding the *global* credit cycle, we have an unbalanced panel of countries and credit ratings, so that the panel would remain unbalanced even if we collapsed our corporate bond returns to returns on corporate bond portfolios. Second, our return predictability regressions for corporate bonds include bond-level characteristics, so that the matrix of additional controls $Z_{i,t}$ is asset-specific. For the most part, the characteristics included in $Z_{i,t}$ are deterministic – for example, bond age and callability – so that concerns about near-collinearity with X_t are somewhat reduced. Finally, since we are working with a large panel of asset returns, our panel has a larger cross-sectional than time series dimension. Restricting the coefficients $b_{i,h}$ to be constant within a country-asset group reduces the size of the effective cross-section, improving the precision of the estimated factors.

We implement the ALS estimator using a three step procedure.

Step 1. Estimate the unrestricted return predictability regression (2) for each country-asset group g to obtain $c_{g,h}^{ols}$. Stacking these N_g estimated coefficient matrices, we obtain the full unrestricted coefficient matrix c_h^{ols}. In addition to the unrestricted coefficient matrix c_h^{ols}, we can also construct the error from the return predictability regression

$$\epsilon_{i,t+h}^{ols} = Rx_{i,t+h} - a_{i,h}^{ols} - F_{i,h}^{ols} Z_{i,t} - \delta_{i,g} c_{g,h}^{ols} X_t.$$

Step 2. Partition the unrestricted estimate c_h^{ols} as

$$c_h^{ols} = \begin{bmatrix} b_h^{ols} & \tilde{c}_h^{ols} \end{bmatrix} \equiv \begin{bmatrix} b_h^{ols} & b_h^{ols}\tilde{\gamma}_h^{\prime,ols} \end{bmatrix},$$

so that

$$\epsilon_{i,t+h}^{ols} = Rx_{i,t+h} - a_{i,h}^{ols} - F_{i,h}^{ols} Z_{i,t} - \delta_{i,g} b_{g,h}^{ols} X_{1,t} - \delta_{i,g} b_{g,h}^{ols} \tilde{\gamma}_h^{\prime,ols} X_{2,t}.$$

Let

$$Rx_{i,t+h}^{e} = Rx_{i,t+h} - a_{i,h}^{ols} - F_{i,h}^{ols} Z_{i,t} - \delta_{i,g} b_{g,h}^{ols} X_{1,t},$$

and construct group-level (unexplained) returns $Rx_{g,t+h}^{e}$ as the volatility-weighted average of $Rx_{i,t+h}^{e}$ within each country-asset group g. We can then estimate $\tilde{\gamma}_m$ from the portfolio-level return regression

$$Rx_{g,t+h}^{e} = \sum_{k=1}^{r} \tilde{\gamma}_{m,k} \left(b_{g,h,k} X_{2,t} \right) + \eta_{g,t+h}. \tag{6}$$

In the empirical implementation, we regularize the estimated matrix $\tilde{\gamma}_m^{ss}$ by retaining only coefficients that a χ^2 test rejects as being 0 at the 5% confidence level, and set the rest of the elements of $\tilde{\gamma}_m^{ss}$ to 0.

Step 3. Using the fact that the factorization of c_h into a b_h and a γ_m is not unique, we construct r orthogonal factors with set magnitude as

$$\rho_t = R\text{cov}\left(\gamma_m^{\prime,ss} X_t\right)^{-1} \gamma_m^{\prime,ss} X_t,$$

where R is a diagonal matrix that selects a size for each factor and

$$\gamma_m^{\prime,ss} = [I_r \quad \tilde{\gamma}_m^{\prime,ss}] \, .$$

3.3 Estimated factors

We implement the procedure described above to construct 2 factors ($r = 2$) – which we will call the global credit and the global risk factors – to summarize the information from a third order ($p = 3$) approximation to one-month ahead expected excess returns. In estimating the return predictability regression for bond excess returns, we control for bond-level duration-matched spreads, duration, convexity, coupon rate, age, amount outstanding (in USD equivalents), and callability, as well as the firm-level EDF, the industry (SIC 1D) of the ultimate corporate parent, and an indicator for bond issuance by parent companies, domestic subsidiaries, or foreign subsidiaries. We scale the first factor such that the estimated coefficient from the one-month ahead return predictability regression for U. S. BBB bonds on the global credit factor is 1 and the second factor such that the estimated coefficient from the one-month ahead U. S. equity on the global risk factor is 1.

Figure 3 plots the time series of the estimated global credit and global risk factors over time. While both factors indicate a tightening of global financial conditions during broad-scale periods of stress such as the global financial crisis and the COVID-19 pandemic, the global credit cycle deviates from the global risk cycle during other periods of time. For example, the late 1990s correspond to a tightening in global financial conditions from the perspective of the global credit factor without a corresponding deterioration in the global risk factor.

How non-linear are the estimated factors? Figure 4 plots the global credit and global risk factors as a function of the VIX and the U. S. duration-adjusted spread. Starting with the top row, which plots the overall relationship of the global credit and risk factors with the

VIX and the U. S. duration-adjusted spread, we see that both factors are highly nonlinear in the two underlying risk metrics but the shape of the nonlinearity is distinct across the two factors. The middle left panel shows that the relationship of the global risk factor, conditional on a level of the U. S. duration-adjusted spread is nearly flat, while the relationship of the global credit factor with the VIX (middle right panel) appears more cubic. Instead, both factors increase as the U. S. duration-adjusted spread increases, especially for low levels of the VIX.

An obvious question is to what extent our estimated measures of the global credit and global risk factor are related to other proxies of global financial conditions. To address this question, in Figure 5 we plot 8 commonly used broad measures of global financial conditions together with our estimated global credit and global risk factors. In particular, we plot the VIX/VXO, the Gilchrist and Zakrajšek (2012) "G-Z" spread and excess bond premium (EBP), the 12-month change in the broad dollar index, the original Miranda-Agrippino and Rey (2015) and the updated Miranda-Agrippino et al. (2020) global factor, and U. S. and global Goldman-Sachs financial conditions indices (GS FCI). Figure 5 shows that while the G-Z spread is relatively strongly correlated with our global credit factor and the VIX with our global risk factor – justifying our interpretation of the non-linear factors we extract – the relationship of either factor to the rest of the commonly used FCIs is weak, especially outside of crisis periods. In Table 3 we report the full sample correlations, as well as correlations in the pre-crisis period (January 1975 – July 2007) and the post-crisis, pre-pandemic period (January 2010 – December 2019). Overall, the results in Figure 5 and Table 3 suggest that our estimated global credit and global risk factors contain differential information relative to commonly used measures of global financial conditions.

We end this section with a discussion of how our factor construction is different from that in Miranda-Agrippino and Rey (2015).[9] First, we focus on extracting factors that predict risky

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

asset returns while the factor construction in Miranda-Agrippino and Rey (2015) targets explaining contemporaneous comovement in financial variables. In Section 5, we use our factors to predict real activity. One potential concern with this exercise is that the predictive relationship arises mechanically given the forward-looking nature of our factors. However, it is important to note that we use only one-month returns to build the factors, while we document real activity predictability at substantially longer horizons. Second, we specify our factors to be non-linear 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. Given our focus in understanding whether there is a global credit cycle that is distinct from the global financial cycle, we tilt the composition of our sample towards corporate bonds while the composition of the sample in Miranda-Agrippino and Rey (2015) tilts towards equity market variables.

4 Return predictability

In this section, we investigate the risky asset return predictability by the global credit and global risk factors. Throughout, we estimate return predictability regressions of the form

$$Rx_{i,t+h} = a_{i,h} + b_{g,h}^{credit}\text{global credit}_t + b_{g,h}^{risk}\text{global risk}_t + F_{i,h}Z_{i,t} + \epsilon_{i,t+h},$$

maintaining the restriction that the loadings $b_{g,h}^{credit}$ and $b_{g,h}^{risk}$ are constant within a country-asset group g.

4.1 Baseline results

Table 4 reports the estimated coefficients together with the Hodrick (1992) standard errors[10] from the baseline predictive regression of one-month ahead risky asset excess returns on the global risk and global credit factors for advanced and emerging market economies, country-by-country and asset category-by-asset category. Each column in the table corresponds to a different country; each set of six rows to a different asset category. The results summarized in Table 4 show three striking facts.

First, comparing the estimated coefficients for each factor across asset categories within a country (moving across rows within a column), we can observe the differential response of assets to the global factors as asset category riskiness changes. In particular, the safest assets (corporate bonds rated higher than BBB) have the smallest – and, in some cases, negative – exposures to the global credit factor, while the riskiest assets (high yield corporate bonds) have the largest exposures to the global credit factor. For countries in which the aggregate equity market is also exposed to the global credit factor, equity returns have an even larger exposure to the global credit factor than high yield bonds do. Similarly, as we move from corporate bonds rated higher than BBB to BBB-rated bonds to high yield bonds to equities, the exposure to the global risk factor increases. That is, moving across rows within a country, we see that the exposures to the global factors increase monotonically as the riskiness of the asset category increases.

For example, in column (7) of Table 4a, we see that exposures of French corporate bonds to the global credit factor increase from -3.11 to -1.73 to 6.66 as we move from above BBB to BBB to high yield bonds.[11] This monotonic relationship with a sign reversal is consistent with a flight-to-safety within the French corporate bond market. That is, as the

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

[11] The estimated exposure of French equities to the global credit factor is not statistically significant.

global credit factor increases (global credit conditions tighten), expected excess returns on high yield bonds increase while expected excess returns on investment grade bonds decline, especially for those rated above BBB.

These estimates are both statistically and economically significant. A one standard deviation increase in the global credit factor (slightly below the increase in the global credit factor around the collapse of Long-Term Capital Management, LTCM, in 1998) corresponds to a 9.38 percentage point (p.p.) increase in annualized one-month ahead expected excess returns on French high yield bonds, a 2.4 p.p. decrease in expected excess returns on French BBB bonds, and a 4.4 p.p. decrease in expected returns on French bonds rated higher than BBB. These represent meaningful changes relative to unconditional average excess returns of 12.6%, 5.5%, and 6.6% across high yield, BBB, and above BBB-rated French corporate bonds, respectively.

Second, comparing the exposures to the global factors *across* countries, we once again see a near monotone ordering, with exposures higher in riskier countries. We can see this pattern more clearly in Figure 6, which plots the estimated coefficients for each country-asset category against the volatility of year-over-year real GDP growth.[12] The estimated exposures to both the global risk and the global credit factor increase as the country-level volatility of real GDP growth increases, so that asset returns in countries with more volatile growth appear to be more exposed to global factors.

In Figure 7, we compare the estimated exposures to the global credit and global risk factors with asset exposures (βs) to the return on the U. S. equity and U. S. corporate bond indices. The estimated exposure to the global risk factor increases almost one-for-one with the exposure to the U. S. equity return. The estimated exposure to the global credit factor likewise increases with exposure to the U. S. corporate bond index return, though the equity portfolios are somewhat of an outlier with regards to the magnitude of the point estimate

[12] We compute real GDP growth volatility in the pre-pandemic (pre-2020) sample.

of the exposure to the global credit factor. Remarkably, exposures to our factors have a monotone relationship with their CAPM β counterpart not just across countries but also within each individual asset category.

While Figures 6 and 7 show that there is a monotone ordering of exposures to global credit and global risk factors individually across asset category and country riskiness, a natural question to ask is whether the overall expected excess return due to exposures to global factors also varies monotonically across asset (and country) riskiness. Figure 8 plots the implied expected excess return (normalized by realized excess return volatility) across our four asset categories for the U. S., averaged across advanced economies excluding the U. S., and averaged across emerging market economies as a function of the U. S. credit spread for a given level of the VIX (left column) and as a function of the VIX for a given level of the U. S. credit spread (right column). Focusing on the middle row, which considers average levels of the VIX and average levels of the credit spread, respectively, we see that the ordering across asset categories remains even in expected excess return space. That is, for example, the expected excess return on the equity portfolios increases the most (and expected excess returns on the above BBB corporate bonds increases the least) as credit spreads increase. Similarly, the expected excess return on the equity portfolios increases the most (and expected excess returns on the above BBB corporate bonds increases the least) as VIX increases. For low levels of the U. S. credit spread, the expected excess returns on the equity portfolios are even below those of the corporate bond portfolios, highlighting the nonlinearity in our predicted excess returns relative to the VIX and credit spreads.

Finally, Table 4 shows that equities in advanced economy countries are an outlier in terms of their exposure to the global credit factor. Out of the 13 advanced economy countries included in our baseline sample, only equity returns in South Korea, Australia, the Netherlands and Spain have a statistically significant exposure to the global credit factor. For these four countries, however, as highlighted above, equities do have the largest exposures to the global credit factor across the four asset categories. In contrast, equity returns in almost all emerging market economy countries have statistically significant exposure to both global factors. These results highlight the distinct nature of the global credit and the global risk cycles.

4.2 Robustness

The results above demonstrate that the global credit and global risk factors predict one-month ahead excess returns systematically, across different countries and different asset riskiness. We now evaluate the robustness of this predictive relationship by considering how the predictive relationship changes when we control for common measures of financial conditions, across predictive horizons, different subperiods in our sample, and for additional test assets.

Controlling for other financial conditions measures. Table 5 replicates Table 4 but controlling for measures of global financial conditions commonly used in the literature: the VIX, the U. S. average default adjusted credit spread and predicted duration-adjusted credit spread, the broad dollar index, and the Miranda-Agrippino et al. (2020) global factor. The table shows that, for the most part, the global credit and global risk factors remain statistically significant predictors of excess returns even after controlling for other measures of global financial conditions. This is particularly surprising since the VIX and U. S. credit spreads are an integral part of the factor construction. That is, the nonlinear relationship between the global factors and the VIX and U. S. credit spreads is an important contributor to the predictive power of the global credit and global risk factors for excess returns.

While showing results adding proxies one-by-one (instead of all together) for each country and asset category is not feasible, Table 7a presents this exercise for a particular choice of a country and asset category: German BBB bonds. As discussed in the previous paragraph, global credit and global risk factors remain statistically significant predictors of excess returns on German BBB bonds as we add alternative measures of financial conditions. In contrast, some of these alternative measures either do not predict excess returns even when included by themselves or lose their statistical significance in regressions including our global factors.

Return predictability in subsamples. A natural question to ask in the return predictability setting is whether the full (time series) sample return predictability results in Table 4 are driven by particular extreme episodes, such as the global financial crisis and the market disruptions associated with the COVID-19 pandemic. As discussed previously, showing the full breakdown of the results in Table 4 for each country, asset class, and subperiod is infeasible. Thus, we once again focus on the same German BBB corporate bond bucket, and, in Table 7b, report the estimated coefficients for the full sample, "normal" periods (pre-July 2007, January 2010 – December 2019), the GFC (August 2007 – December 2009), 2020, and 2021 – 2022. While the adjusted R^2 is somewhat higher during both the GFC and 2020, the global credit factor remains a statistically significant predictor of excess returns across subperiods. The negative exposure to the global credit factor is amplified during the GFC and over 2021–2022. Interestingly, the exposure of German BBB bonds to the global credit factor is positive during 2020. This reversal of the relationship with the global credit factor is consistent with the larger price dislocations in safer securities during March 2020 documented in e.g. Haddad et al. (2021). In contrast, the full sample results for the global risk factor seem to be entirely driven by the crisis episodes, with a *negative* relationship between excess returns and the global risk factor during normal periods.

Return predictability across horizons. Table 6 replicates Table 4 but for alternative predictive horizons: 3-months ahead, 6-months ahead, and 12-months ahead. The table shows that the global credit and global risk factors remain statistically significant predictors of excess returns even at these longer horizons. To the extent that multi-period ahead excess returns are not perfectly correlated with one-month ahead returns, return predictability for these alternative horizons – which were not used in constructing the factors – provides external validity for the return predictability results described above.

To understand how return predictability changes across horizons, we focus once again on the German BBB-rated corporate bond bucket. Table 7c reports the estimated coefficients for horizons between one and twelve months ahead. The table shows that the magnitude of the estimated exposures to the global credit factor declines monotonically (trends toward 0) as the predictive horizon increases. The estimates, however, remain both statistically and economically significant even at the 12-month ahead horizon. A one standard deviation increase in the global credit factor corresponds to a 1 p.p. decrease in German BBB 12-month ahead expected excess returns, relative to an unconditional average level of 7.9%.

Return predictability in other assets. We conclude this section by investigating whether our global credit and risk factors predict excess returns even for assets not included as return predictability targets in constructing the factors. Table 8 reports the estimated coefficients from the return predictability regression for one-month ahead excess returns on 10 year nominal sovereign bonds (both for countries included in our baseline sample as well as additional countries),[13] and equity returns for countries not included in our baseline estimation. Across these alternative test assets, the global risk and global factors remain statistically significant predictors of excess returns, with sovereign bonds exhibiting flight-to-safety. For example, as documented in Adrian et al. (2019a), the excess return on 10 year U. S. Treasuries has the opposite sign of the exposure to the global risk factor as U. S. equities do. It is worth re-emphasizing that none of the assets discussed in this paragraph were used in constructing the factors and, as such, the results in Table 8 are in a sense an out-of-sample exercise.

[13] We construct returns on 10 year nominal sovereign bonds from smoothed zero coupon yield curves constructed for each country. The one-month return on a 10 year bond is the price difference between the 10 year bond in month t and the 9 year, 11 month bond in month $t+1$. Details on zero coupon curve construction are available in Boyarchenko et al. (2023).

5 Real activity

The return predictability results in the previous section demonstrate the non-linear but distinct nature of the global credit cycle: not only are global risky asset returns predictable by non-linear functions of the VIX and U. S. credit spreads, but also the global credit factor is distinct from the global risk factor. We now turn to the implications of the global credit and risk cycles for global business cycles. We do this in two steps. First, we provide evidence that the global credit cycle has differential implications for global capital flows than the global risk cycle, thus providing suggestive evidence on a transmission mechanism for global credit cycle to affect economic conditions at a local country level. Second, we study the importance of the global credit cycle for country-level business cycles, both in terms of average growth and in terms of predicting economic crises.

5.1 The global credit cycle and capital flows

Given the prominent role of global capital flows in propagating U. S. financial conditions around the world, we start by exploring how tightenings in global credit and global risk factors drive extreme capital flow events. Since we focus on extreme movements in capital flows, rather than small "day-to-day" fluctuations, our proposed predictors are *changes* in the global credit and global risk factors: we would not expect an extreme capital flow event to be generated by a high *level* of the global credit (or risk) factor but rather by a rapid tightening in it.[14]

While most of the literature has focused on extreme events in overall capital flows, the distinct nature of the global credit and global risk cycles suggest a potential differential impact on different types of capital flows. The disaggregated capital flow data that we use

[14] We aggregate the monthly time series of the global credit and global risk factors to a quarterly frequency by adding within a quarter (since our factors have the interpretation of expected excess returns). We then use one-quarter changes in the factors as predictors in the extreme event regressions described below.

allows us to explore extreme flow events in debt portfolio flows, equity portfolio flows, and bank/other flows separately. Starting with data on capital flows, we use the methodology explained in detail in Appendix A to build a set of indicator variables at the quarterly level that identify four type of episodes: stops (large drops in inflows by foreign investors), surges (large increases in inflows by foreign investors), flight (large increases in outflows by domestic investors), and retrenchment (large decreases in outflows by domestic investors). We build these indicators for both the overall capital flows, as well as debt portfolio, equity portfolio, and bank flows individually.

We explore the role of the credit and risk factors on the conditional probability of experiencing a capital flow event in subsequent quarters. We follow the probabilistic model in Forbes and Warnock (2012, 2021), but augment it to include the global credit and the global risk factors. More specifically, we estimate:

$$\begin{aligned}\text{Prob}\left(e_{i,t+k}=1\right) = 1 - \exp\Big(-\exp\Big(&\beta_e^{credit}\Delta\text{global credit}_{t-1} + \beta_e^{risk}\Delta\text{global risk}_{t-1} \\ &+\beta_{t-1}^{Global}X_{t-1}^{Global} + \beta_t^{Contagion}X_t^{Contagion} + \beta_{i,t-1}^{Local}X_{i,t-1}^{Local}\Big)\Big),\end{aligned} \tag{7}$$

where $e_{i,t+k}$ is an episode dummy that is equal to one if country i is experiencing an event at time $t+k$, X_{t-1}^{Global} and $X_{i,t-1}^{Local}$ are vectors of global and local variables, and $X_t^{Contagion}$ is an indicator equal to one if countries in the same region are experiencing the same type of episode.[15] We use the complimentary log-log specification since there are relatively few capital flow episodes in the sample (so that most observations of $e_{i,t+k}$ are equal to zero). As in Forbes and Warnock (2012, 2021), we estimate a seemingly unrelated regression version of the complimentary log-log specification to account for correlation between episodes in

[15] We use the data provided by Forbes and Warnock (2021) for our measures of the global variables (growth in global money supply, global long-term interest rates, and global GDP growth) and local variables (local GDP growth), as well as the regional contagion dummies. The contagion dummies in the Forbes and Warnock (2021) dataset are defined using the total flow series (not by type of flow). We thus control for contagion at a total level instead of at the flow type level, implicitly allowing for e.g. a stop episode in debt portfolio flows in one country to be used as a contagion indicator for stop episodes in equity portfolio flows in another country. The dataset can be found at https://mitmgmtfaculty.mit.edu/kjforbes/research/.

different types of flows. Throughout, we exclude the pandemic and post-pandemic period from our estimation and use the 44 largest advanced and emerging economies, excluding the U. S. and China.[16]

Table 9 presents the estimated coefficients from the complimentary log-log regression (7) for stop, surge, flight, and retrenchment episodes. Starting with stop episodes in Table 9a, we see that, in the full sample (columns 1–4), a tightening in either the global credit or the global risk factors predicts a higher probability of stop episodes, both for total flows as well as individually for each capital flow type. This is particularly noteworthy considering that none of the global, regional nor local variables of Forbes and Warnock (2012, 2021) – with the exception of global long term rates – predict all flow types. That is, the information captured in the global credit and global risk factors is fundamentally different from the information in standard measures of global conditions. The fact that both our global factors and long term rates are significant predictors of stop episodes indicates that global conditions beyond the global interest rate environment affect capital flows.

Given that a significant number of stop episodes in our sample occur during the global financial crisis (GFC), in columns 5 – 8 we report results excluding the crisis period (2008 – 2009) from the sample. While the global risk factor is no longer a significant predictor of stop episodes during "normal" times, the global credit factor remains a significant predictor of stops in total capital flows and also in debt portfolio flows. This suggests that the normal-time predictability of total capital flows by the global credit factor is driven by the predictability of stops in debt portfolio flows. Importantly, predictability by the global credit factor of stops in debt portfolio flows but not stops in equity portfolio flows nor stops in bank flows is consistent with a global credit cycle.

Turning to capital flow surges (Table 9b), we see that the global factors do not predict surges in total capital flows. Instead, the global credit factor predicts surges in debt and equity

[16] Table A.2 in the Appendix reports the estimated coefficients from the complimentary log-log regression excluding our factors.

portfolio flows, both for the full sample and during the normal periods (excluding the GFC). This is in contrast to the global, regional, and local variables of Forbes and Warnock (2012, 2021), which primarily predict surges in total flows and not the individual flow types, except for global long-term rates.

The final two panels of Table 9 focus on episodes in capital flows of domestic investors. Consistent with the global credit cycle mostly driving the behavior of global investors, our global factors do not add much predictability for flight episodes in either the full sample or during normal periods. That is, a loosening in either global credit or risk conditions is not sufficient by itself to induce domestic investors to invest abroad. On the other hand, our global factors do predict retrenchment episodes in the full sample, consistent with theories of home bias during periods of elevated uncertainty.

Finally, it is worth emphasizing that, in the cases in which the global credit and global risk factors are statistically significant predictors of capital flow episodes, they are also economically meaningful predictors. Relative to a 10% unconditional probability of a stop episode in total capital flows during normal times, the probability of a stop increases by 2% following a one standard deviation increase (tightening) in the global credit factor. In the full sample, the probability of a stop episode in total flows increases by 3.5% (relative to a 14% unconditional probability) following a one standard deviation increase (tightening) in the global credit factor.

5.2 The global credit cycle and real activity

We now study the impact of the global credit and global risk cycles on local economic activity. We are interested in understanding how shocks to our global credit and global risk factors are transmitted in a global economy. The standard approach to studying global transmission is with a global vector autoregression (GVAR) (see e.g. Pesaran et al., 2004; Dees et al., 2007), which allows domestic real outcomes to be affected by lags of domestic fundamentals and, importantly, lags of foreign fundamentals as well. More specifically, let $y_{i,t}$ be the vector of macroeconomic variables of interest (in changes) for country i in quarter t, let $y^*_{i,t}$ be the vector of foreign fundamentals relevant for country i in quarter t, and let x_t be the vector of the global credit and global risk factors in quarter t. The GVAR formulation postulates that

$$
\begin{aligned}
y_{i,t} &= \sum_{l=1}^{L_y} \Psi_{i,l} y_{i,t-l} + \sum_{l=1}^{L_y} \Psi^*_{i,l} y^*_{i,t-l} + \sum_{k=0}^{L_x} B_{i,k} x_{t-k} + \epsilon_{i,t} \\
x_t &= \sum_{l=1}^{L_y} \delta_{x,l} z_{t-l} + \sum_{k=1}^{L_x} \Phi_{x,k} x_{t-k} + \eta_t,
\end{aligned}
$$

where z_t is a vector of (global) fundamentals that affects the evolution of the global credit and risk factors. The foreign fundamentals are constructed as trade-weighted averages of fundamentals in other countries.

We implement the intuition of a GVAR in our setting using local projections. In particular, for our two outcome variables of interest – real GDP growth and growth in private credit to GDP – we estimate

$$
\begin{aligned}
\Delta_h y_{i,t,t+h} = \alpha_h &+ \sum_{l=0}^{L} \beta^{(l)}_{credit,h} \text{Global credit}_{t-l} + \sum_{l=0}^{L} \beta^{(l)}_{risk,h} \text{Global risk}_{t-l} \\
&+ \sum_{l=0}^{L} \beta^{(l)}_{y,h} \Delta y_{i,t-l+1,t-l} + \sum_{l=0}^{L} \beta^{*,(l)}_{y,h} \Delta y^*_{i,t-l+1,t-l} \\
&+ \sum_{l=0}^{L} \beta^{(l)}_{r,h} \text{real rate}_{i,t-l+1} + \sum_{l=0}^{L} \beta^{*,(l)}_{r,h} \text{real rate}^*_{i,t-l+1} + \epsilon_{i,t},
\end{aligned} \tag{8}
$$

where the vector domestic fundamentals $y_{i,t}$ includes (log) real GDP and private credit to GDP. The vector of foreign fundamentals only includes foreign average private credit to GDP.

Figure 9 plots the estimated coefficients from the local projection regressions (8) for real

GDP growth and growth in private credit. Starting with the top row, we can see that both the global credit and the global risk factors affect future real GDP growth. The effect of the global credit factor is temporary, with the peak impact on one-year ahead cumulative real GDP growth. In contrast, the effect of a shock to the global risk factor appears more permanent, with a deterioration in the global risk factor predicting a lower cumulative real GDP growth at even the 3 year horizon. These estimates are both economically and statistically significant. A one standard deviation tightening in the global credit factor predicts 50 bps lower one-year ahead cumulative real GDP growth; a one standard deviation tightening in the global risk factor predicts 60 bps lower one-year ahead cumulative real GDP growth.

The bottom row shows the estimated impulse response function of growth in private credit to GDP on the global factors. The bottom left panel shows that the global credit cycle occurs not just in global credit spreads but also in credit quantities. A tightening in the global credit factor predicts lower cumulative growth in private credit to GDP at around the 6 quarter horizon, with a one standard deviation tightening predicting cumulative growth 1 percentage point lower 6 quarters ahead. This decline in future credit growth is persistent, with the estimated coefficients remaining negative even at the three year horizon. In contrast, a tightening in the global risk factor has marginal effects on growth in private credit. It is important to remember that this predictive relationship is not mechanical. Our factors are built to predict *one-month* ahead returns while the predictability shown in Figure 9 is at the one- to three-year ahead horizon.

We conclude this section by examining whether deteriorations in the global credit and global risk factors not only have a detrimental impact on average growth but also on the tails of the growth distribution. We define a crisis episode as year-over-year real GDP growth falling below 2% and, as discussed in the context of the capital flows episodes, estimate a complimentary log-log regression for the probability of a crisis in h quarters as a function of one quarter changes in the global factors, three year domestic growth rate of private credit to GDP, and three year foreign growth rate of private credit to GDP.

Figure 10 plots the estimated coefficients from the complimentary log-log regression.[17] Starting with the top row, which plots the estimated coefficients on our global factors, we see that tightenings in both the credit and the risk factor correspond to a higher crisis probability. The coefficient observed in the credit factor's IRF is significant for 4 quarters (5 quarters for the risk factor's IRF), implying a higher probability of a crisis for 8 months (given that the crisis definition is based on the forward-looking year-over-year measure of GDP growth). In terms of magnitudes, the initial response to the global credit factor (0.55) is equivalent to the probability of a crisis increasing by 2.5% following a one standard deviation increase (tightening) of the factor. Similarly, the probability of a crisis goes up by 1.7% following a one standard deviation decrease (tightening) of the risk factor.

Finally, consistent with the literature showing that private credit expansions predict both lower subsequent GDP growth and a higher probability of a crisis in the medium term (Mian et al., 2017; Schularick and Taylor, 2012), the bottom row shows that growth in both domestic and foreign private credit corresponds to a higher probability of a crisis. A one standard deviation increase in the growth of domestic credit/GDP corresponds to a 1.9% increase in the crisis probability; a one standard deviation increase in the growth of foreign credit/GDP corresponds to a 2.1% increase in the crisis probability.

It is worth noting that the size of the estimated effect of a tightening in the credit and risk factors is similar to that of an increase in the stock of credit. This is remarkable given that (1) our factors are global (as opposed to the local credit to GDP series frequently used in this literature) and (2) our factors are constructed using asset prices and, as such, one would expect their information content to dissipate at a faster pace.

[17] Note that horizon $h = 0$ corresponds to a crisis occurring between dates t and $t + 4$, so that the horizon corresponds to the start date of a potential crisis.

6 Conclusion

In this paper, we investigate the central role of global credit conditions in driving global macroeconomic cycles. We build a global credit and a global risk factor with the goal of predicting risky asset excess returns at a granular level. The factors we construct exhibit very significant excess return predictability at the bond level, across credit ratings, countries, predictive horizons, and subperiods. Moreover, the loadings exhibit intuitive monotone patterns, consistent with flight to safety: riskier assets have higher loadings (and expected excess returns) on the global credit and risk factors, while safer assets have lower (and even negative) loadings on the factors. We thus uncover a global credit cycle in asset prices that is distinct from the global risk cycle and is driven by U. S. credit spreads and U. S. equity volatility.

We next document that the global credit cycle in *asset prices* translates into a global credit cycle in credit *quantities*. Consistent with international capital flows serving as a transmission channel for global cycles, we show that tightenings in the global credit factor predict stops in capital flows, not just at the level of overall flows but, importantly, differentially across types of capital flows. Even excluding the global financial crisis and the COVID-19 pandemic, a tightening in the global credit factor predicts a higher probability of stop episodes because they predict a higher probability of stop episodes in debt portfolio flows. Moreover, a tightening in the global credit factor predicts lower average real GDP growth, lower average private credit growth, and a higher probability of extreme contractions in growth.

While a large literature has documented that expansions in quantities of domestic private credit predict downturns, with both lower GDP growth and a higher probability of a financial crisis, we document that a global factor built from credit *prices* also significantly predicts downturns around the world. Thus, the *global* pricing of credit is a fundamental factor in driving *local* credit conditions and real outcomes.

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Table 1: Country-level variables and sources. This table reports the country-level variables used in the paper and their sources. Daily variables are aggregated to a quarterly/yearly frequency. We complement our data using an index built based on online prices following Cavallo (2013) to obtain CPI data for Argentina for the period 2007-2017.

Variable	Frequency	Source
Real GDP	Quarterly	WB WDI
Capital Flows	Quarterly	IMF IFS
Private Investment	Quarterly	IMF IFS
Debt Statistics	Quarterly	BIS
Bilateral Trade	Quarterly	IMF DOT
Policy Rates	Daily/Monthly	BIS CBPOL, IMF IFS
CPI Inflation	Monthly/Quarterly	IMF IFS
Exchange Rates	Daily	BIS
USD Broad Dollar Index	Daily	FR Board
FCIs		
GSFCI	Daily	Goldman Sachs
VIX	Daily	CBOE/Haver
G-Z spread/EBP	Monthly	FR Board/Haver
GFC	Monthly	Miranda-Agrippino et al. (2020)

Table 2: U. S. excess return predictability: VIX and credit spread polynomials. This table reports the estimated coefficients from the regression of 3 month excess holding period returns to the U. S. MSCI equity index and the U. S. Bloomberg corporate bond index on polynomials of the VIX and the Gilchrist and Zakrajšek (2012) "G-Z" spread. Hodrick (1992) standard errors reported in parentheses below point estimates; number of observations and adjusted R^2 in brackets. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	U. S. equity		U. S. credit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VIX	0.15	-3.38	0.21	0.14			0.69
	(0.15)	(1.19)***	(0.09)**	(0.91)			(0.84)
VIX^2		1.35		-0.09			-0.33
		(0.40)***		(0.32)			(0.28)
VIX^3		-0.15		0.02			0.05
		(0.04)***		(0.03)			(0.03)*
G-Z spread					0.15	-1.58	-1.62
					(0.07)**	(0.49)***	(0.51)***
G-Z spread^2						0.51	0.54
						(0.14)***	(0.15)***
G-Z spread^3						-0.04	-0.05
						(0.01)***	(0.01)***
Adj. R-sqr.	0.01	0.05	0.03	0.05	0.03	0.06	0.08
N. of obs	405	405	405	405	405	405	405

Table 3: Factor correlations. This table reports correlations between our constructed factors and other common proxies for risk and global financial conditions. Columns 1-2 report results for the full sample, Columns 3-4 for the pre-July 2007 sample, columns 5-6 for the January 2010 – December 2019 sample.

	Full sample		Pre-crisis		Post-crisis	
	Global credit factor	Global risk factor	Global credit factor	Global risk factor	Global credit factor	Global risk factor
VIX	0.48***	-0.63***	0.47***	-0.66***	0.46***	-0.73***
VIX^3	0.42***	-0.62***	0.40***	-0.58***	0.45***	-0.65***
G-Z spread	0.83***	-0.25***	0.82***	0.06	0.79***	-0.45***
EBP	0.58***	-0.37***	0.41***	-0.15***	0.44***	-0.30***
USD TWI	-0.03	-0.09**	-0.26***	-0.09*	0.08	0.14
GFC (original)	-0.44***	0.18***	-0.21***	0.15**	-0.61***	0.20
GFC (updated)	-0.04	0.14***	0.13**	0.23***	-0.03	0.02
U. S. GS FCI	0.45***	-0.25***	0.20***	-0.21***	0.57***	-0.38***
Global GS FCI	0.59***	-0.43***	-0.43	-0.37	0.38***	-0.29***

Table 4: Non-linearities in return predictability. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global risk and credit factors. All bond return predictability regressions include bond and firm characteristics and 2 digit SIC industry fixed effects. Hodrick (1992) standard errors reported in parentheses below point estimates; number of observations and adjusted R^2 in brackets. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Advanced economies

	US	KR	JP	CA	GB	NL	FR	AU	DE	CH	IE	IT	ES
Above BBB:													
Global credit	1.38	0.02	-0.60	-0.39	-0.86	-1.91	-3.11	-3.83	-2.98	-0.55	-0.35	-2.72	-0.49
	(0.06)***	(0.46)	(0.13)***	(0.25)	(0.15)***	(0.70)***	(0.30)***	(0.60)***	(0.36)***	(0.30)*	(0.40)	(0.64)***	(0.52)
Global risk	0.06	0.12	0.18	-0.06	0.07	0.07	0.04	0.01	0.11	0.05	0.16	-0.17	-0.08
	(0.01)***	(0.03)***	(0.01)***	(0.02)***	(0.01)***	(0.07)	(0.03)*	(0.04)	(0.02)***	(0.02)**	(0.03)***	(0.06)***	(0.06)
	[331,569]	[3,699]	[58,222]	[24,619]	[47,173]	[2,784]	[19,001]	[5,424]	[20,867]	[9,218]	[5,526]	[3,863]	[3,217]
	[0.01]	[0.01]	[0.02]	[0.00]	[0.00]	[-0.00]	[0.01]	[0.01]	[0.01]	[-0.00]	[0.01]	[0.01]	[-0.00]
BBB:													
Global credit	1.00	-2.92	-0.08	-0.76	-0.92	-2.36	-1.73	-3.81	-2.72	-1.62	0.17	-0.03	0.17
	(0.07)***	(0.47)***	(0.53)	(0.25)***	(0.28)***	(0.53)***	(0.47)***	(0.48)***	(0.38)***	(0.62)***	(0.42)	(0.52)	(0.60)
Global risk	0.25	0.20	0.25	0.07	0.14	0.06	0.20	0.09	0.16	0.28	0.32	0.34	0.18
	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.02)***	(0.04)	(0.03)***	(0.04)**	(0.03)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***
	[334,183]	[4,390]	[5,610]	[47,961]	[33,426]	[7,972]	[13,233]	[6,346]	[18,217]	[9,527]	[10,164]	[9,126]	[11,495]
	[0.03]	[0.05]	[0.03]	[0.00]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.04]	[0.03]	[0.01]
High yield:													
Global credit	3.49	9.06	2.64	2.39	3.11	0.56	6.66	5.69	2.41	4.35	2.45	1.71	5.63
	(0.14)***	(2.67)***	(1.51)*	(0.62)***	(0.77)***	(1.49)	(1.57)***	(2.25)**	(1.05)**	(2.78)	(1.23)**	(1.52)	(3.29)*
Global risk	0.55	1.48	0.89	0.63	0.42	0.64	0.82	0.89	0.42	1.25	0.71	0.94	1.06
	(0.01)***	(0.27)***	(0.09)***	(0.05)***	(0.06)***	(0.11)***	(0.12)***	(0.11)***	(0.09)***	(0.28)***	(0.07)***	(0.09)***	(0.23)***
	[169,068]	[436]	[2,403]	[13,619]	[8,437]	[2,879]	[3,190]	[1,270]	[5,023]	[2,219]	[3,078]	[3,486]	[988]
	[0.07]	[0.18]	[0.16]	[0.05]	[0.03]	[0.06]	[0.08]	[0.12]	[0.03]	[0.07]	[0.09]	[0.12]	[0.08]
Equities:													
Global credit	0.87	13.08	0.66	3.03	1.28	7.19	1.70	10.64	2.45	0.91	7.24	1.93	10.70
	(2.14)	(3.77)***	(2.30)	(2.53)	(2.88)	(3.64)**	(3.32)	(2.89)***	(3.42)	(2.35)	(4.85)	(3.73)	(4.41)**
Global risk	1.00	1.79	0.97	1.23	1.15	1.59	1.21	1.57	1.41	1.03	1.83	1.35	1.58
	(0.26)***	(0.20)***	(0.21)***	(0.36)***	(0.30)***	(0.45)***	(0.32)***	(0.37)***	(0.32)***	(0.20)***	(0.44)***	(0.33)***	(0.36)***
	[576]	[288]	[576]	[576]	[576]	[288]	[576]	[288]	[576]	[576]	[288]	[576]	[288]
	[0.10]	[0.18]	[0.05]	[0.09]	[0.08]	[0.22]	[0.07]	[0.24]	[0.10]	[0.08]	[0.22]	[0.06]	[0.19]

(b) Emerging market economies

	CN	MY	TH	IN	MX	BR	RU	CL	AR
Above BBB:									
Global credit	-1.05	-0.91	-9.21		-3.60	-1.80			
	(0.62)*	(2.98)	(3.65)**		(0.96)***	(1.11)			
Global risk	0.16	0.27	0.42		0.28	0.31			
	(0.04)***	(0.18)	(0.17)**		(0.08)***	(0.07)***			
	[2,651]	[417]	[163]		[1,307]	[312]			
	[0.02]	[-0.01]	[0.04]		[0.02]	[0.12]			
BBB:									
Global credit	-5.29	-1.89	-2.71	-6.66	-1.49	1.28	-0.81	-2.13	
	(1.34)***	(1.08)*	(1.21)**	(0.92)***	(0.77)*	(0.73)*	(1.03)	(0.88)**	
Global risk	0.21	0.27	0.27	0.54	0.69	0.44	0.54	0.50	
	(0.07)***	(0.07)***	(0.07)***	(0.05)***	(0.05)***	(0.09)***	(0.05)***	(0.06)***	
	[1,353]	[1,200]	[1,516]	[2,174]	[4,808]	[4,097]	[3,803]	[2,218]	
	[0.02]	[0.03]	[0.01]	[0.16]	[0.13]	[0.06]	[0.04]	[0.12]	
High yield:									
Global credit	7.34	-17.58	2.51	0.06	4.85	6.73	5.55	-4.71	5.26
	(2.54)***	(4.77)***	(4.09)	(1.33)	(3.20)	(1.48)***	(2.19)**	(5.14)	(3.16)*
Global risk	0.64	1.54	2.04	1.03	1.25	0.94	0.81	1.31	1.82
	(0.12)***	(0.30)***	(0.13)***	(0.09)***	(0.15)***	(0.09)***	(0.17)***	(0.40)***	(0.23)***
	[1,008]	[126]	[131]	[1,710]	[1,670]	[5,859]	[1,538]	[333]	[888]
	[0.04]	[0.14]	[0.75]	[0.17]	[0.05]	[0.13]	[0.07]	[0.12]	[0.18]
Equities:									
Global credit	9.27	5.10	11.80	11.92	7.08	14.09	11.71	8.20	7.19
	(4.43)**	(2.44)**	(3.81)***	(4.48)***	(4.31)	(4.96)***	(5.56)**	(3.93)**	(5.03)
Global risk	1.21	0.84	1.39	1.81	1.57	1.84	1.99	0.90	1.77
	(0.29)***	(0.25)***	(0.37)***	(0.41)***	(0.46)***	(0.65)***	(0.49)***	(0.59)	(0.65)***
	[288]	[288]	[288]	[288]	[288]	[264]	[277]	[288]	[288]
	[0.09]	[0.07]	[0.13]	[0.19]	[0.15]	[0.13]	[0.11]	[0.06]	[0.07]

Table 5: Non-linearities in return predictability: controlling for other FCIs. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global risk and credit factors, controlling for the VIX, the U. S. average default adjusted credit spread and predicted duration-adjusted credit spread, the broad dollar index, and the Miranda-Agrippino et al. (2020) global factor. All bond return predictability regressions include bond and firm characteristics and 2 digit SIC industry fixed effects. Hodrick (1992) standard errors reported in parentheses below point estimates; number of observations and adjusted R^2 in brackets. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Advanced economies

	US	KR	JP	CA	GB	NL	FR	AU	DE	CH	IE	IT	ES
Above BBB:													
Global credit	-1.57	-3.37	2.01	-3.23	-5.24	-7.22	-6.29	-8.73	-6.68	-2.25	-7.52	-6.00	-2.10
	(0.11)***	(1.15)***	(0.24)***	(0.61)***	(0.35)***	(2.05)***	(0.61)***	(1.19)***	(0.56)***	(0.75)***	(0.90)***	(1.43)***	(1.56)
Global risk	0.16	0.62	-0.13	0.28	0.32	0.42	0.11	0.53	0.35	0.09	0.73	-0.07	0.03
	(0.01)***	(0.11)***	(0.02)***	(0.06)***	(0.04)***	(0.18)**	(0.06)**	(0.09)***	(0.07)***	(0.09)	(0.07)***	(0.11)	(0.11)
	[259,678]	[2,740]	[47,587]	[20,174]	[38,222]	[2,221]	[14,230]	[4,239]	[16,581]	[5,934]	[4,808]	[3,321]	[2,981]
	[0.00]	[0.04]	[0.00]	[0.00]	[0.01]	[-0.00]	[0.01]	[0.01]	[0.01]	[-0.00]	[0.04]	[0.02]	[-0.01]
BBB:													
Global credit	-1.47	-5.68	1.35	-3.52	-5.05	-7.11	-7.34	-4.96	-8.30	-3.90	-3.26	-8.61	-8.69
	(0.14)***	(0.87)***	(0.85)	(0.53)***	(0.56)***	(1.07)***	(0.91)***	(1.01)***	(0.79)***	(1.24)***	(0.90)***	(1.25)***	(1.28)***
Global risk	0.36	0.76	-0.12	0.35	0.21	0.26	0.26	0.25	0.33	0.31	0.37	0.73	0.56
	(0.01)***	(0.11)***	(0.06)*	(0.05)***	(0.06)***	(0.10)***	(0.09)***	(0.09)***	(0.08)***	(0.12)**	(0.12)***	(0.11)***	(0.12)***
	[242,253]	[2,532]	[3,934]	[33,678]	[22,569]	[6,178]	[10,184]	[3,982]	[10,813]	[6,911]	[6,702]	[6,515]	[8,721]
	[0.01]	[0.05]	[-0.01]	[0.00]	[0.00]	[0.01]	[0.00]	[-0.00]	[0.02]	[-0.00]	[0.00]	[0.01]	[0.01]
High yield:													
Global credit	-0.58	8.94	-9.80	2.76	-4.09	-3.25	-1.29	4.55	-2.26	7.45	-2.56	-17.10	1.28
	(0.27)**	(5.25)*	(2.76)***	(1.19)**	(1.53)***	(2.60)	(2.64)	(4.45)	(1.73)	(2.87)***	(2.43)	(3.17)***	(6.69)
Global risk	0.59	2.66	1.44	0.30	0.48	0.87	0.78	0.77	0.06	-0.56	0.69	3.45	-1.18
	(0.03)***	(0.67)***	(0.23)***	(0.12)**	(0.16)***	(0.40)**	(0.30)**	(0.37)**	(0.26)	(0.22)**	(0.25)***	(0.38)***	(0.80)
	[130,012]	[415]	[1,788]	[10,016]	[6,385]	[2,565]	[1,997]	[974]	[4,276]	[1,679]	[2,540]	[2,180]	[564]
	[0.02]	[0.16]	[0.04]	[0.00]	[-0.00]	[0.01]	[-0.01]	[0.01]	[-0.01]	[-0.01]	[0.00]	[0.05]	[-0.04]
Equities:													
Global credit	-3.78	9.03	-2.89	-1.33	0.56	-0.83	0.14	6.85	0.43	-1.33	2.93	-1.00	8.45
	(1.96)*	(4.39)**	(2.74)	(2.68)	(2.45)	(3.89)	(2.93)	(3.56)*	(2.90)	(2.28)	(4.04)	(3.76)	(3.75)**
Global risk	1.03	1.54	1.11	1.16	1.06	0.96	1.08	0.79	1.18	0.90	0.77	1.38	0.70
	(0.26)***	(0.36)***	(0.32)***	(0.38)***	(0.31)***	(0.42)**	(0.32)***	(0.27)***	(0.32)***	(0.24)***	(0.40)*	(0.40)***	(0.29)**
	[471]	[244]	[471]	[471]	[471]	[244]	[471]	[244]	[471]	[471]	[244]	[471]	[244]
	[0.04]	[0.05]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]	[0.03]	[0.02]	[0.01]	[-0.00]	[0.02]	[0.01]

(b) Emerging market economies

	CN	MY	TH	IN	MX	BR	RU	CL	AR
Above BBB:									
Global credit	-3.67	-13.71	-12.02		-4.78	-4.85			
	(1.81)**	(5.06)***	(4.96)**		(2.25)**	(1.80)***			
Global risk	0.76	1.47	0.05		0.60	0.62			
	(0.24)***	(0.37)***	(0.33)		(0.19)***	(0.13)***			
	[1,011]	[347]	[163]		[922]	[312]			
	[-0.01]	[0.06]	[-0.00]		[0.00]	[0.06]			
BBB:									
Global credit	-4.53	-5.60	-4.98	-5.72	1.45	0.34	-12.80	0.72	
	(4.29)	(2.09)***	(2.78)*	(1.42)***	(1.59)	(2.04)	(1.93)***	(1.82)	
Global risk	0.73	0.73	0.83	1.05	0.72	0.07	1.13	0.02	
	(0.60)	(0.18)***	(0.24)***	(0.16)***	(0.17)***	(0.16)	(0.16)***	(0.21)	
	[288]	[806]	[946]	[1,134]	[3,125]	[3,322]	[3,091]	[1,401]	[1,401]
	[-0.08]	[0.03]	[0.00]	[0.02]	[0.03]	[-0.01]	[0.03]	[-0.02]	[-0.02]
High yield:									
Global credit	-5.96	-14.76	10.39	-7.21	-0.52	-4.80	-12.59	-3.71	-28.99
	(5.36)	(9.90)	(4.91)**	(4.04)*	(3.92)	(3.34)	(4.14)***	(11.98)	(9.17)***
Global risk	1.74	2.22	1.92	1.65	0.15	1.05	2.29	0.80	2.96
	(0.70)**	(1.33)*	(0.34)***	(0.47)***	(0.44)	(0.45)**	(0.48)***	(1.06)	(0.88)***
	[691]	[82]	[131]	[920]	[1,352]	[3,440]	[1,428]	[313]	[469]
	[-0.04]	[-0.19]	[0.42]	[0.00]	[-0.03]	[0.00]	[0.04]	[-0.05]	[-0.01]
Equities:									
Global credit	7.60	3.73	8.61	9.26	3.69	10.29	9.48	-0.09	0.42
	(4.88)	(3.81)	(4.91)*	(5.77)	(4.97)	(5.68)*	(6.91)	(4.40)	(7.31)
Global risk	0.55	0.86	0.99	1.69	1.01	-0.00	1.99	0.16	1.11
	(0.43)	(0.38)**	(0.52)*	(0.67)**	(0.51)**	(0.55)	(0.71)***	(0.49)	(0.77)
	[244]	[244]	[244]	[244]	[244]	[220]	[244]	[244]	[244]
	[-0.01]	[0.01]	[0.01]	[0.06]	[0.00]	[-0.02]	[0.03]	[-0.03]	[-0.02]

Table 6: Non-linearities in return predictability: Across horizons. This table reports the estimated coefficients from the regression of 1 month excess holding period returns on the global risk and credit factors. All bond return predictability regressions include bond and firm characteristics and 2 digit SIC industry fixed effects. "Pre-crisis" defined as January 1998 – July 2007. "Post-crisis, pre-pandemic" defined as January 2010 – December 2019. Hodrick (1992) standard errors reported in parentheses below point estimates; number of observations and adjusted R^2 in brackets. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Advanced economies

	US			KR			JP			CA		
	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M
Above BBB:												
Global credit	1.14	0.12	-0.59	-0.27	-1.84	0.25	-0.66	-0.03	-1.83	-1.66	-4.14	-3.88
	(0.06)***	(0.04)***	(0.03)***	(2.04)	(0.93)**	(0.79)	(0.24)***	(0.17)	(0.13)***	(0.31)***	(0.19)***	(0.13)***
Global risk	-0.15	-0.11	-0.12	-0.21	-0.20	0.06	-0.12	0.09	0.09	-0.16	-0.19	-0.20
	(0.00)***	(0.00)***	(0.00)***	(0.13)	(0.07)***	(0.05)	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***
	[117,114]	[111,016]	[99,941]	[300]	[292]	[273]	[9,042]	[8,712]	[8,080]	[8,787]	[8,553]	[8,101]
	[0.02]	[0.02]	[0.03]	[-0.02]	[0.07]	[-0.03]	[0.00]	[0.00]	[0.04]	[0.00]	[0.05]	[0.11]
BBB:												
Global credit	1.36	0.65	-0.12	0.57	-0.24	-0.58	6.17	3.61	0.64	-0.92	-2.64	-1.68
	(0.08)***	(0.05)***	(0.04)***	(0.62)	(0.33)	(0.18)***	(1.13)***	(0.78)***	(0.50)	(0.37)**	(0.22)***	(0.13)***
Global risk	-0.12	-0.12	-0.11	0.07	0.04	0.07	-0.00	-0.13	-0.01	-0.04	-0.09	-0.07
	(0.00)***	(0.00)***	(0.00)***	(0.07)	(0.04)	(0.02)***	(0.06)	(0.05)***	(0.03)	(0.03)	(0.02)***	(0.01)***
	[87,069]	[82,555]	[74,098]	[609]	[579]	[514]	[1,206]	[1,166]	[1,086]	[5,794]	[5,612]	[5,246]
	[0.01]	[0.02]	[0.03]	[-0.03]	[-0.02]	[0.07]	[0.01]	[0.03]	[-0.02]	[-0.01]	[0.02]	[0.02]
High yield:												
Global credit	3.04	1.69	0.87	2.12	-0.70	0.19	12.15	2.54	-3.61	3.98	1.12	1.11
	(0.16)***	(0.10)***	(0.06)***	(1.53)	(0.78)	(0.23)	(3.72)***	(2.36)	(1.30)***	(0.72)***	(0.45)**	(0.32)***
Global risk	0.03	-0.05	-0.10	0.44	0.10	-0.03	0.26	0.16	0.29	0.20	0.01	-0.06
	(0.01)***	(0.01)***	(0.00)***	(0.11)***	(0.05)*	(0.02)	(0.24)	(0.15)	(0.09)***	(0.06)***	(0.03)	(0.02)***
	[37,280]	[34,528]	[30,299]	[254]	[241]	[221]	[359]	[324]	[279]	[1,766]	[1,646]	[1,435]
	[0.01]	[0.01]	[0.02]	[-0.00]	[-0.04]	[-0.06]	[0.03]	[-0.03]	[0.03]	[-0.00]	[-0.01]	[0.01]
Equities:												
Global credit	0.20	0.65	0.42	6.04	5.92	5.23	-0.21	0.16	0.08	2.25	2.39	1.74
	(1.20)	(0.93)	(0.61)	(2.21)***	(1.51)***	(0.74)***	(1.43)	(0.94)	(0.59)	(1.92)	(1.35)*	(0.77)**
Global risk	0.17	0.07	-0.03	0.34	0.06	-0.15	0.31	0.17	0.03	0.19	-0.05	-0.15
	(0.08)**	(0.06)	(0.03)	(0.12)***	(0.11)	(0.06)**	(0.10)***	(0.07)**	(0.04)	(0.12)	(0.09)	(0.04)***
	[576]	[576]	[576]	[288]	[288]	[288]	[576]	[576]	[576]	[576]	[576]	[576]
	[0.01]	[0.00]	[-0.00]	[0.03]	[0.04]	[0.10]	[0.01]	[0.00]	[-0.00]	[0.01]	[0.01]	[0.02]

	GB			NL			FR			AU		
	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M
Above BBB:												
Global credit	-0.39	-1.60	-1.85	-5.30	-5.63	-4.82	-5.47	-4.04	-2.75	-2.67	-2.42	-1.22
	(0.18)**	(0.12)***	(0.08)***	(0.93)***	(0.74)***	(0.54)***	(0.80)***	(0.54)***	(0.39)***	(0.86)***	(0.57)***	(0.43)***
Global risk	-0.17	-0.19	-0.12	-0.47	-0.29	-0.18	-0.44	-0.25	-0.14	-0.20	-0.13	0.11
	(0.01)***	(0.01)***	(0.01)***	(0.08)***	(0.06)***	(0.05)***	(0.07)***	(0.05)***	(0.03)***	(0.07)***	(0.05)**	(0.04)***
	[11,761]	[11,263]	[10,295]	[1,319]	[1,297]	[1,230]	[1,171]	[1,133]	[1,047]	[638]	[626]	[602]
	[0.01]	[0.03]	[0.04]	[-0.00]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[-0.02]	[-0.01]	[0.00]
BBB:												
Global credit	-0.64	-1.17	-1.71	-1.78	-2.09	-1.62	-1.68	-2.26	-2.93	-3.30	-1.41	-0.57
	(0.32)**	(0.20)***	(0.14)***	(0.55)***	(0.33)***	(0.20)***	(1.00)*	(0.69)***	(0.48)***	(1.64)**	(0.82)*	(0.64)
Global risk	-0.03	-0.07	-0.01	-0.14	-0.13	-0.10	0.26	0.27	0.27	-0.41	-0.28	0.03
	(0.03)	(0.02)***	(0.01)	(0.04)***	(0.03)***	(0.02)***	(0.08)***	(0.07)***	(0.04)***	(0.11)***	(0.07)***	(0.05)
	[3,733]	[3,607]	[3,347]	[2,141]	[2,040]	[1,860]	[1,334]	[1,258]	[1,101]	[191]	[180]	[162]
	[-0.01]	[-0.00]	[0.04]	[-0.00]	[0.01]	[0.01]	[-0.01]	[0.01]	[0.07]	[0.02]	[0.06]	[-0.08]
High yield:												
Global credit	1.72	0.98	-0.74	-2.86	-4.12	-3.70	-1.97	-4.12	-1.14	26.77	-5.36	-6.20
	(0.95)*	(0.45)**	(0.27)***	(3.12)	(1.92)**	(1.44)***	(2.04)	(1.19)***	(0.70)	(6.94)***	(3.65)	(1.77)***
Global risk	0.01	-0.20	-0.18	0.48	0.31	0.29	0.07	0.11	-0.01	-0.98	1.38	0.71
	(0.12)	(0.08)**	(0.04)***	(0.19)**	(0.11)***	(0.07)***	(0.14)	(0.08)	(0.06)	(1.17)	(0.45)***	(0.18)***
	[724]	[675]	[587]	[386]	[371]	[340]	[420]	[383]	[331]	[33]	[33]	[33]
	[-0.03]	[-0.02]	[-0.01]	[-0.03]	[-0.02]	[-0.01]	[-0.05]	[-0.02]	[-0.05]	[-0.21]	[-0.00]	[0.08]
Equities:												
Global credit	0.55	0.67	-0.01	3.06	3.80	2.68	0.20	0.90	0.10	6.61	5.83	4.36
	(1.88)	(1.50)	(0.93)	(2.10)	(1.61)**	(0.90)***	(1.82)	(1.45)	(0.86)	(2.08)***	(1.54)***	(0.83)***
Global risk	0.26	0.08	-0.11	0.41	0.26	-0.02	0.30	0.10	-0.11	0.40	0.09	-0.14
	(0.10)**	(0.09)	(0.04)***	(0.14)***	(0.14)*	(0.08)	(0.09)***	(0.08)	(0.04)***	(0.13)***	(0.12)	(0.06)**
	[576]	[576]	[576]	[288]	[288]	[288]	[576]	[576]	[576]	[288]	[288]	[288]
	[0.01]	[-0.00]	[0.01]	[0.04]	[0.05]	[0.03]	[0.01]	[-0.00]	[0.00]	[0.08]	[0.08]	[0.13]

	DE			CH			IE			IT			ES		
	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M
Above BBB:															
Global credit	-2.92	-2.94	-3.40	-2.30	-2.45	-1.19	0.17	-1.72	-0.90	-4.05	-2.34	-1.92	-3.09	-3.66	-4.61
	(0.41)***	(0.29)***	(0.19)***	(0.71)***	(0.49)***	(0.30)***	(0.43)	(0.34)***	(0.20)***	(0.90)***	(0.60)***	(0.39)***	(0.84)***	(0.63)***	(0.48)***
Global risk	-0.17	-0.13	-0.09	-0.26	-0.20	-0.04	-0.09	-0.05	0.03	-0.28	-0.19	-0.08	-0.26	-0.30	-0.25
	(0.04)***	(0.03)***	(0.02)***	(0.06)***	(0.04)***	(0.03)	(0.04)**	(0.03)*	(0.02)**	(0.07)***	(0.05)***	(0.03)**	(0.08)***	(0.06)***	(0.04)***
	[3,469]	[3,273]	[2,880]	[897]	[823]	[670]	[1,411]	[1,339]	[1,214]	[898]	[877]	[829]	[968]	[940]	[888]
	[0.01]	[0.02]	[0.07]	[-0.00]	[0.00]	[0.00]	[-0.01]	[0.00]	[0.01]	[0.00]	[0.00]	[0.01]	[-0.00]	[0.02]	[0.08]
BBB:															
Global credit	-1.88	-1.15	-0.99	0.56	0.37	-0.44	1.86	0.59	-0.86	-2.91	-1.55	-0.19	0.80	-0.87	-1.60
	(0.49)***	(0.31)***	(0.22)***	(0.77)	(0.45)	(0.30)	(0.67)***	(0.40)	(0.30)***	(1.01)***	(0.52)***	(0.29)	(0.67)	(0.41)**	(0.27)***
Global risk	-0.11	-0.05	0.02	0.06	0.03	0.02	-0.02	-0.14	-0.14	0.08	0.06	0.07	-0.10	-0.12	-0.03
	(0.04)***	(0.02)**	(0.02)	(0.07)	(0.04)	(0.03)	(0.06)	(0.04)***	(0.03)***	(0.06)	(0.04)	(0.02)***	(0.05)*	(0.03)***	(0.02)
	[2,618]	[2,446]	[2,123]	[1,037]	[1,000]	[944]	[1,310]	[1,247]	[1,110]	[960]	[943]	[905]	[992]	[956]	[875]
	[-0.01]	[-0.01]	[0.01]	[-0.02]	[-0.02]	[-0.02]	[-0.01]	[0.01]	[0.00]	[-0.01]	[-0.01]	[-0.01]	[-0.01]	[-0.00]	[0.02]
High yield:															
Global credit	0.64	-2.40	-0.55	-31.88	10.83	2.64	9.27	1.06	1.61	-47.28	-29.88	-7.89	-5.63	-55.02	-0.10
	(3.33)	(2.08)	(0.86)	(7.90)***	(6.07)*	(1.64)	(2.22)***	(1.07)	(0.59)***	(11.01)***	(4.01)***	(2.39)***	(16.41)	(.)	(.)
Global risk	0.48	0.46	0.10	1.61	-0.93	-0.15	0.37	-0.09	-0.08	3.56	1.25	0.56	-10.72	-14.08	0.27
	(0.24)**	(0.17)***	(0.07)	(0.59)***	(0.36)**	(0.11)	(0.17)**	(0.08)	(0.04)*	(0.68)***	(0.23)***	(0.14)***	(10.14)	(.)	(.)
	[300]	[274]	[237]	[203]	[175]	[124]	[360]	[332]	[304]	[126]	[117]	[99]	[12]	[9]	[3]
	[-0.06]	[-0.03]	[-0.07]	[0.02]	[-0.03]	[-0.07]	[0.03]	[-0.03]	[0.04]	[0.13]	[0.23]	[0.08]	[-2.40]	[1.01]	[1.00]
Equities:															
Global credit	0.67	1.07	0.52	0.13	0.64	0.14	2.38	1.91	1.03	0.79	1.19	-0.44	5.54	5.08	2.91
	(1.92)	(1.44)	(0.81)	(1.48)	(1.19)	(0.75)	(2.17)	(1.68)	(1.05)	(2.36)	(1.74)	(1.08)	(2.06)***	(1.60)***	(0.82)***
Global risk	0.34	0.15	-0.04	0.29	0.19	-0.00	0.55	0.30	0.10	0.42	0.19	-0.08	0.41	0.19	-0.08
	(0.10)***	(0.09)	(0.04)	(0.07)***	(0.07)***	(0.04)	(0.13)***	(0.13)**	(0.08)	(0.11)***	(0.10)**	(0.04)*	(0.14)***	(0.12)	(0.07)
	[576]	[576]	[576]	[576]	[576]	[576]	[288]	[288]	[288]	[576]	[576]	[576]	[288]	[288]	[288]
	[0.01]	[0.00]	[-0.00]	[0.02]	[0.01]	[-0.01]	[0.05]	[0.02]	[-0.00]	[0.01]	[0.00]	[-0.00]	[0.06]	[0.06]	[0.04]

(b) Emerging market economies

	CN			MY			TH			IN			MX		
	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M
Above BBB:															
Global credit	2.01	1.09	0.78	-3.00	-0.83	0.12	-3.62	-1.83	-1.00				-1.07	-0.85	-0.78
	(0.28)***	(0.18)***	(0.15)***	(0.92)***	(0.51)	(0.23)	(1.45)**	(0.70)***	(0.33)***				(0.59)*	(0.39)**	(0.24)***
Global risk	-0.04	-0.04	0.00	0.12	0.04	-0.03	0.24	0.11	0.03				0.04	-0.01	0.01
	(0.01)***	(0.01)***	(0.01)	(0.06)*	(0.03)*	(0.01)***	(0.07)***	(0.03)***	(0.02)				(0.02)*	(0.02)	(0.01)
	[2,517]	[2,315]	[1,901]	[411]	[402]	[379]	[163]	[163]	[163]				[1,262]	[1,195]	[1,070]
	[0.01]	[0.01]	[-0.00]	[0.00]	[-0.03]	[-0.03]	[0.06]	[0.03]	[-0.01]				[-0.01]	[-0.01]	[-0.01]
BBB:															
Global credit	-0.47	-0.72	0.02	-0.39	-0.24	-0.34	1.05	0.46	0.46	0.22	-0.18	0.58	0.23	-0.39	-0.08
	(0.62)	(0.44)	(0.29)	(0.47)	(0.25)	(0.16)**	(0.58)*	(0.42)	(0.27)*	(0.41)	(0.27)	(0.17)***	(0.43)	(0.28)	(0.15)
Global risk	0.04	-0.02	-0.03	0.07	0.01	-0.00	0.08	0.00	0.00	0.14	0.01	-0.02	0.11	-0.01	-0.02
	(0.02)*	(0.02)	(0.01)**	(0.03)**	(0.01)	(0.01)	(0.03)**	(0.02)	(0.01)	(0.02)***	(0.01)	(0.01)***	(0.02)***	(0.01)	(0.01)***
	[1,256]	[1,113]	[838]	[1,162]	[1,105]	[1,000]	[1,456]	[1,366]	[1,194]	[2,106]	[2,004]	[1,783]	[4,650]	[4,432]	[4,034]
	[-0.02]	[-0.02]	[-0.03]	[-0.01]	[-0.02]	[-0.01]	[-0.00]	[-0.01]	[-0.01]	[0.03]	[-0.01]	[-0.01]	[0.01]	[-0.00]	[-0.00]
High yield:															
Global credit	7.67	2.96	0.78	-4.14	-1.64	-0.62	-25.31	-18.21	-5.25	5.07	3.61	2.54	5.29	0.84	0.02
	(1.39)***	(0.64)***	(0.57)	(2.58)	(1.20)	(0.85)	(5.58)***	(3.20)***	(2.25)**	(0.67)***	(0.41)***	(0.28)***	(1.85)***	(1.32)	(0.61)
Global risk	0.05	-0.05	0.01	0.76	0.12	-0.04	1.85	0.70	0.02	0.22	-0.01	-0.04	0.29	-0.04	-0.03
	(0.05)	(0.02)***	(0.03)	(0.18)***	(0.08)	(0.04)	(0.22)***	(0.13)***	(0.09)	(0.04)***	(0.02)	(0.01)***	(0.11)***	(0.03)	(0.03)
	[944]	[836]	[645]	[114]	[97]	[61]	[125]	[116]	[98]	[1,637]	[1,520]	[1,278]	[1,593]	[1,474]	[1,247]
	[0.00]	[-0.02]	[-0.04]	[0.04]	[-0.13]	[-0.28]	[0.50]	[0.09]	[-0.00]	[0.06]	[0.03]	[0.05]	[0.00]	[-0.02]	[-0.02]
Equities:															
Global credit	5.51	4.63	4.06	3.19	3.41	3.43	7.34	7.57	6.29	6.29	5.25	4.23	3.31	3.44	2.61
	(2.10)***	(1.52)***	(0.86)***	(1.66)*	(1.19)***	(0.63)***	(2.37)***	(1.32)***	(0.73)***	(3.54)*	(2.23)**	(1.14)***	(2.36)	(1.66)**	(0.93)***
Global risk	0.24	0.02	-0.04	0.19	0.01	-0.11	0.34	0.10	-0.15	0.55	0.09	-0.13	0.35	0.08	-0.13
	(0.12)*	(0.13)	(0.11)	(0.08)**	(0.07)	(0.04)**	(0.14)**	(0.11)	(0.07)**	(0.18)***	(0.15)	(0.08)	(0.16)**	(0.11)	(0.05)***
	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]	[288]
	[0.02]	[0.02]	[0.05]	[0.01]	[0.02]	[0.07]	[0.05]	[0.09]	[0.17]	[0.06]	[0.03]	[0.06]	[0.02]	[0.02]	[0.04]

	BR			RU			CL			AR		
	3M	6M	12M	3M	6M	12M	3M	6M	12M	3M	6M	12M
Above BBB:												
Global credit	-0.44	0.68	0.49									
	(0.55)	(0.31)**	(0.17)***									
Global risk	0.04	-0.02	-0.03									
	(0.04)	(0.02)	(0.01)***									
	[308]	[302]	[288]									
	[-0.03]	[-0.02]	[-0.00]									
BBB:												
Global credit	0.92	0.71	0.83	-0.51	0.06	0.62	0.14	-0.24	-0.20			
	(0.29)***	(0.13)***	(0.09)***	(0.52)	(0.30)	(0.17)***	(0.45)	(0.26)	(0.14)			
Global risk	0.06	-0.02	-0.05	0.15	0.00	-0.06	0.03	-0.04	-0.02			
	(0.03)**	(0.01)**	(0.01)***	(0.03)***	(0.01)	(0.01)***	(0.02)*	(0.01)***	(0.01)***			
	[3,933]	[3,695]	[3,280]	[3,692]	[3,528]	[3,202]	[2,152]	[2,053]	[1,855]			
	[0.00]	[0.00]	[0.04]	[0.01]	[-0.01]	[0.02]	[-0.01]	[-0.00]	[-0.00]			
High yield:												
Global credit	4.09	2.89	1.71	1.86	1.16	-0.01	1.59	1.30	0.43	14.23	5.04	2.80
	(0.59)***	(0.28)***	(0.19)***	(1.04)*	(0.53)**	(0.36)	(2.62)	(0.96)	(0.34)	(2.01)***	(0.73)***	(0.41)***
Global risk	0.02	-0.08	-0.08	0.13	-0.05	-0.05	0.34	0.13	-0.07	0.18	-0.19	-0.05
	(0.03)	(0.01)***	(0.01)***	(0.06)**	(0.02)*	(0.02)***	(0.21)	(0.07)*	(0.02)***	(0.07)**	(0.03)***	(0.02)***
	[5,594]	[5,202]	[4,420]	[1,498]	[1,432]	[1,298]	[319]	[298]	[260]	[843]	[783]	[665]
	[0.01]	[0.03]	[0.04]	[-0.00]	[-0.01]	[-0.00]	[0.01]	[-0.00]	[-0.02]	[0.08]	[0.06]	[0.04]
Equities:												
Global credit	8.58	6.33	3.85	5.12	3.71	2.81	6.07	4.79	4.32	4.73	4.77	2.84
	(2.69)***	(1.87)***	(1.17)***	(4.08)	(2.63)	(1.52)*	(1.48)***	(0.98)***	(0.58)***	(3.00)	(2.14)**	(1.40)**
Global risk	0.32	-0.05	-0.20	0.38	-0.03	-0.25	0.03	-0.14	-0.22	0.51	0.37	0.05
	(0.26)	(0.14)	(0.09)**	(0.18)**	(0.14)	(0.07)***	(0.14)	(0.07)*	(0.04)***	(0.19)***	(0.17)**	(0.12)
	[264]	[264]	[264]	[275]	[272]	[266]	[288]	[288]	[288]	[288]	[288]	[288]
	[0.03]	[0.03]	[0.05]	[0.01]	[0.00]	[0.04]	[0.03]	[0.06]	[0.13]	[0.01]	[0.02]	[0.00]

Table 7: Non-linearities in return predictability: German BBB bonds. This table reports the estimated coefficients from the regression of excess returns on German BBB-rated corporate bonds for different alternative regression specifications. Table 7a illustrates how return predictability changes as we control for additional predictors; Table 7b illustrates how return predictability changes across subperiods; Table 7c illustrates how return predictability changes across horizons. In Table 7a, G-Z spread and predicted and default-adjusted credit spread are as in Gilchrist and Zakrajšek (2012); USD TWI is the 12-month change in the broad dollar index; GFC is the updated Miranda-Agrippino et al. (2020) global factor. In Table 7b, "normal" is January 1997 – July 2007 and January 2010 – December 2019; GFC is August 2007 – December 2009. In Table 7c, each column corresponds to a return predictability horizon (in months). Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Controlling for other predictors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Global credit	-2.72		-6.52		-7.38		-1.45		-6.19		-2.55		-2.81	-7.11	-8.30
	(0.38)***		(0.66)***		(0.65)***		(0.37)***		(0.61)***		(0.39)***		(0.42)***	(0.64)***	(0.79)***
Global risk	0.16		0.23		0.27		-0.10		0.12		0.16		-0.13	0.18	0.33
	(0.03)***		(0.03)***		(0.03)***		(0.06)*		(0.06)**		(0.03)***		(0.04)***	(0.07)***	(0.08)***
G-Z spread		-1.01	9.41											9.75	
		(0.63)	(1.18)***											(0.89)***	
Predicted spread				-5.91	1.92			-5.93	0.83						-1.99
				(1.11)***	(1.35)			(1.11)***	(1.31)						(1.67)
Default-adjusted spread				0.15	14.66			3.51	13.32						13.14
				(0.75)	(1.40)***			(0.82)***	(1.32)***						(1.70)***
VIX						-4.66	-6.59	-5.28	-3.76					7.77	9.48
						(0.52)***	(1.15)***	(0.55)***	(1.05)***					(1.26)***	(1.50)***
USD TWI										-0.28	-0.20			0.18	-0.08
										(0.05)***	(0.05)***			(0.06)***	(0.07)
GFC (updated)												0.81	0.12	1.21	2.97
												(0.42)*	(0.44)	(0.33)***	(0.52)***
Adj. R-sqr.	0.01	-0.00	0.02	-0.00	0.03	0.01	0.02	0.02	0.03	-0.00	0.01	-0.00	0.01	0.04	0.03
N. of obs	18,217	18,217	18,217	18,217	18,217	18,217	18,217	18,217	18,217	18,217	18,217	10,813	10,813	13,614	10,813

(b) Predictability across subperiods

	Full sample	Normal	GFC	2020	2021 – 2022
Global credit	-2.72	-3.26	-7.15	3.48	-4.77
	(0.38)***	(0.42)***	(1.00)***	(1.03)***	(1.20)***
Global risk	0.16	-0.28	0.16	0.38	1.21
	(0.03)***	(0.03)***	(0.07)**	(0.04)***	(0.14)***
Adj. R-sqr.	0.01	0.01	0.05	0.13	0.03
N. of obs	18,217	10,825	1,009	2,336	4,046

(c) Predictability across horizons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Global credit	-2.72	-1.75	-2.08	-2.08	-1.68	-1.52	-1.37	-1.11	-0.98	-0.96	-0.81	-0.71
	(0.38)***	(0.25)***	(0.20)***	(0.16)***	(0.13)***	(0.11)***	(0.11)***	(0.10)***	(0.09)***	(0.09)***	(0.08)***	(0.08)***
Global risk	0.16	0.09	0.03	0.00	0.02	0.03	0.02	0.02	0.02	0.03	0.03	0.03
	(0.03)***	(0.01)***	(0.01)***	(0.01)	(0.01)**	(0.01)***	(0.01)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***
Adj. R-sqr.	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
N. of obs	18,217	17,612	17,025	16,461	15,915	15,409	14,916	14,419	13,930	13,458	12,997	12,553

Table 8: Non-linearities in return predictability: Other assets. This table reports the estimated coefficients from the regression of 1 month excess holding period returns for assets not included in the baseline estimation on the global risk and credit factors. Hodrick (1992) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) 10Y sovereign: Baseline country sample

	US	KR	JP	CA	GB	FR	AU	DE	CH	IT	ES	MX	IN
Global credit	-0.23	-2.23	-0.64	-2.83	-2.29	-1.47	-5.85	-2.21	-14.42	-22.01	-10.02	2.96	0.17
	(0.88)	(1.06)**	(0.82)	(0.62)***	(0.96)**	(2.11)	(0.40)***	(0.94)**	(9.55)	(12.02)*	(3.22)***	(0.37)***	(1.22)
Global risk	-0.20	-0.75	0.15	-0.56	-0.72	0.07	-0.86	-0.39	-0.32	1.87	-1.20	-0.42	-0.47
	(0.06)***	(0.09)***	(0.08)*	(0.08)***	(0.14)***	(0.64)	(0.09)***	(0.17)**	(0.21)	(1.34)	(0.93)	(0.11)***	(0.06)***
Adj. R-sqr.	0.00	0.18	-0.00	0.08	0.08	-0.02	0.13	0.01	-0.01	-0.01	0.01	0.05	0.08
N. of obs	576	270	408	408	408	155	312	408	408	155	95	252	288

(b) 10Y sovereign: Additional countries

	DK	SK	HK	TW	SG	NZ	ZA
Global credit	-2.58	-6.69	-1.63	-0.20	-0.90	-4.66	-4.96
	(0.60)***	(1.24)***	(1.35)	(0.68)	(0.88)	(1.04)***	(2.74)*
Global risk	-0.42	-0.39	-0.34	-0.28	-0.38	-0.79	-0.59
	(0.14)***	(0.05)***	(0.06)***	(0.07)***	(0.04)***	(0.11)***	(0.24)**
Adj. R-sqr.	0.04	0.06	0.05	0.06	0.09	0.11	0.06
N. of obs	312	60	270	270	270	312	301

(c) Equity returns: Additional AE countries

	FI	NO	SE	AT	BE	PT	CZ	IL	HK	TW	SG	NZ
Global credit	7.14	11.45	10.10	13.86	9.73	7.39	9.38	4.56	8.30	9.79	10.39	8.38
	(3.20)**	(1.68)***	(1.81)***	(3.00)***	(2.37)***	(1.50)***	(2.71)***	(3.04)	(1.94)***	(1.78)***	(1.68)***	(3.20)***
Global risk	1.48	2.01	1.56	2.39	1.84	1.36	1.69	1.02	1.28	1.37	1.61	1.23
	(0.15)***	(0.18)***	(0.23)***	(0.20)***	(0.24)***	(0.26)***	(0.19)***	(0.34)***	(0.09)***	(0.14)***	(0.13)***	(0.14)***
Adj. R-sqr.	0.10	0.25	0.18	0.30	0.27	0.15	0.16	0.08	0.17	0.13	0.24	0.17
N. of obs	288	288	288	288	288	288	288	288	288	288	288	288

(d) Equity returns: Additional EM countries

	HU	PO	TR	EG	PH	ID	SA	PE	CO
Global credit	16.48	11.07	16.45	10.46	9.86	16.53	12.73	12.61	14.15
	(1.88)***	(2.80)***	(4.52)***	(2.44)***	(2.16)***	(3.83)***	(3.06)***	(2.47)***	(5.34)***
Global risk	2.46	1.94	1.93	1.87	1.45	2.05	1.50	1.24	1.50
	(0.18)***	(0.16)***	(0.23)***	(0.22)***	(0.29)***	(0.24)***	(0.31)***	(0.24)***	(0.53)***
Adj. R-sqr.	0.24	0.18	0.08	0.14	0.10	0.17	0.16	0.09	0.10
N. of obs	288	288	288	288	319	288	288	288	288

Table 9: Capital flow predictability. This table reports the estimated coefficients from the complimentary log-log regression of an indicator of a flow episode occurring at date t on lagged changes in the global credit and global risk factors, as well as the global and local controls and the regional contagion indicator of Forbes and Warnock (2012, 2021). "Global liquidity" is the growth in the global money supply. The regional contagion dummy is an indicator equal to one if countries in the same region are experiencing the same type of episode (at the total flows level). Columns (1) – (4) in each panel report the results for the full, pre-pandemic sample; columns (5) – (8) report the results excluding the global financial crisis (excluding 2008 – 2009). Standard errors clustered at the country level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Stops

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.ΔGlobal credit	0.31	0.33	0.29	0.14	0.21	0.25	0.06	-0.08
	(0.03)***	(0.05)***	(0.06)***	(0.05)***	(0.10)**	(0.09)***	(0.09)	(0.12)
L.ΔGlobal risk	-0.18	-0.11	-0.12	-0.12	-0.07	0.00	-0.01	-0.08
	(0.02)***	(0.03)***	(0.03)***	(0.03)***	(0.06)	(0.06)	(0.06)	(0.08)
L.Global liquidity	0.02	0.02	0.01	0.03	-0.00	-0.00	-0.01	0.01
	(0.01)*	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)
L.Global interest rates	0.06	0.07	0.11	0.08	0.10	0.10	0.14	0.11
	(0.03)**	(0.03)**	(0.03)***	(0.03)***	(0.03)***	(0.04)***	(0.03)***	(0.03)***
L.Global GDP growth	-0.26	-0.02	0.03	-0.32	-0.18	0.18	0.13	-0.31
	(0.04)***	(0.05)	(0.05)	(0.04)***	(0.09)**	(0.07)***	(0.07)*	(0.11)***
Regional contagion	0.53	0.37	0.25	0.17	0.44	0.33	0.17	0.06
	(0.15)***	(0.13)***	(0.13)*	(0.12)	(0.15)***	(0.14)**	(0.14)	(0.12)
L.Local GDP growth	-0.08	-0.01	-0.01	-0.09	-0.09	-0.02	-0.02	-0.10
	(0.02)***	(0.01)	(0.01)	(0.02)***	(0.02)***	(0.02)	(0.02)	(0.02)***
Log pseudolikelihood	-6211.94				-5297.39			
N. of obs	4,357				4,005			

(b) Surges

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.ΔGlobal credit	-0.10	-0.36	-0.18	-0.05	-0.04	-0.43	-0.16	-0.16
	(0.10)	(0.07)***	(0.08)**	(0.10)	(0.10)	(0.09)***	(0.10)*	(0.09)*
L.ΔGlobal risk	0.05	-0.00	-0.01	-0.02	0.02	-0.10	-0.04	-0.05
	(0.04)	(0.03)	(0.03)	(0.05)	(0.06)	(0.07)	(0.04)	(0.06)
L.Global liquidity	-0.03	0.01	0.03	-0.02	-0.03	0.02	0.04	-0.02
	(0.01)**	(0.01)	(0.02)*	(0.01)	(0.01)*	(0.01)	(0.02)*	(0.01)*
L.Global interest rates	0.13	0.15	0.11	0.09	0.13	0.14	0.11	0.10
	(0.02)***	(0.02)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.04)***	(0.03)***
L.Global GDP growth	0.29	-0.05	0.02	0.34	0.26	-0.08	0.03	0.34
	(0.07)***	(0.04)	(0.05)	(0.07)***	(0.08)***	(0.07)	(0.06)	(0.08)***
Regional contagion	0.78	0.18	0.30	0.59	0.80	0.19	0.33	0.55
	(0.23)***	(0.12)	(0.13)**	(0.17)***	(0.24)***	(0.12)	(0.14)**	(0.18)***
L.Local GDP growth	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02
	(0.01)***	(0.01)***	(0.00)***	(0.01)*	(0.01)***	(0.01)***	(0.00)***	(0.01)*
Log pseudolikelihood	-6467.06				-6067.75			
N. of obs	4,357				4,005			

(Table 9 continued)

(c) Flights

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.ΔGlobal credit	-0.09	-0.07	-0.20	-0.14	-0.04	-0.09	-0.12	-0.12
	(0.07)	(0.06)	(0.08)***	(0.07)**	(0.10)	(0.08)	(0.09)	(0.09)
L.ΔGlobal risk	0.06	0.04	0.02	-0.00	0.03	0.05	-0.02	-0.01
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.07)
L.Global liquidity	-0.00	-0.02	0.01	0.01	0.00	-0.02	0.01	0.01
	(0.01)	(0.01)**	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
L.Global interest rates	0.15	0.19	0.07	0.12	0.14	0.18	0.08	0.11
	(0.02)***	(0.03)***	(0.03)**	(0.03)***	(0.02)***	(0.03)***	(0.03)**	(0.03)***
L.Global GDP growth	0.19	0.01	0.04	0.11	0.17	-0.07	0.12	0.05
	(0.06)***	(0.05)	(0.04)	(0.04)***	(0.07)**	(0.07)	(0.06)**	(0.06)
Regional contagion	0.51	0.14	0.43	0.32	0.50	0.17	0.43	0.33
	(0.13)***	(0.12)	(0.15)***	(0.13)**	(0.13)***	(0.11)	(0.16)***	(0.13)**
L.Local GDP growth	0.01	-0.01	0.01	0.01	0.01	-0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log pseudolikelihood	-7043.99				-6607.16			
N. of obs	4,343				3,991			

(d) Retrenchment

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.ΔGlobal credit	0.21	0.25	0.26	0.21	0.05	0.17	-0.07	-0.00
	(0.04)***	(0.07)***	(0.06)***	(0.05)***	(0.09)	(0.09)*	(0.12)	(0.09)
L.ΔGlobal risk	-0.11	-0.07	-0.16	-0.12	0.00	0.01	-0.02	-0.05
	(0.02)***	(0.03)**	(0.03)***	(0.03)***	(0.08)	(0.08)	(0.07)	(0.10)
L.Global liquidity	0.02	0.05	0.05	0.01	-0.00	0.02	0.03	-0.01
	(0.01)*	(0.01)***	(0.02)***	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
L.Global interest rates	0.06	0.04	0.04	0.08	0.10	0.08	0.09	0.14
	(0.03)**	(0.02)**	(0.04)	(0.03)***	(0.03)***	(0.02)***	(0.04)**	(0.04)***
L.Global GDP growth	-0.26	-0.04	-0.09	-0.26	-0.23	0.16	0.02	-0.09
	(0.07)***	(0.05)	(0.04)**	(0.05)***	(0.12)*	(0.09)*	(0.09)	(0.10)
Regional contagion	0.53	0.19	0.47	0.19	0.49	0.16	0.37	0.17
	(0.15)***	(0.11)*	(0.13)***	(0.17)	(0.14)***	(0.13)	(0.15)**	(0.18)
L.Local GDP growth	-0.03	0.02	0.00	-0.03	-0.01	0.02	0.00	-0.02
	(0.03)	(0.01)**	(0.01)	(0.02)	(0.03)	(0.00)***	(0.01)	(0.02)
Log pseudolikelihood	-6233.22				-5169.47			
N. of obs	4,343				3,991			

Figure 1. Composition of secondary market bond data. This figure plots the composition across credit ratings of nonfinancial bonds included in corporate bond indices. Composition measured in amount outstanding in USD equivalents. "AE ex U. S." includes South Korea, Japan, Canada, United Kingdom, Netherlands, France, Australia, Germany, Switzerland, Ireland, Italy, and Spain; "EM" includes China, Malaysia, Thailand, India, Mexico, Brazil, Russia, Chile, and Argentina.

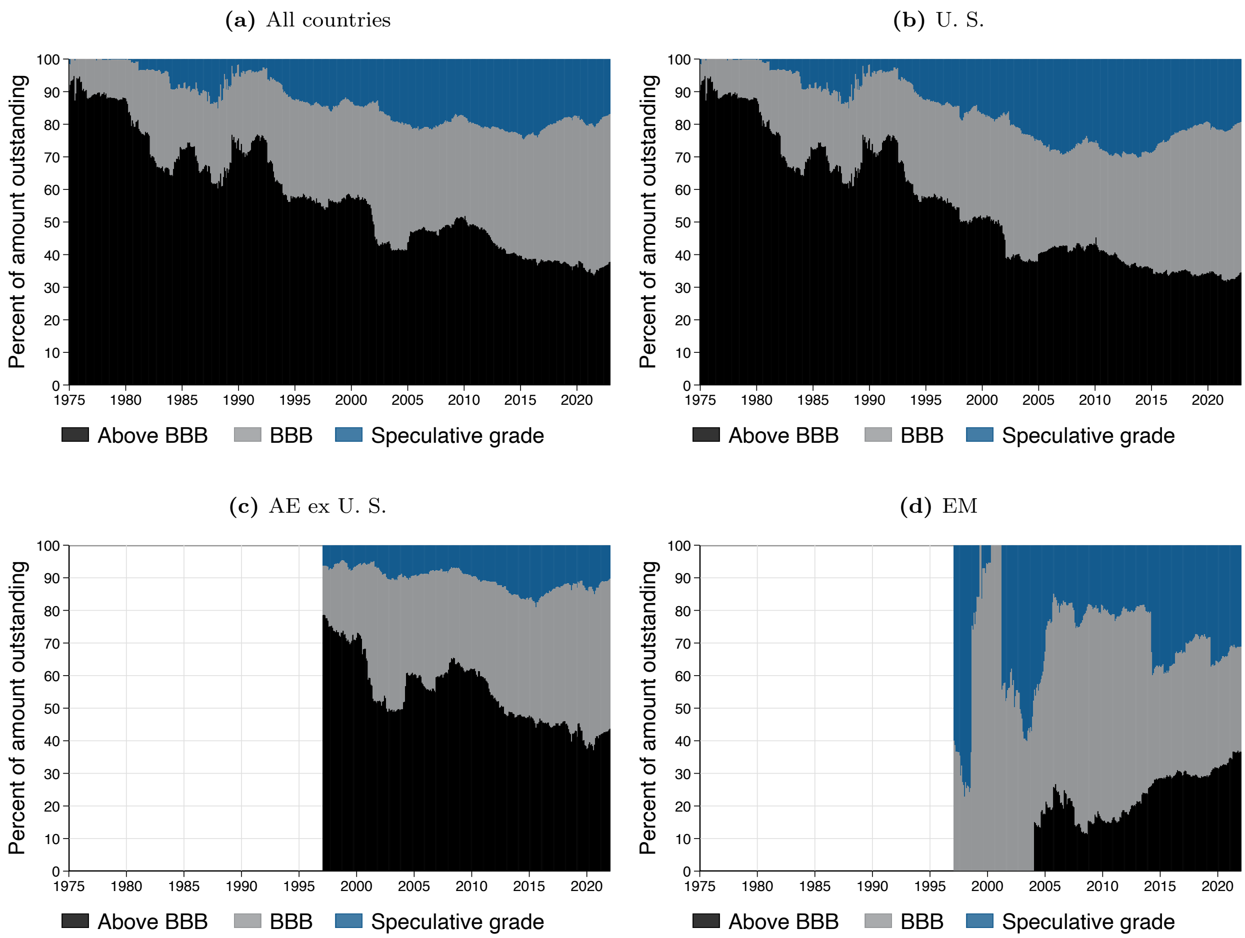
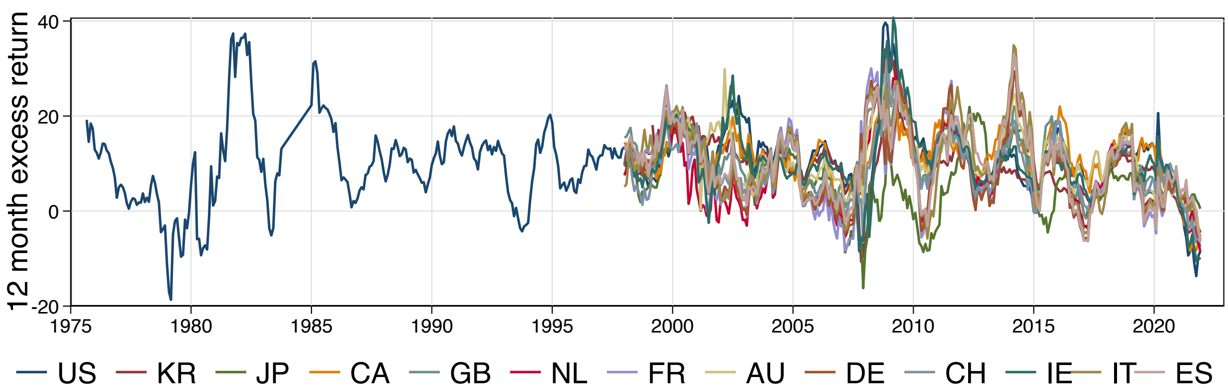


Figure 2. 12-month-ahead bond excess returns. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) 12-month-ahead excess returns for non-financial corporate, senior fixed-coupon bonds issued by ultimate parents domiciled within the 22 countries of our sample. Sample AE countries are: United States, South Korea, Japan, Canada, United Kingdom, Netherlands, France, Australia, Germany, Switzerland, Ireland, Italy, and Spain. Sample EM countries are: China, Malaysia, Thailand, India, Mexico, Brazil, Russia, Chile, and Argentina.

(a) Advanced economies



(b) Emerging market economies

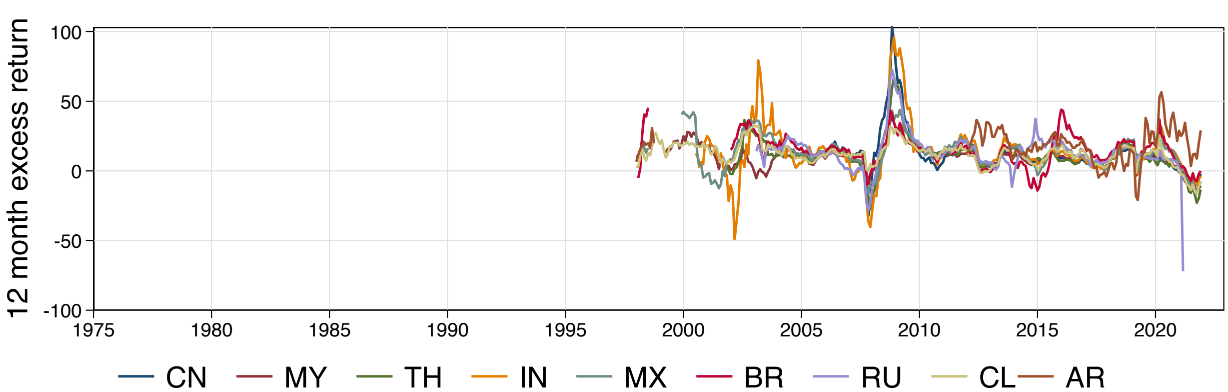


Figure 3. Time series of estimated factors. This figure plots the time series of the global risk factor and the global credit factor estimated by reduced-rank regression. To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations.

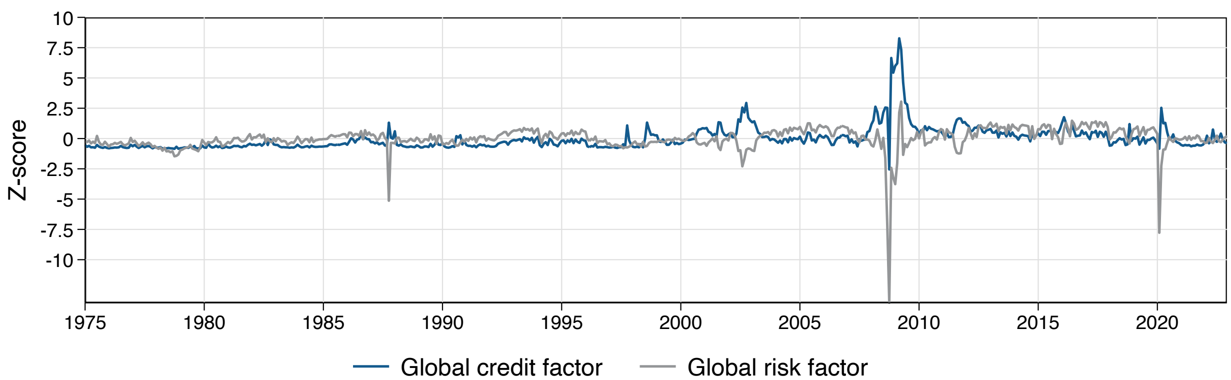
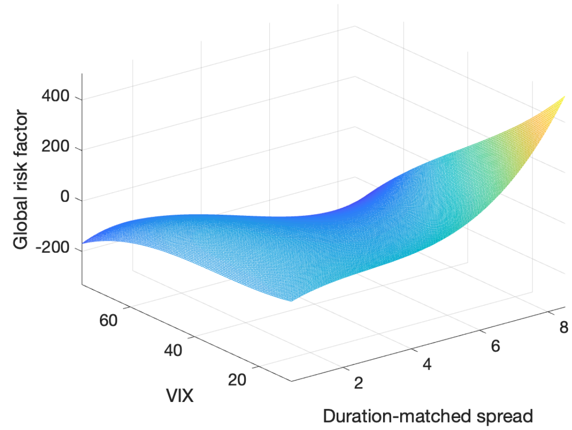
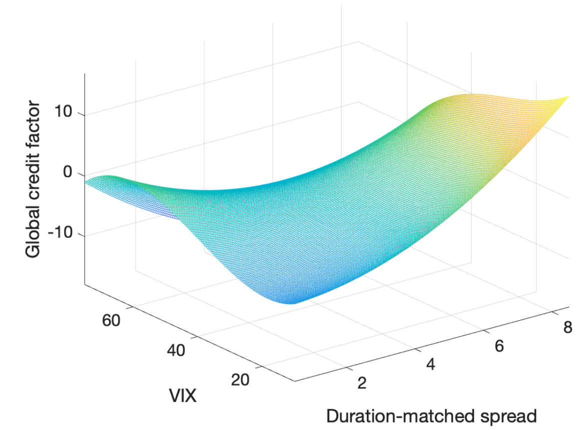


Figure 4. Estimated factors. This figure plots the estimated global risk and global credit factors as a function of realizations of the VIX and the U. S. average duration-matched spread.

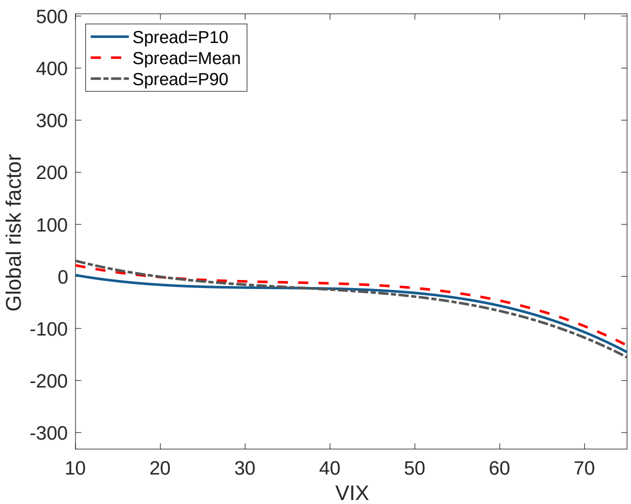
(a) Global risk factor



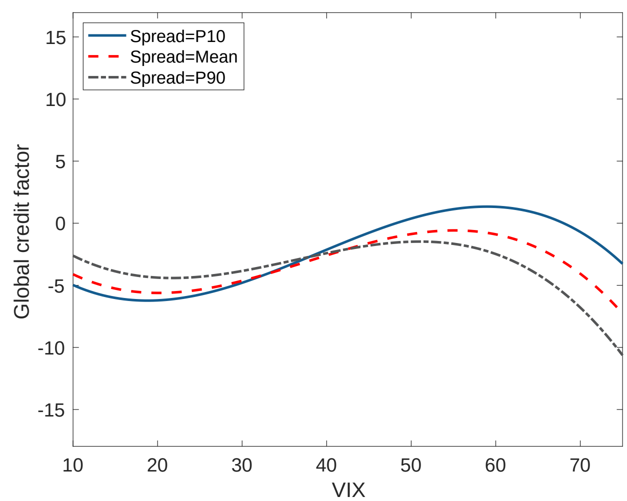
(b) Global credit factor



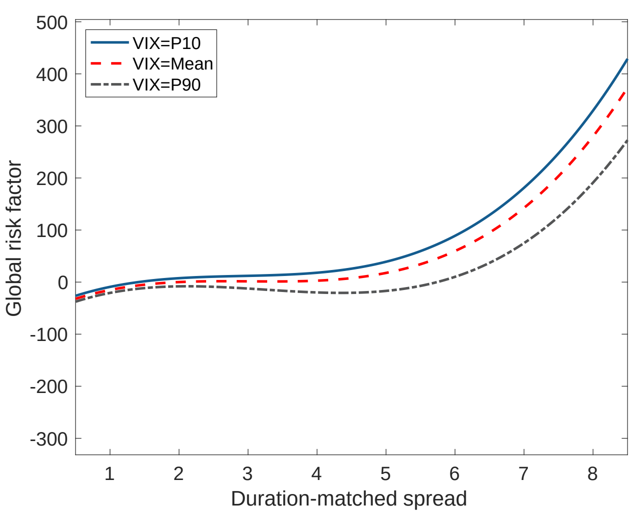
(c) Global risk factor vs VIX



(d) Global credit factor vs VIX



(e) Global risk factor vs duration-matched spread



(f) Global credit factor vs duration-matched spread

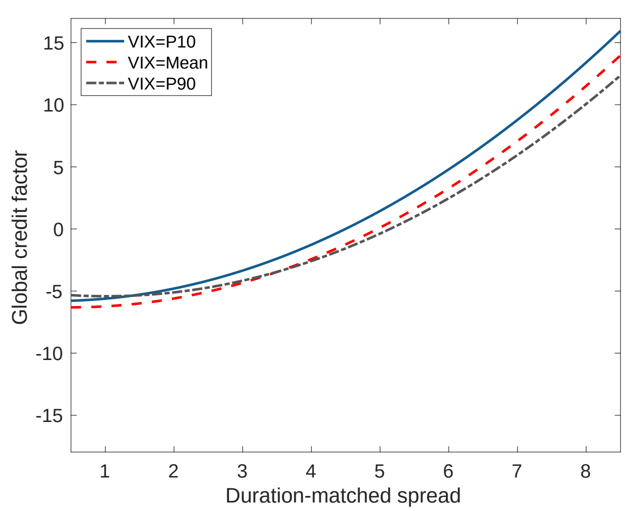
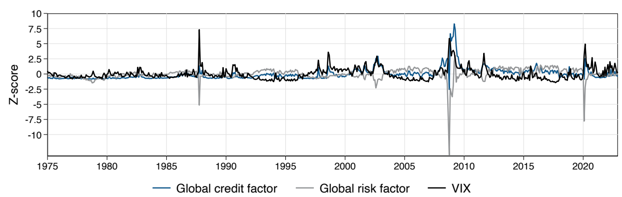
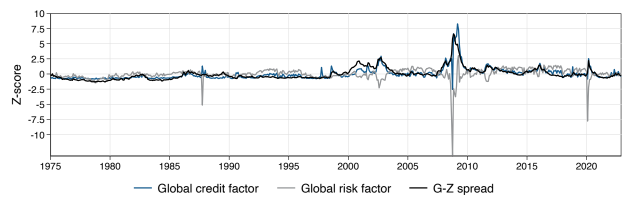


Figure 5. Comparison to other variables. This figure plots the time series of the global risk factor and the global credit factor estimated by reduced-rank regression against commonly used measures of financial conditions: VXO/VIX, Gilchrist and Zakrajšek (2012) "G-Z" spread and excess bond premium (EBP), the 12-month change in the broad dollar index, the original Miranda-Agrippino and Rey (2015) and the updated Miranda-Agrippino et al. (2020) global factor, and U. S. and global Goldman-Sachs financial conditions indices (GS FCI). To facilitate visual comparisons, all variables are demeaned and scaled by their unconditional standard deviations.

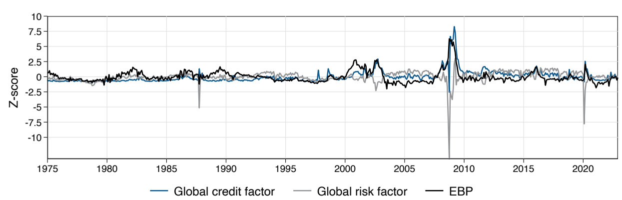
(a) VXO/VIX



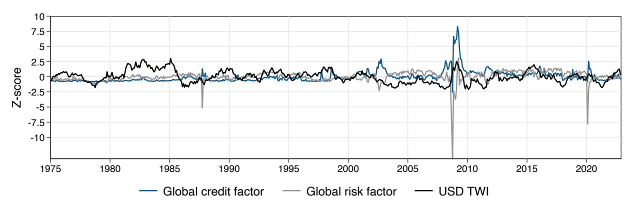
(b) GZ-spread



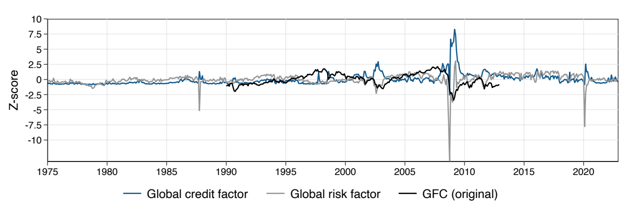
(c) EBP



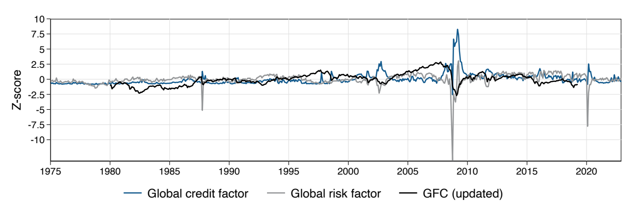
(d) Broad dollar index



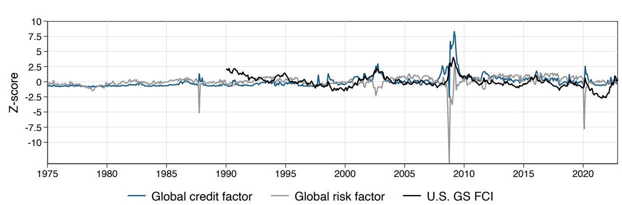
(e) GFC (original)



(f) GFC (updated)



(g) U. S. GS FCI



(h) Global GS FCI

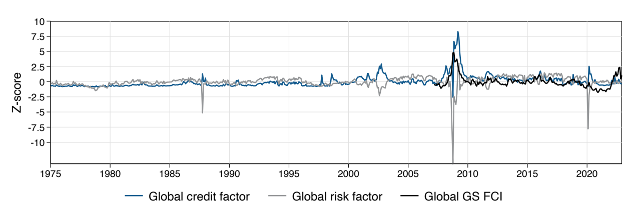
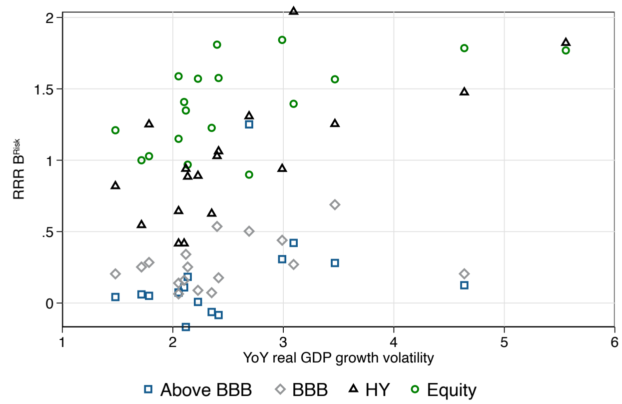


Figure 6. Return predictability and country risk. This figure plots the estimated coefficients from the return predictability regression of one-month ahead returns on the global risk and global credit factors for each country-asset category vs country risk, as measured by the pre-pandemic volatility of year-over-year real GDP growth.

(a) Global risk



(b) Global credit

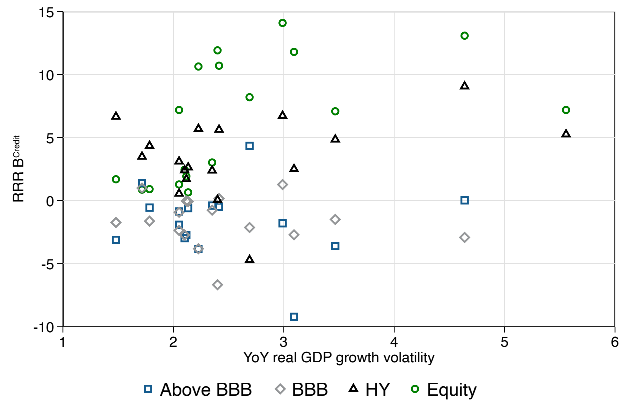
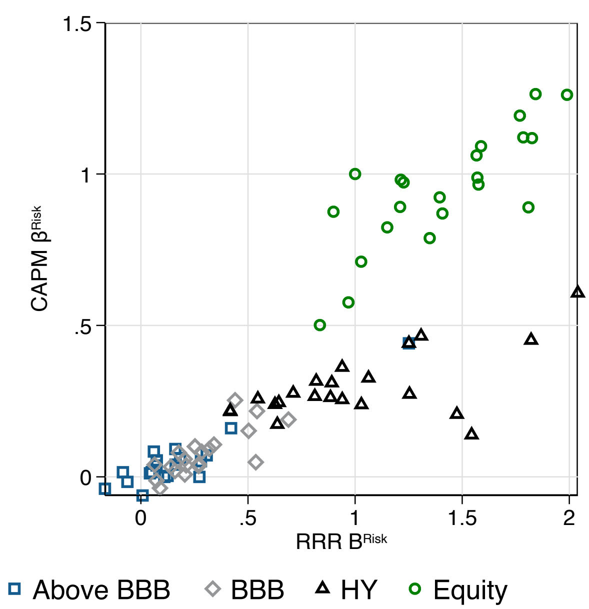


Figure 7. Return predictability and CAPM betas. This figure plots the estimated coefficients from the return predictability regression of one-month ahead returns on the global risk and global credit factors for each country-asset category vs market βs. Equity market return measured using the U. S. MSCI equity total return index; bond market return measured using the Bloomberg U. S. Corporate Index.

(a) Global risk



(b) Global credit

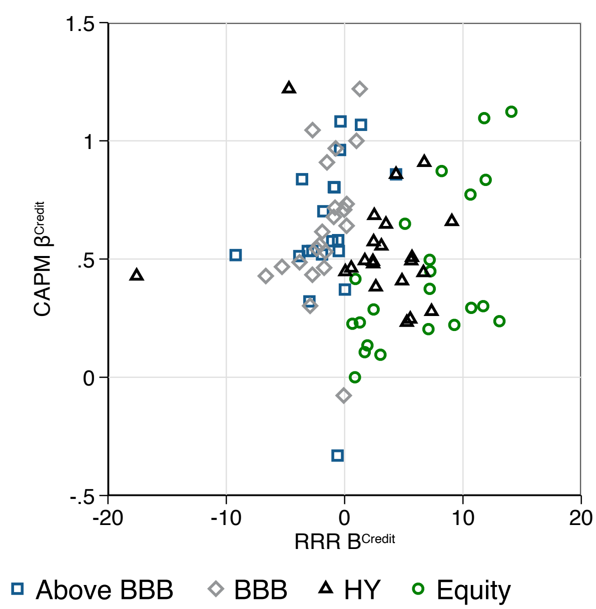
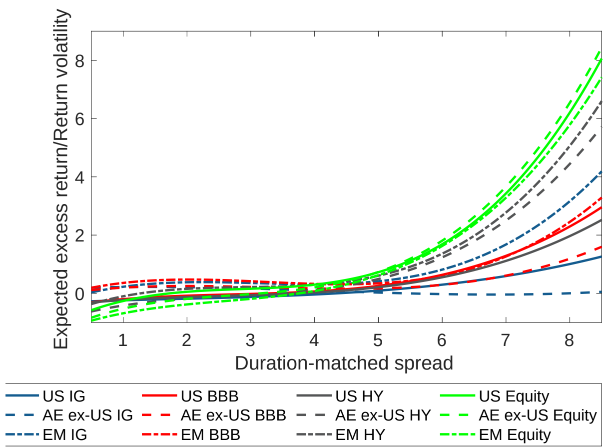
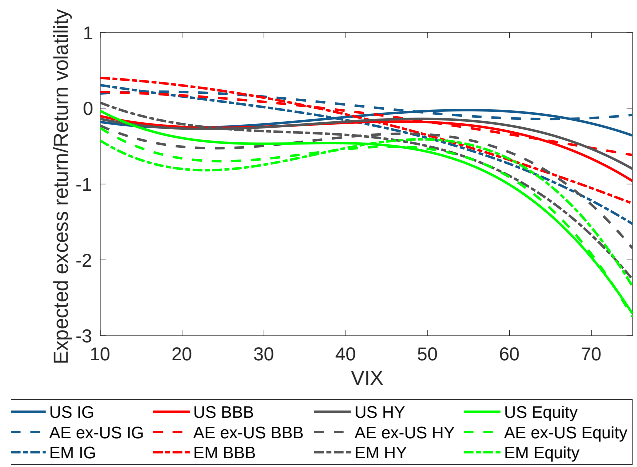


Figure 8. Flight to safety in expected excess returns. This figure plots the expected excess returns based on the reduced rank estimates of global credit and risk factors as a function of the VIX and U. S. credit spreads.

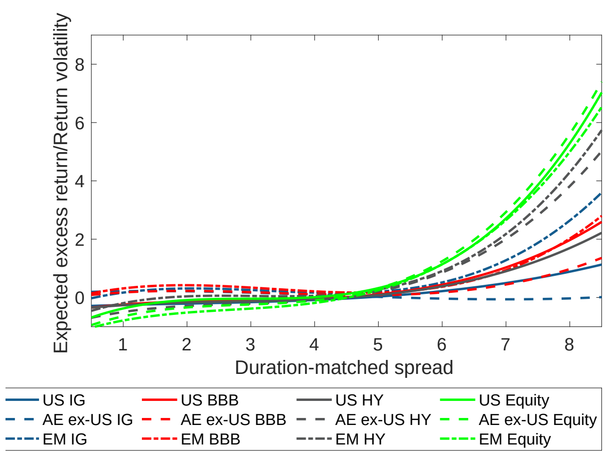
(a) Low VIX



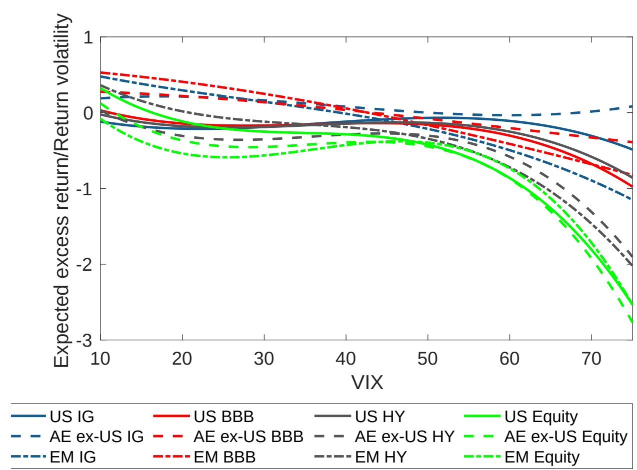
(b) Low credit spread



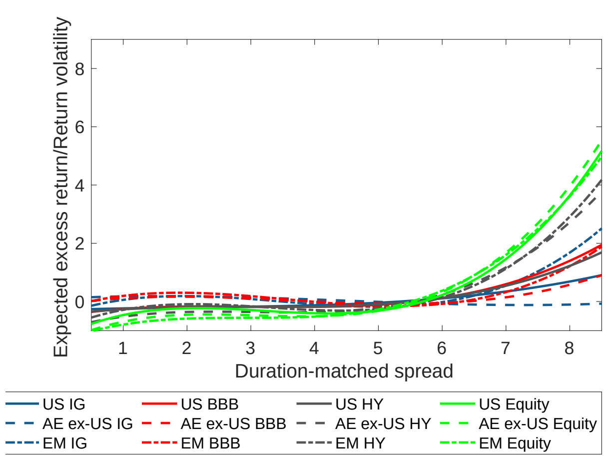
(c) Mean VIX



(d) Mean credit spread



(e) High VIX



(f) High credit spread

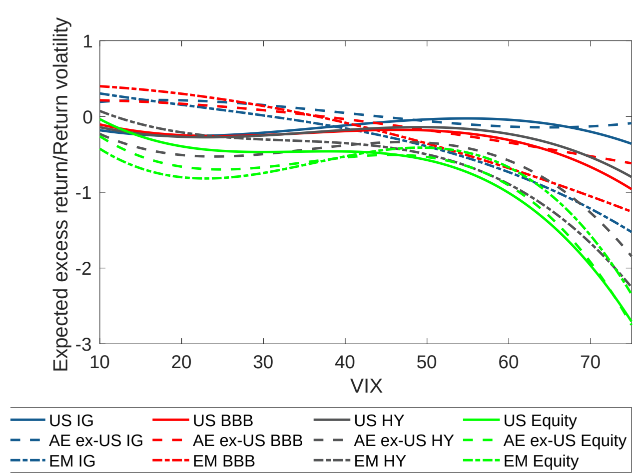
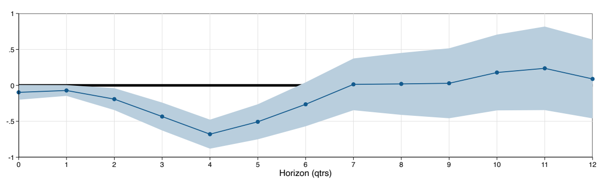
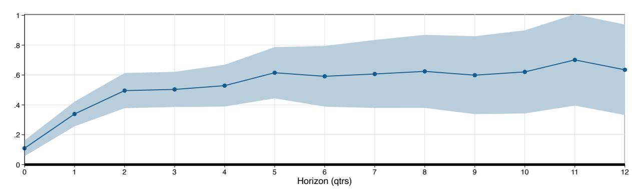


Figure 9. Impulse response functions. This figure plots the impulse response functions of real GDP growth and private credit to GDP growth to a shock to the global credit factor and the global risk factor. Private credit measured as the sum of household credit and nonfinancial corporate credit. Impulse response functions estimated via local projections. 95% confidence bands based on standard errors clustered at the country level plotted as the shaded area around point estimates.

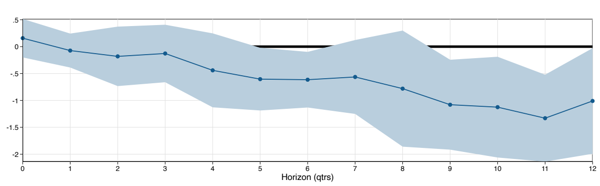
(a) Global credit → Real GDP



(b) Global risk → Real GDP



(c) Global credit → Private credit/GDP



(d) Global risk → Private credit/GDP

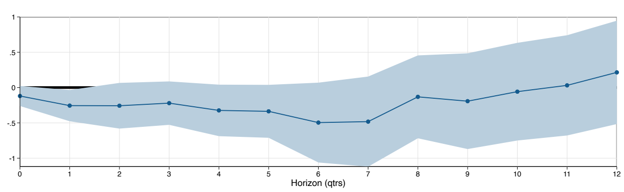
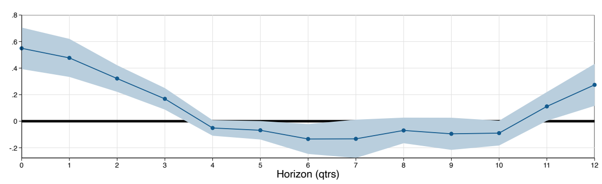
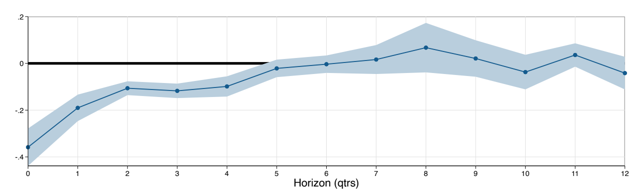


Figure 10. Crisis probabilities. This figure plots the estimated coefficient from the complimentary log-log regression of the probability of a crisis in h quarters time. Crisis defined as the forward looking year-over-year real GDP growth falling below 2%. Private credit measured as the sum of household credit and nonfinancial corporate credit. 95% confidence bands based on standard errors clustered at the country level plotted as the shaded area around point estimates.

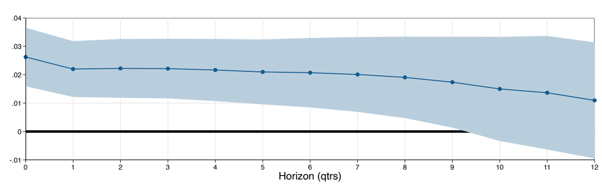
(a) Global credit



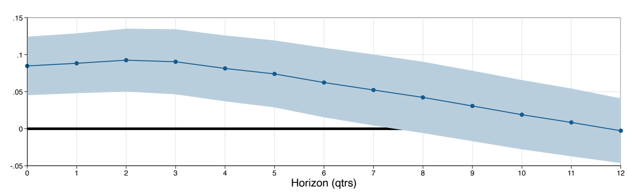
(b) Global risk



(c) 3 year change in domestic private credit



(d) 3 year change in foreign private credit



A Capital flow data and definitions

We use international capital flows data from the IMF's International Financial Statistics (IMF IFS). These data contain quarterly capital flows disaggregated by type (e.g. debt and equity portfolio, banks/other, FDI) as well as by the residency of the asset (domestic vs. foreign). This level of disaggregation allows us to observe inflows/outflows at the type level. For instance, we observe "debt portfolio inflows" defined as the net (purchases minus sales) acquisition of domestic investments involving debt securities (cross-border transactions and positions). Following Forbes and Warnock (2012, 2021), we interpret net cross-border transactions of domestic assets (inflows) as being driven by foreign investors and net cross-border transactions of foreign assets (outflows) as being driven by local investors. Netting inflows and outflows gives net flows, the measure of capital flows more commonly used in the less-recent literature (before data on gross flows became available).

Given our focus on how global financial conditions transmit around the world, the distinction between net and gross flows is particularly important. This is because, while net flows might mask counterbalancing forces between flows by domestic and foreign investors, looking at gross flows allows us to explore how global financial conditions affect flows by each type of investor differently. Moreover, given our focus on the *credit* cycle, using disaggregated data by type of flows allows us to explore whether certain types of flows (e.g. debt portfolio or bank flows) are more affected by global credit conditions than others (e.g. equity portfolio or FDI flows).

Given our flows data, we construct quarterly episode dummies by type of flow and type of investor following Forbes and Warnock (2012, 2021). Their methodology is designed to capture episodes in which changes in flows are large relative to the recent path of changes in flows at the country-level. More specifically, we compute 4-quarter moving sums of flows –for each time series– and then calculate year-on-year changes. We then construct, for each quarter, the 5-year rolling mean and standard deviation of the year-on-year changes. The procedure can be summarized as follows:

- Starting from the quarterly series on gross flows in quarter t, into/out of country i of type k (debt/equity portfolio, banks/other, FDI) and nationality n of the investor –domestic or foreign: $F_{t,i,k,n}$
- Compute 4-quarter sum of flows: $C_{t,i,k,n} = \sum_{i=0}^{3} F_{t,i,k,n}$ and the change in $\Delta C_{t,i,k,n} = C_{t,i,k,n} - C_{t-4,i,k,n}$
- Compute 5-year rolling means and standard deviations of $\Delta C_{t,i,k,n}$
- Define episodes as quarters (spells of quarters) in which:
  - $\Delta C_{t,i,k,n}$ falls below/above 2 standard deviations below its mean.
  - The episode starts when $\Delta C_{t,i,k,n}$ decreases/increases more than 1 standard deviation below/above its mean.

- The episode ends when $\Delta C_{t,i,k,n}$ is back to within 1 standard deviation of the series mean.

The procedure above generates a dummy variable that simply identifies whether a quarter belongs to an episode or not. Given that episodes can last many quarters, one potential shortcoming of the procedure is that it does not differentiate between quarters within an episode. In our context, for instance, one could expect global financial conditions to have different predictive power for the beginning of an episode than for other quarters within an episode. In unreported results, we explore the robustness of our results to alternative definitions of the event episodes. For alternative definitions, we follow Elias (2021) in identifying potential subsets of the sample of events that might be of interest. For instance, we explore how global financial conditions predict the beginning of episodes or how global financial conditions predict episodes that follow "normal times", that is, episodes that do not follow other episodes in the recent past.

B Additional data details

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

Figure A.1 plots the time series of amount-outstanding-weighted nonfinancial corporate bond yields for the 10 largest (by number of nonfinancial corporate bond issues) advanced economy and emerging market economy countries. For each country $\mathcal{K}$ and each month t, we compute the country-level nonfinancial corporate bond yield as the amount-outstanding-weighted average of bond yields for all bonds associated with ultimate parent companies domiciled in that country

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

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

Figure A.1 shows that, prior to the post-COVID-19 pandemic monetary policy tightening, corporate bond yields for advanced economy countries have on average been declining in our sample period, outside of periods of stress such as the global financial crisis and the market dislocations associated with the COVID-19 pandemic. The figure also shows a large degree of commonality in the evolution of corporate bond yields in advanced economies. The convergence in advanced economy corporate bond yields to a common credit cycle comes against the backdrop of a shortening effective duration of corporate bonds in the same countries (Figure A.2). Corporate bond yields in emerging market economies instead show more individual cycles for a large part of the sample and a more stable distribution of effective duration.

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

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

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

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

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

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

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

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

Figure A.3 plots the time series of the average credit spread differential to USD-denominated corporate bonds for the currencies present in our sample. Similar to the results in Liao (2020), Figure A.3 shows that currency credit spread differentials were small in the pre-crisis period, increased significantly during the global financial crisis, and, though narrowed somewhat from their crisis-period highs, have remained elevated in the post-crisis sample.

Adjusting the weighted average yields we saw in Figure A.1 for duration and currency differentials reveals the global nature of the credit cycle, especially for advanced economies.

The weighted-average nonfinancial currency-adjusted duration-matched credit spreads plotted in Figure A.4 comove together to a large extent, with the local credit cycle being an amplification of the global pattern.

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

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

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

Table A.1 reports the estimated coefficients from regression (A.1) for the 10 largest advanced economy and emerging market economy countries. The coefficient on (log) one year EDFs is remarkably stable across countries, suggesting that global credit spreads price default risk in a systematic fashion across countries. In the time series, Figure A.5 shows that adjusting for predictable variation in credit spreads due to bond and firm fundamentals brings the country-level credit cycles even more in-line with each other, even for emerging market economies. In the rest of the paper, we explore the global credit cycle and its implications for real activity.

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

(a) Advanced economies

	US	KR	JP	CA	GB	NL	FR	TW	AU	DE
Log EDF	0.14	0.18	0.16	0.14	0.14	0.11	0.15	0.12	0.17	0.12
	(0.00)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***
Sub in home country	0.05	0.03	0.11	-0.03	0.01	-0.10	0.01	-0.07	0.12	0.06
	(0.00)***	(0.04)	(0.03)***	(0.01)**	(0.01)	(0.04)***	(0.02)	(0.06)	(0.03)***	(0.02)***
Sub in foreign country	0.14	-0.05	-0.08	0.07	0.08	0.16	-0.01	0.00	0.29	0.18
	(0.02)***	(0.06)	(0.04)**	(0.02)***	(0.01)***	(0.03)***	(0.04)	(.)	(0.07)***	(0.03)***
Log duration	0.32	0.19	0.12	0.31	0.29	0.23	0.26	0.21	0.26	0.26
	(0.00)***	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.03)***	(0.02)***	(0.01)***
Log coupon	0.35	0.16	0.07	0.51	0.24	0.27	0.20	0.17	0.34	0.15
	(0.00)***	(0.03)***	(0.01)***	(0.02)***	(0.01)***	(0.02)***	(0.01)***	(0.05)***	(0.02)***	(0.01)***
Log age	0.02	0.02	-0.02	-0.02	-0.02	-0.04	-0.04	0.03	-0.07	-0.02
	(0.00)***	(0.01)**	(0.00)***	(0.00)***	(0.00)***	(0.01)***	(0.01)***	(0.02)**	(0.01)***	(0.00)***
Callable	0.13	-0.06	-0.08	0.04	-0.02	0.07	-0.05	0.09	0.07	-0.06
	(0.01)***	(0.04)	(0.02)***	(0.01)***	(0.01)**	(0.02)***	(0.01)***	(0.11)	(0.02)***	(0.02)***
Log amt out (USD)	0.05	-0.13	-0.01	-0.03	0.00	0.02	-0.02	0.02	0.01	0.05
	(0.00)***	(0.02)***	(0.01)	(0.01)***	(0.01)	(0.01)**	(0.01)**	(0.03)	(0.01)	(0.01)***
W/in adj. R-sqr.	0.37	0.21	0.18	0.41	0.33	0.32	0.33	0.32	0.32	0.31
N. of obs	849594	8670	67331	87231	90452	13906	36362	751	13242	45120
N. of clusters	49044	722	2614	4496	4361	945	2451	110	1311	1998

(b) Emerging market economies

	CN	MY	TH	IN	ID	MX	BR	RU	CL	AR
Log EDF	0.10	-0.03	0.12	0.12	0.28	0.07	0.15	0.19	0.07	0.24
	(0.01)***	(0.02)	(0.02)***	(0.01)***	(0.03)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.02)***
Sub in home country	-0.35	0.17	-0.21	-0.02	-0.97	0.06	0.00	0.10	0.00	0.03
	(0.06)***	(0.09)*	(0.04)***	(0.04)	(0.21)***	(0.03)*	(0.03)	(0.17)	(.)	(0.06)
Sub in foreign country	-0.32	-0.28		0.01		-0.06	-0.13	0.00	0.28	
	(0.08)***	(0.15)*		(0.05)		(0.03)*	(0.05)***	(.)	(0.06)***	
Log duration	0.24	0.21	0.24	0.28	0.01	0.33	0.24	0.22	0.24	-0.03
	(0.02)***	(0.04)***	(0.02)***	(0.02)***	(0.07)	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.04)
Log coupon	0.29	0.20	0.07	0.22	0.43	0.57	0.44	0.07	0.72	0.33
	(0.04)***	(0.06)***	(0.06)	(0.05)***	(0.14)***	(0.03)***	(0.04)***	(0.04)*	(0.06)***	(0.18)*
Log age	-0.05	0.05	0.03	0.03	-0.00	-0.02	-0.02	-0.04	-0.07	0.02
	(0.01)***	(0.02)***	(0.02)**	(0.01)***	(0.03)	(0.01)**	(0.01)***	(0.01)***	(0.01)***	(0.01)*
Callable	-0.15	0.07	-0.14	0.19	0.24	0.11	-0.07	0.03	0.02	-0.05
	(0.04)***	(0.05)	(0.04)***	(0.05)***	(0.22)	(0.02)***	(0.02)***	(0.05)	(0.07)	(0.05)
Log amt out (USD)	0.01	-0.24	-0.00	-0.13	0.43	-0.00	-0.05	-0.13	-0.03	-0.07
	(0.02)	(0.06)***	(0.05)	(0.02)***	(0.12)***	(0.01)	(0.01)***	(0.03)***	(0.04)	(0.04)
W/in adj. R-sqr.	0.28	0.13	0.40	0.36	0.33	0.42	0.32	0.32	0.32	0.33
N. of obs	5133	1766	1840	4005	579	7911	10474	5372	2589	942
N. of clusters	738	433	237	614	184	936	1062	442	381	114

Table A.2: Capital flow predictability. This table reports the estimated coefficients from the complimentary log-log regression of an indicator of a flow episode occurring at date t on the global and local controls and the regional contagion indicator of Forbes and Warnock (2012, 2021). "Global risk" is the year-over-year change in the VXO. "Global liquidity" is the growth in the global money supply. The regional contagion dummy is an indicator equal to one if countries in the same region are experiencing the same type of episode (at the total flows level). Columns (1) – (4) in each panel report the results for the full, pre-pandemic sample; columns (5) – (8) report the results excluding the global financial crisis (excluding 2008 – 2009). Standard errors clustered at the country level reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Stops

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.Risk	0.04	0.04	0.03	0.01	0.03	0.03	0.03	-0.00
	(0.01)***	(0.01)***	(0.01)***	(0.01)*	(0.01)***	(0.01)***	(0.01)***	(0.01)
L.Global liquidity	0.01	0.01	0.01	0.03	-0.00	-0.00	-0.00	0.01
	(0.01)	(0.01)	(0.01)	(0.02)*	(0.01)	(0.02)	(0.01)	(0.02)
L.Global interest rates	0.07	0.06	0.11	0.08	0.09	0.09	0.13	0.11
	(0.03)***	(0.03)**	(0.03)***	(0.03)***	(0.03)***	(0.04)**	(0.03)***	(0.03)***
L.Global GDP growth	-0.14	0.05	0.09	-0.26	-0.22	0.16	0.11	-0.31
	(0.04)***	(0.04)	(0.04)**	(0.04)***	(0.09)**	(0.07)**	(0.07)	(0.12)***
Regional contagion	0.56	0.38	0.24	0.19	0.43	0.34	0.15	0.04
	(0.15)***	(0.14)***	(0.14)*	(0.12)	(0.15)***	(0.14)**	(0.14)	(0.12)
L.Local GDP growth	-0.08	-0.01	-0.01	-0.09	-0.10	-0.03	-0.02	-0.10
	(0.02)***	(0.02)	(0.01)	(0.02)***	(0.02)***	(0.02)	(0.02)	(0.02)***
Log pseudolikelihood	-6115.40				-5198.88			
N. of obs	4,319				3,967			

(b) Surges

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.Risk	-0.01	-0.04	-0.02	0.01	-0.01	-0.04	-0.02	0.00
	(0.01)*	(0.01)***	(0.01)***	(0.01)	(0.01)*	(0.01)***	(0.01)***	(0.01)
L.Global liquidity	-0.03	0.01	0.04	-0.02	-0.03	0.01	0.03	-0.03
	(0.01)**	(0.01)	(0.02)*	(0.01)*	(0.01)**	(0.01)	(0.02)	(0.01)**
L.Global interest rates	0.14	0.15	0.12	0.09	0.13	0.16	0.12	0.10
	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.04)***	(0.03)***
L.Global GDP growth	0.29	-0.13	-0.02	0.35	0.27	-0.05	0.05	0.35
	(0.07)***	(0.04)***	(0.05)	(0.07)***	(0.08)***	(0.07)	(0.06)	(0.08)***
Regional contagion	0.76	0.17	0.28	0.58	0.78	0.19	0.30	0.53
	(0.23)***	(0.12)	(0.14)**	(0.17)***	(0.24)***	(0.12)	(0.15)**	(0.18)***
L.Local GDP growth	0.02	0.03	0.02	0.02	0.02	0.03	0.02	0.02
	(0.01)***	(0.01)***	(0.00)***	(0.01)*	(0.01)***	(0.01)***	(0.00)***	(0.01)*
Log pseudolikelihood	-6365.41				-5960.17			
N. of obs	4,319				3,967			

(Table A.2 continued)

(a) Flights

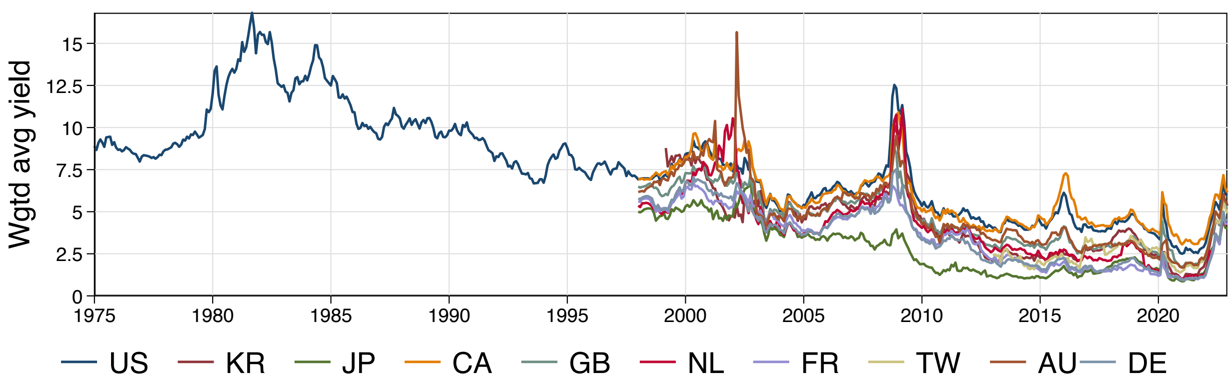
	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.Risk	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.03	-0.01
	(0.01)**	(0.01)**	(0.01)***	(0.01)	(0.01)*	(0.01)	(0.01)***	(0.01)
L.Global liquidity	-0.01	-0.02	0.01	0.00	-0.01	-0.02	-0.00	0.01
	(0.01)	(0.01)*	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
L.Global interest rates	0.15	0.20	0.07	0.12	0.14	0.18	0.09	0.11
	(0.03)***	(0.03)***	(0.03)**	(0.03)***	(0.03)***	(0.03)***	(0.03)***	(0.04)***
L.Global GDP growth	0.19	-0.01	0.00	0.09	0.18	-0.07	0.14	0.05
	(0.07)***	(0.05)	(0.04)	(0.04)**	(0.07)**	(0.07)	(0.05)***	(0.06)
Regional contagion	0.53	0.14	0.43	0.36	0.52	0.16	0.41	0.37
	(0.14)***	(0.12)	(0.15)***	(0.14)**	(0.15)***	(0.11)	(0.16)***	(0.14)***
L.Local GDP growth	0.01	-0.01	0.01	0.01	0.01	-0.01	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Log pseudolikelihood	-6927.04				-6482.78			
N. of obs	4,305				3,953			

(b) Retrenchment

	Full sample				Normal			
	Total	Debt portfolio	Equity portfolio	Bank/other	Total	Debt portfolio	Equity portfolio	Bank/other
L.Risk	0.03	0.03	0.04	0.03	0.03	0.02	0.03	0.01
	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)**	(0.01)**	(0.01)
L.Global liquidity	0.02	0.05	0.05	0.02	0.01	0.03	0.04	-0.00
	(0.01)*	(0.01)***	(0.02)***	(0.01)	(0.01)	(0.01)*	(0.02)**	(0.02)
L.Global interest rates	0.07	0.05	0.05	0.09	0.09	0.08	0.08	0.14
	(0.03)***	(0.02)**	(0.04)	(0.03)***	(0.03)***	(0.02)***	(0.04)**	(0.04)***
L.Global GDP growth	-0.16	0.02	0.01	-0.17	-0.25	0.15	-0.00	-0.09
	(0.07)**	(0.05)	(0.04)	(0.05)***	(0.12)**	(0.09)*	(0.09)	(0.10)
Regional contagion	0.54	0.20	0.47	0.20	0.48	0.17	0.35	0.15
	(0.16)***	(0.12)*	(0.14)***	(0.17)	(0.14)***	(0.13)	(0.15)**	(0.18)
L.Local GDP growth	-0.03	0.02	-0.00	-0.03	-0.01	0.02	0.00	-0.02
	(0.03)	(0.01)**	(0.01)	(0.02)	(0.04)	(0.00)***	(0.01)	(0.02)
Log pseudolikelihood	-6148.34				-5116.09			
N. of obs	4,305				3,953			

Figure A.1. Raw secondary market quote data. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) yields quoted in ICE for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

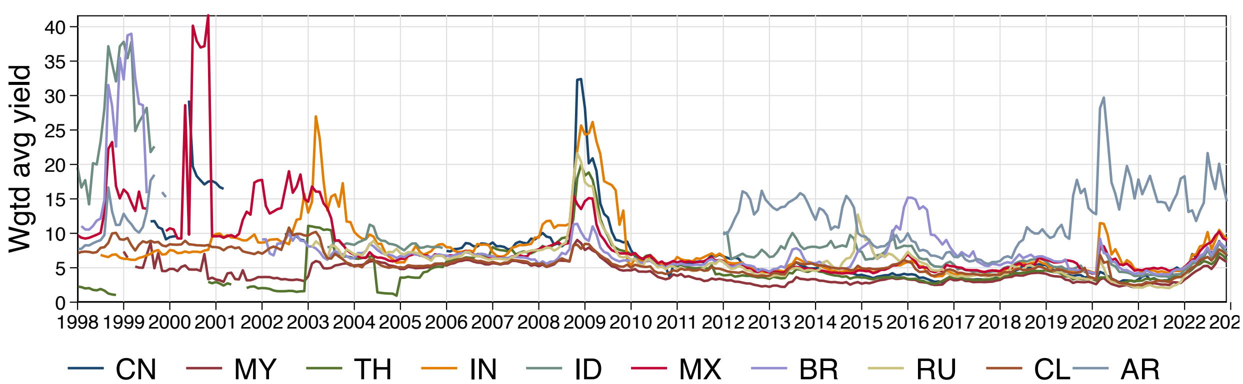
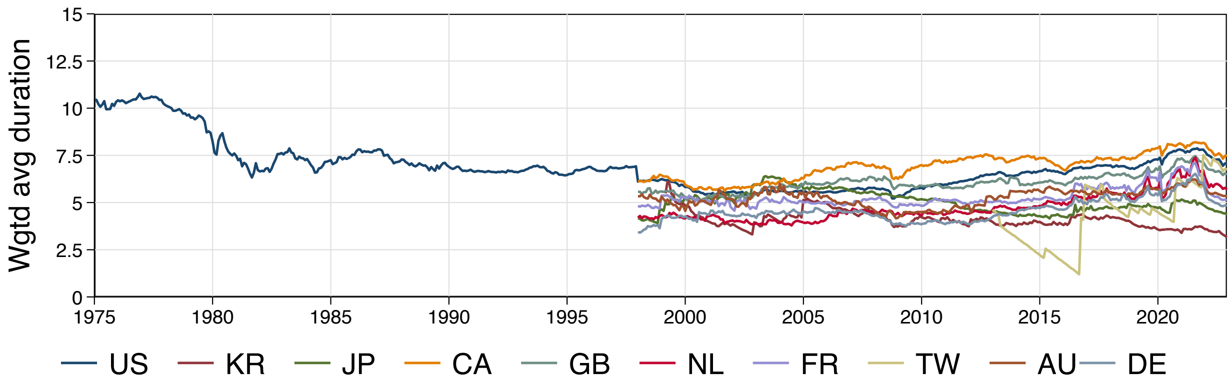


Figure A.2. Secondary market duration data. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) duration for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

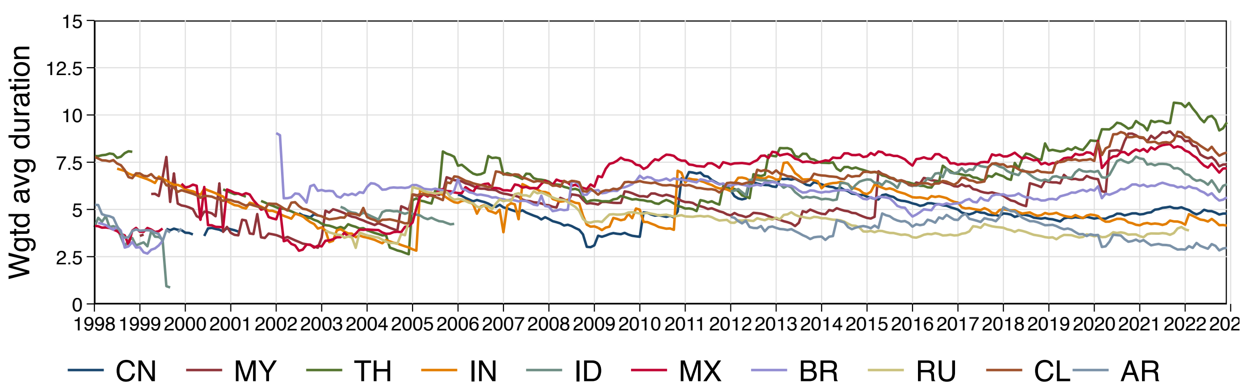


Figure A.3. Average differential to USD credit spreads. This figure plots the time series of the average credit spread between non-USD denominated bonds and USD denominated non-financial corporate, senior fixed-coupon bonds. Average credit spreads estimated from repeated cross-sectional regressions of duration-adjusted credit spreads for firms with bonds outstanding in multiple currencies on currency, firm, and rating fixed effects.

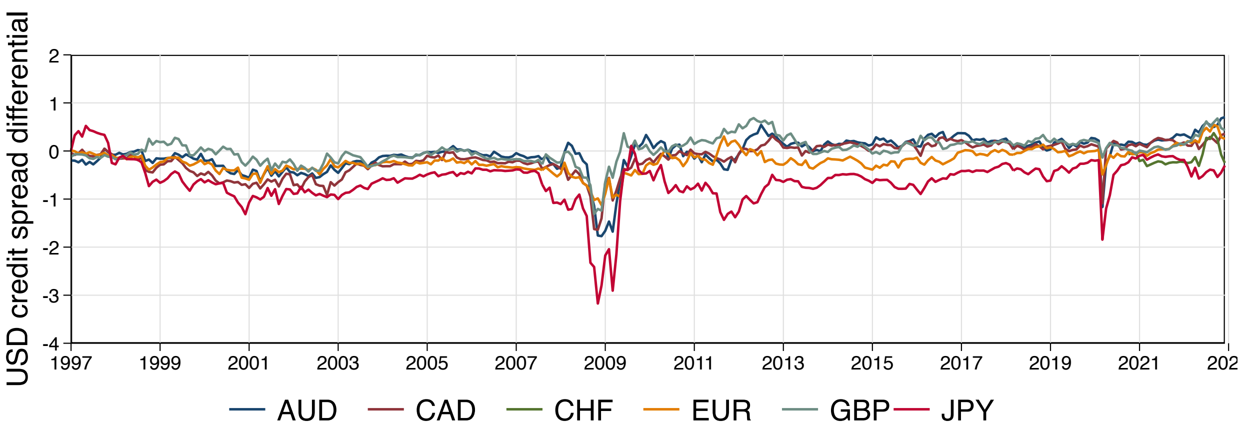
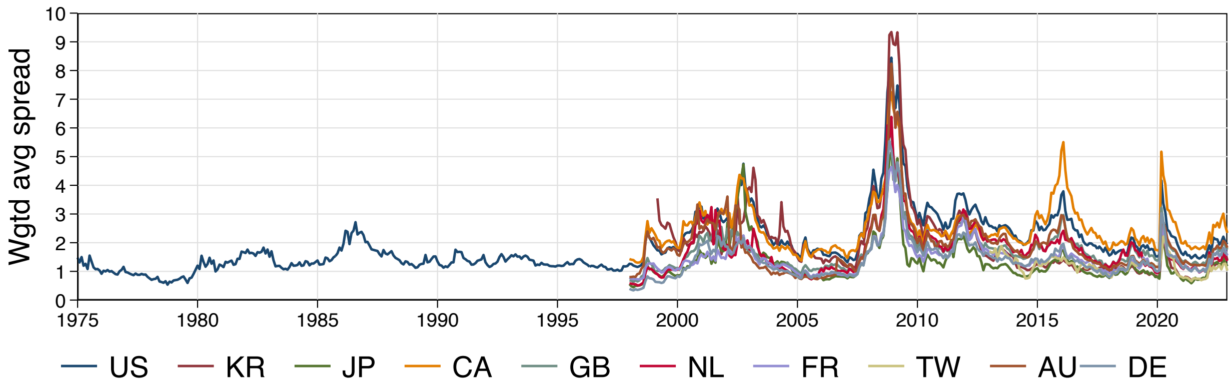


Figure A.4. Secondary market duration-matched, currency-adjusted spreads. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) duration-matched, currency-adjusted spreads for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10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

(a) Advanced economies



(b) Emerging market economies

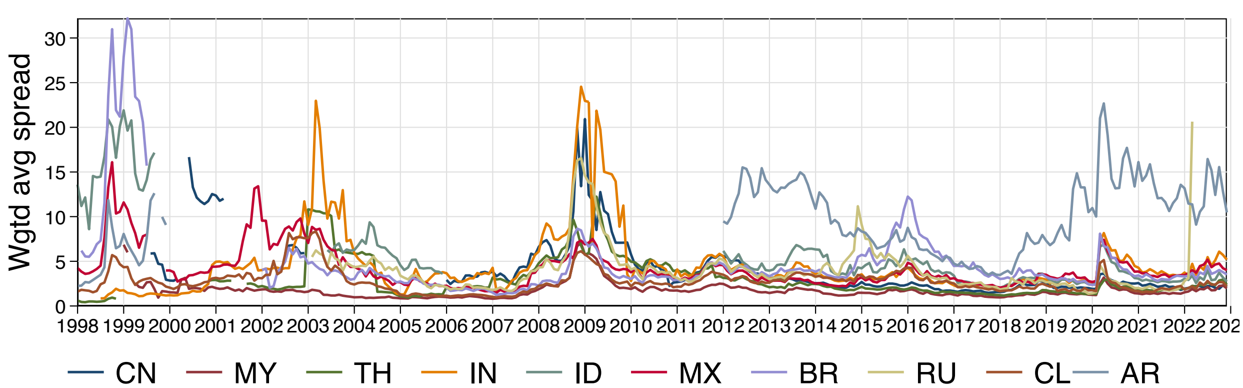
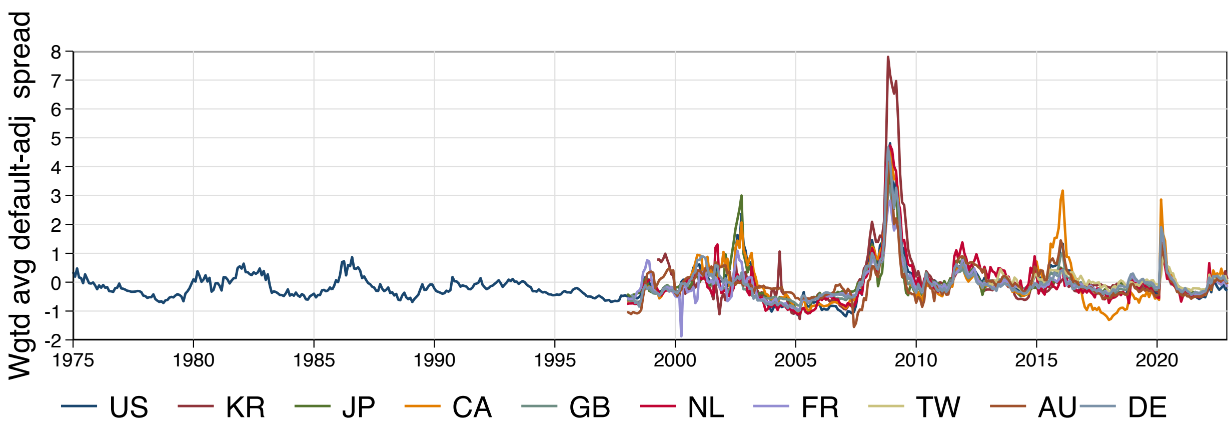


Figure A.5. Estimated default-adjusted spreads. This figure plots the time series of the weighted average (using USD-equivalent amount outstanding) default-adjusted credit spreads for non-financial corporate, senior fixed-coupon bonds issued by firms in the top 10 advanced economies, the top 10 emerging market economies, the remaining advanced economies and the remaining emerging market economies. Countries ranked based on total number of unique non-financial corporate fixed-rate bonds issued by issuers domiciled within the country.

(a) Advanced economies



(b) Emerging market economies

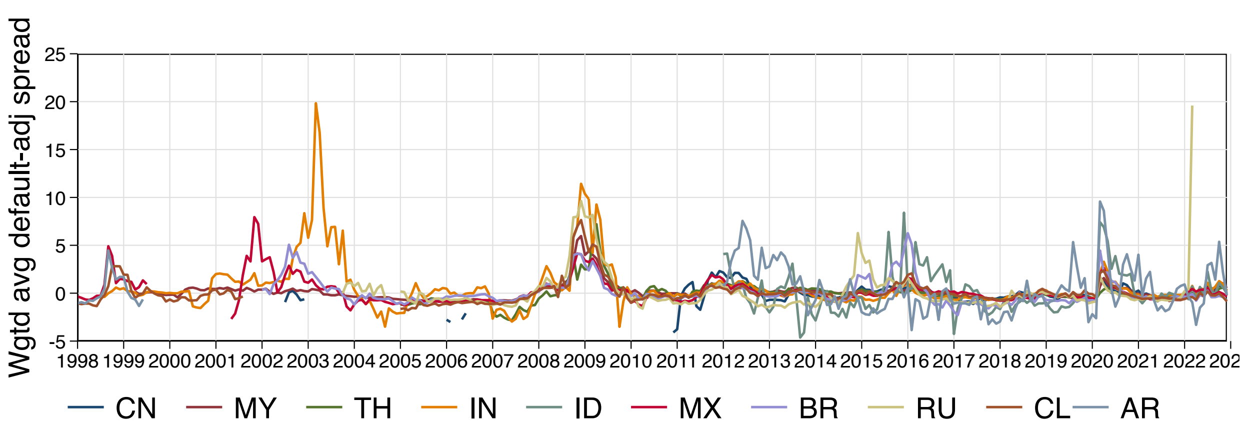
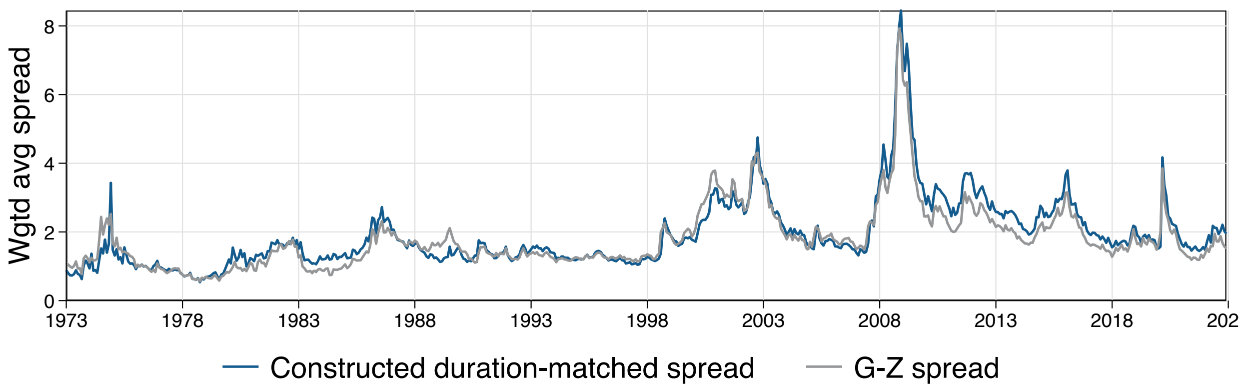


Figure A.6. Comparison to G-Z series. This figure plots the time-series of U. S. average duration-adjusted and default-adjusted credit spreads in our sample versus the Gilchrist and Zakrajšek (2012) spreads..

(a) Duration-matched spread



(b) Default-adjusted spread