The Global Credit Cycle

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Motivation

- Large and increasing importance of global corporate bond markets
  - Size
    - \$18.6 trillion outstanding: 62% issued in G-7 countries, 25% in China, 13% in RoW
  - Bond prices key driver of cost of financing
    - 77% of firm debt in the U. S., 16% (and rising) outside the U. S.

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    - 77% of firm debt in the U. S., 16% (and rising) outside the U. S.
- Large degree of synchronization
  - In 37% of the months, more than 80% of bonds in ICE Global Bond Indices moved in the same direction
  - $\approx$ 1,000 bonds per month, 50 countries, 80 SIC 2D industries, ...

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This paper:

- Uncover a global credit cycle in expected bond returns
- Show that it generates predictable comovement in bond prices globally

This paper

Measure the global credit cycle as global price of credit risk

- Sieve reduced rank regression for credit risk premia (expected returns) in AE bond portfolios as a function of EBP, VIX

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The global credit factor:

- Predicts *bond*-level returns
  - Across ratings, countries, subsamples, ...
  - Low expected returns for safest, high expected returns for riskiest
  - 40% R^2 at portfolio level, 13% at bond level
  - "Better" proxy for price of risk than EBP, VIX, GFCy, TWI, ...

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The global credit factor:

- Predicts *bond*-level returns
- Tight global credit conditions $\Rightarrow$ persistent deterioration in local credit conditions. . .

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The global credit factor:

- Predicts *bond*-level returns
- Tight global credit conditions $\Rightarrow$ persistent deterioration in local credit conditions. . .
- And outflows from global bond funds

Outline of talk

1. Data

2. Measuring global price of credit risk

3. Global credit risk premia

Outline

1. Data

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Credit market data

1. End-of-month bond-level quotes from:
   - ICE-BAML global corporate bond and global corporate bond high yield indices: international bonds issued in global currencies, 1997–2024
   - Lehman-Warga Fixed Income database: U. S.only, 1973–1998
   - Use to construct bond-level excess returns from the perspective of U. S. investor
     - Duration-risk hedged but not exchange-rate hedged
   - Use to construct portfolio-level excess returns for factor estimation
2. Firm-level expected default frequencies: Moody's KMV CreditEdge
   - Augmented Merton (1973) model
3. Fund-level flow data: EPFR

Data details in Boyarchenko and Elias (2023): "Corporate Credit Conditions Around the World: Novel Facts Through Holistic Data"

▸ Ratings Distribution ▸ U. S.Spreads ▸ International Spreads ▸ Summary statistics

Outline

1. Data
2. Measuring global price of credit risk
3. Global credit risk premia

Approach

No arbitrage + equilibrium pricing kernel $\Rightarrow$

- Expected returns: $\mathbb{E}_t\left[rx_{i,t+h}\right] = \beta_{i,t}\lambda_t^{(h)}$

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$$rx_{i,t+h} = \beta_{i,t}\lambda_t^{(h)} + \epsilon_{i,t+h}$$

- Approximate $\lambda_t^{(h)}$ using a bi-variate spline basis: $\lambda_t \propto \varphi\left(cs_t, \mathrm{VIX}_t\right) \equiv \gamma_h' X_{m,t}$
- Observation equations:

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

- Estimate $\vec{b}_h$, γ_h using a reduced rank regression

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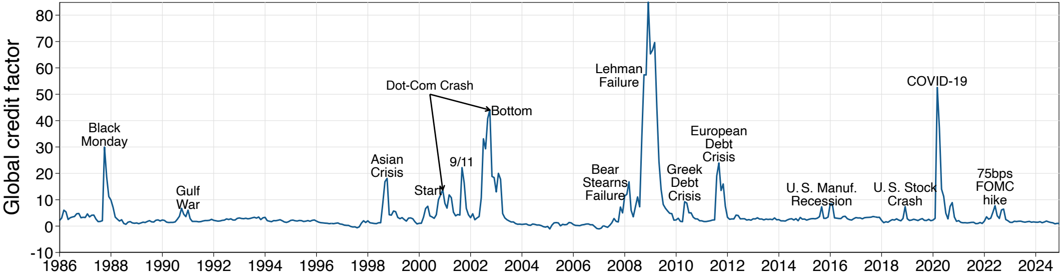
- Estimate $\vec{b}_h$, γ_h using a reduced rank regression
    - Test portfolios: advanced economy bonds, sorted into rating buckets (AAA/AA, A, BBB, high yield)
    - Use out-of-sample performance criterion to select degree of nonlinearity, univariate vs bivariate, interactions vs no interactions, number of factors

Global credit factor



- High VIX and spreads ⇒ high GCC level (e.g. GFC and COVID)
- Low VIX and low level of spreads ⇒ low GCC level (e.g. pre-Asian crisis, pre-GFC)
- Volatility paradox: slack in intermediary constraints (low GCC) leads to risk taking and higher future risk of tight intermediary constraints (high GCC)

▸ Alternative methodologies ▸ Factor shape ▸ Cross-sectional tests

Is the price of credit risk truly global?

Baseline: AE Portfolios $\Leftrightarrow$ VIX and US EBP

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Examine sensitivity with respect to:

1. Target portfolios
   - Portfolios of bonds of U. S.firms; portfolios of bonds of firms in AE outside of the U. S.; portfolios of bonds in firms in EM
   - Keep same choice of basis but re-estimate coefficients γ_h using data 1998–2024

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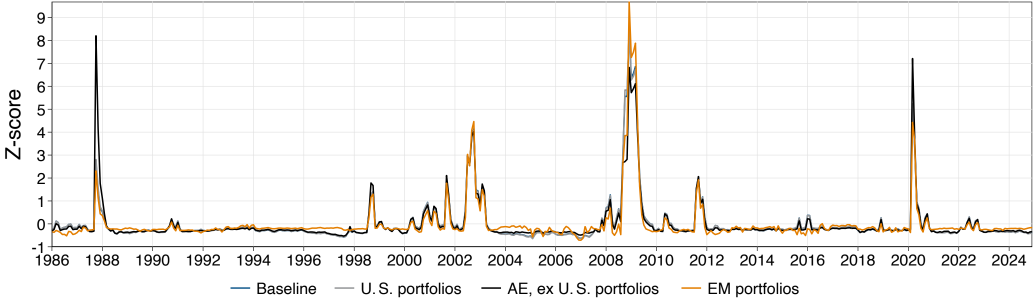
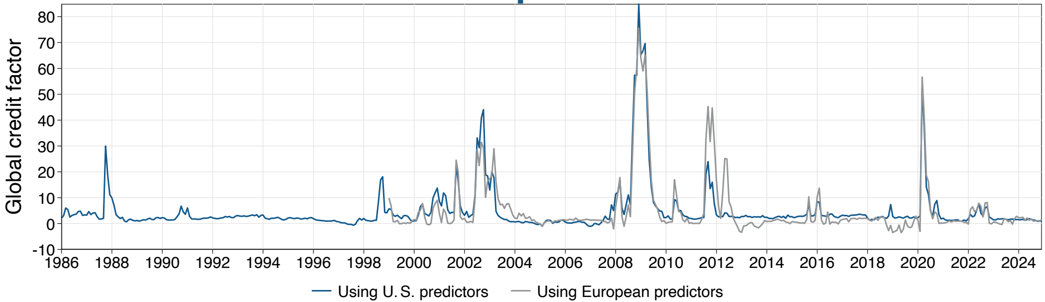
2. Predictors
   - Use European counterparts to VIX and EBP
   - VSTOXX and average EBP across same 8 countries as VSTOXX
   - Re-select optimal basis using out-of-sample performance

Global credit factor: Alternative portfolios



- Estimated global price of credit risk virtually insensitive to target portfolios choice
- Correlations with baseline:
  - U. S. portfolios factor: 99%
  - AE, ex U. S. portfolios factor: 93% (97% post-1998)
  - EM portfolios factor: 97%

Global credit factor: Alternative predictors



- Global price of credit risk constructed using European predictors similar to baseline (92% correlation)
- But local episodes
  - Larger tightening in European-predictors-based factor during European debt crisis
  - Tightening in U. S.-predictors-based factor in December 2018 (U. S.stock crash)

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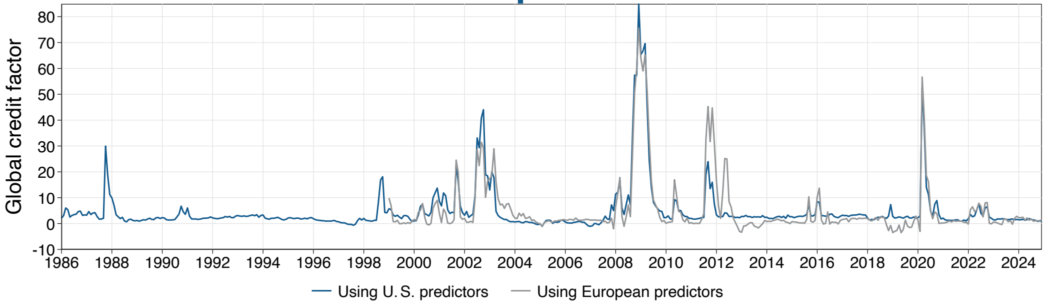

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Truly *global* credit factor

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1. Data

2. Measuring global price of credit risk

3. Global credit risk premia

Bond-level risk premia

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

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		Regions			Currencies	
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
GCC	0.68***					
BBB × GCC	-0.32***					
A × GCC	-0.48***					
AAA/AA × GCC	-0.58***					
In-sample R^2	9.4					
Out-of-sample R^2	5.9					
N. of obs	2,376,804					
N. bonds	40,103					

- $+$ive $\beta \Rightarrow$ high global credit factor $\rightarrow$ high expected excess return

▸ Portfolio-level ▸ By rating ▸ With other characteristics ▸ With other portfolios ▸ With European predictors ▸ Sources of risk
▸ Other asset classes ▸ Alt. standard errors

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	Full sample	U.S.	AE, ex U.S.	EM	USD	Non-USD
GCC	0.68***	0.64***	0.75***	0.87***		
BBB × GCC	-0.32***	-0.28***	-0.43***	-0.35***		
A × GCC	-0.48***	-0.43***	-0.58***	-0.55***		
AAA/AA × GCC	-0.58***	-0.48***	-0.70***			
In-sample R^2	9.4	9.2	9.4	13.3		
Out-of-sample R^2	5.9	5.8	5.8	8.1		
N. of obs	2,376,804	1,449,575	800,004	127,225		
N. bonds	40,103	24,630	14,252	2,434		

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- Within each country: AAA/AA < A < BBB < HY

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A × GCC	-0.48***	-0.43***	-0.58***	-0.55***	-0.46***	-0.46***
AAA/AA × GCC	-0.58***	-0.48***	-0.70***		-0.53***	-0.55***
In-sample R^2	9.4	9.2	9.4	13.3	9.6	8.8
Out-of-sample R^2	5.9	5.8	5.8	8.1	6.0	5.7
N. of obs	2,376,804	1,449,575	800,004	127,225	1,807,898	568,906
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- Within each country: AAA/AA $<$ A $<$ BBB $<$ HY
- USD-denominated bonds more exposed

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- $+$ive $\beta \Rightarrow$ high global credit factor $\rightarrow$ high expected excess return
- Within each country: AAA/AA $<$ A $<$ BBB $<$ HY
- USD-denominated bonds more exposed
- OOS R^2 similar to in-sample $\Rightarrow$ predictability not driven by overfitting

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- Time-series R^2: Does variation in the price of risk capture overall return movements?
- Cross-sectional R^2: Are bonds differentially exposed to movements in the price of risk?
- Market-timing R^2: Are expected returns particularly large when exposures and price of risk rise simultaneously?

Understanding predictability

	(1) GCC	(2) EBP	(3) VIX	(4) $\varphi\,(EBP)$	(5) $\varphi\,(VIX)$	(6) $\varphi_1\,(EBP) + \varphi_2\,(VIX)$
Total R^2	9.4					
Time-series R^2	7.1					
Cross-sectional R^2	0.8					
Market-timing R^2	1.5					
N. of obs	2,376,804					
N. bonds	40,103					

- GCC captures overall variation in returns and bonds differentially exposed to GCC, especially in periods of stress

Understanding predictability

Key elements of factor construction:

- Both EBP and VIX: compare to univariate
- Nonlinearities: compare linear and nonlinear specifications
- Interactions between EBP and VIX: compare to additive factor

Understanding predictability

	(1) GCC	(2) EBP	(3) VIX	(4) $\varphi(EBP)$	(5) $\varphi(VIX)$	(6) $\varphi_1(EBP)+\varphi_2(VIX)$
Total R^2	9.4	4.7	4.2			
Time-series R^2	7.1	4.0	1.9			
Cross-sectional R^2	0.8	-0.1	1.8			
Market-timing R^2	1.5	0.8	0.5			
N. of obs	2,376,804	2,376,804	2,376,804			
N. bonds	40,103	40,103	40,103			

- Performance of linear specifications poor $\Rightarrow$ need nonlinearity
- EBP performs poorly in XS, VIX in the TS $\Rightarrow$ need both predictors

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Market-timing R^2	1.5	0.8	0.5	1.2	1.4	1.5
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- Performance of linear specifications poor $\Rightarrow$ need nonlinearity
- EBP performs poorly in XS, VIX in the TS $\Rightarrow$ need both predictors
- Performance improves significantly with nonlinearities
- Additive factor still underperforms $\Rightarrow$ need interactions between EBP and VIX

Paper: GCC outperforms particularly during loose credit conditions Tight and loose periods

GCC vs. other FCIs

	(1) GCC	(2) VIX	(3) GFCy	(4) Δ TWI	(5) GS FCI
FCI	0.68***	0.51***	-7.27***	0.82***	0.08***
BBB × FCI	-0.32***	-0.30***	1.32***	-0.32***	-0.05***
A × FCI	-0.48***	-0.40***	4.01***	-0.54***	-0.07***
AAA/AA × FCI	-0.58***	-0.45***	5.59***	-0.69***	-0.07***
Total R^2	9.4	4.2	5.4	1.6	1.6
N. of obs	2,376,804	2,376,804	2,376,804	2,376,804	2,305,623
N. bonds	40,103	40,103	40,103	40,103	39,708

- GCC outperforms other proxies for global financial conditions

▸ Correlations

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- vs. GFCy: significantly more XS R^2

▸ Correlations

Recap: Global credit cycle and return predictability

Tighter global credit conditions:

$\Rightarrow$ Higher expected future returns

$\Rightarrow$ Especially for riskier bonds, for bonds in riskier countries

Recap: Global credit cycle and return predictability

Tighter global credit conditions:

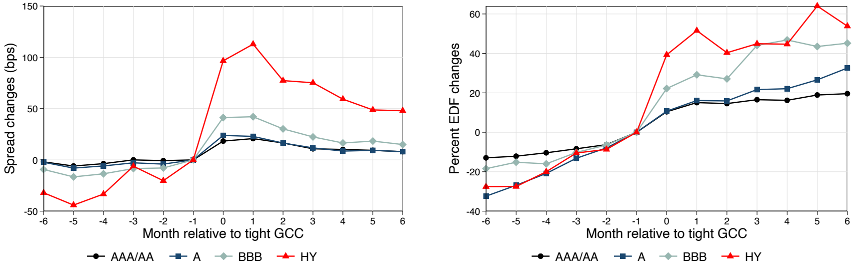
⇒ Higher expected future returns

⇒ Especially for riskier bonds, for bonds in riskier countries

Are there broader implications?

1. Persistent increases in credit spreads, default probabilities ⇒ adverse outcomes for affected firms
2. Increase in bond risk ⇒ losses to corporate bond investors?
3. Mutual fund outflows ⇒ not just re-pricing but also reallocation ▸ Details

Tight GCC ⇒ persistent deterioration in credit conditions



- Spreads remain elevated for up to 6 months after start of GCC tightening
  - Interest costs increases for new debt
  - Deterioration in ability to issue new debt
- EDFs remain elevated 6 months after start of GCC tightening

GCC tightening corresponds to persistently increased risks

▸ Spreads ▸ Spreads Horizons ▸ EDF ▸ EDF Horizons ◂ Back

Wrap-up

Conclusion

Investigate global pricing of risk in corporate bond returns

- Nonlinear function of VIX and US credit spreads prices a large panel of bonds globally
- Monotonic factor loadings: across credit ratings and countries
- Tightenings in the global credit factor
  - $\rightarrow$ Outflows from global bond funds
  - $\rightarrow$ Increases in spreads and EDFs
  - $\rightarrow$ Pricing of risk associated with worse credit conditions faced by firms

Increases in global price of credit risk $\Rightarrow$ outflows from bond mutual funds $\Rightarrow$ persistent deteriorations in credit conditions

Broader research agenda

Interaction between credit markets, firms' decisions, and real activity

- Use rich heterogeneity in debt capital structures across firms, countries, ...
- Elias (2021): "Capital flows and the real effects of corporate rollover risk"
  - Real effects of rollover risk during stop episodes
- Boyarchenko and Elias (2024): "Financing Private Credit"
  - Composition of firms' liabs and of fin sector affects the transmission of mon policy
- Boyarchenko and Elias (2024b): "Corporate Debt Structure over the GCC"
  - GCC drives firms' capital structure decisions
- Boyarchenko and Elias (2026a): "The GCC and Real Activity "
  - A global cycle in credit prices transmits into local business cycles
- Boyarchenko and Elias (2026b): "Financing firm-level growth through the GCC"
  - Changing credit market access through GCC drives firm-level growth

Boyarchenko and Elias (2023): dataset construction and stylized facts about primary market issuance, secondary market pricing, amounts outstanding,...

Appendix

Measuring credit spreads: U. S.

1. Compute duration-matched credit spread for each bond-date observation:

$$z_{b,t} = y_{b,t} - rf_t^{(\tau_{b,t})}$$

   - $\tau_{b,t}$: Duration of bond b at date t
   - $rf_t^{(\tau_{b,t})}$: risk-free (Treasury) yield with duration $\tau_{b,t}$

2. Estimate predicted credit spread:

$$\log z_{b,t} = \alpha + \beta \log \mathrm{EDF}_{f,t} + \vec{\gamma}' X_{b,t} + \epsilon_{b,t}$$

   - $\mathrm{EDF}_{f,t}$: 1 year EDF
   - $X_{b,t}$: bond and firm characteristics

3. Compute default-adjusted credit spread:

$$d_{b,t} = z_{b,t} - \exp\left(\widehat{\log z_{b,t}} + \frac{\sigma_\epsilon^2}{2}\right)$$

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Measuring credit spreads: International

1. Compute duration-matched credit spread for each bond-date observation:

$$z_{b,t} = y_{b,t} - rf_{c,t}^{(\tau_{b,t})}$$

   - $rf_{c,t}^{(\tau_{b,t})}$: sovereign yield for currency c with duration $\tau_{b,t}$

2. For each month, estimate cross-sectional regression of duration-matched credit spreads on currency, firm and rating fixed effects (as in Liao, 2020):

$$z_{b,t} = \alpha_{c,t} + \alpha_{f,t} + \alpha_{rating,t} + \epsilon_{b,t}$$

3. Compute currency-adjusted credit spreads:

$$z_{b,t}^{\$} = z_{b,t} - (\alpha_{c,t} - \alpha_{\$,t})$$

4. Estimate predicted credit spread using currency-adjusted credit spreads
5. Compute default-adjusted credit spread

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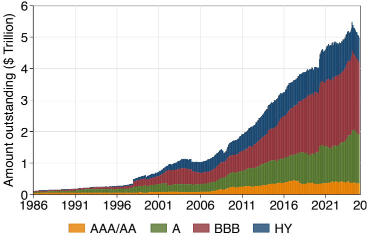
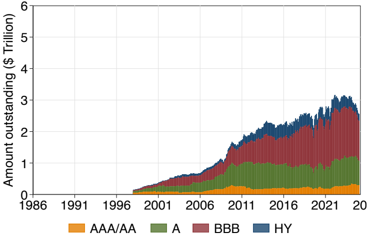
Bond rating distribution

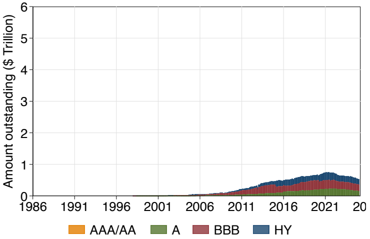
U. S.



AE, ex U. S.



EM



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Sample summary stats

- ICE USD sample slightly below BBB on average
- JPY above A on average
- Everyone else between A and BBB

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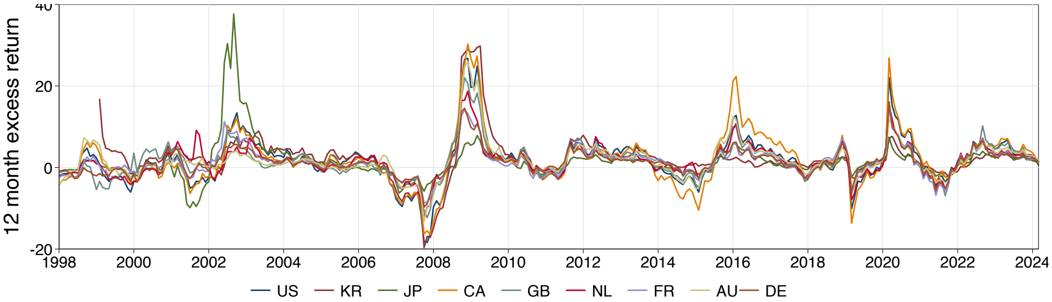
Large degree of comovement in average returns . . .



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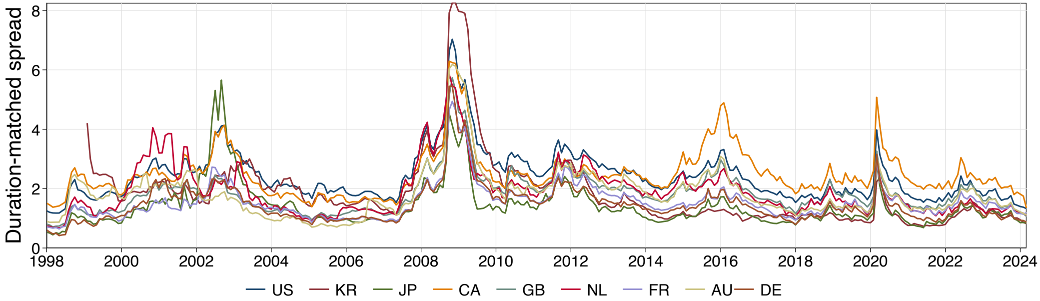
. . . and of comovement in credit spreads



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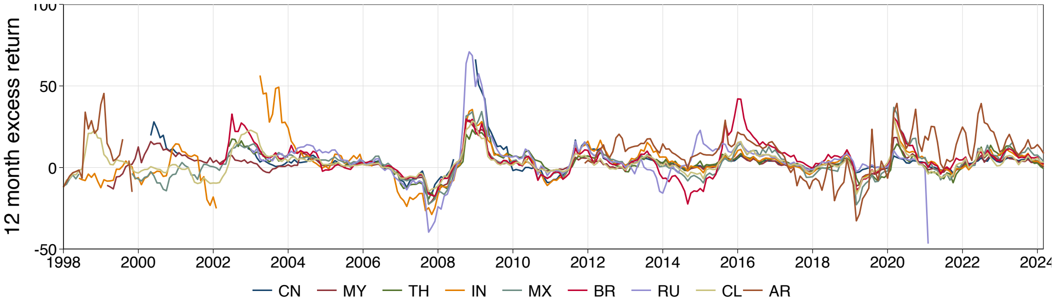
EM returns



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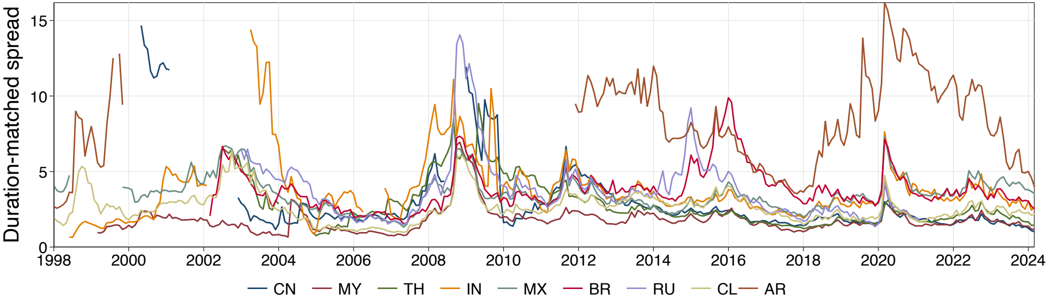
EM duration matched spread



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Factor Construction: Comparison to alternatives

- Reduced rank regression: factor(s) to maximize variance explained of conditional mean

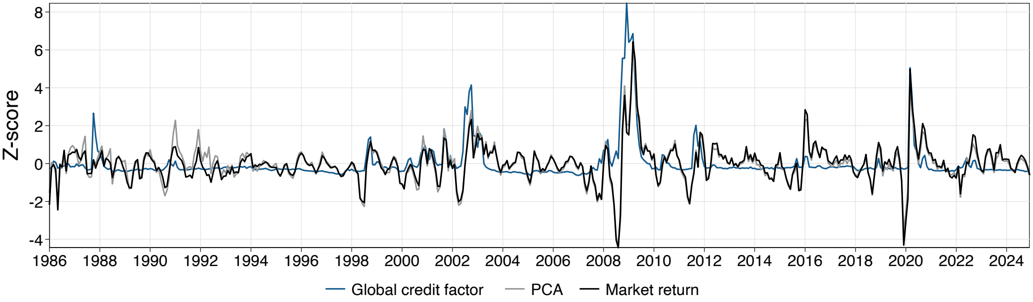
$$\min_{\vec{b}_h,\gamma_h} \left|\left| \overrightarrow{rx}_{t+h} - \vec{b}_h \left(\gamma_h' X_{m,t}\right) \right|\right|^2 \equiv \min_{U,V} \left|\left| V \overrightarrow{rx}_{t+h} - U X_{m,t} \right|\right|^2$$

  - "Weights" in RRR: AAA/AA: 10%; A: 17%; BBB: 28%; HY: 45%
- PCA/DFA: factor(s) to maximize variance of LHS explained

$$\min_{w} \left|\left| \overrightarrow{rx}_{t+h} - \left(ww'\right) \overrightarrow{rx}_{t+h} \right|\right|^2$$

  - Weights in PCA: AAA/AA: 25%; A: 28%; BBB: 28%; HY: 20%
- Factor models: pre-specified weights
  - Market weights in Jan 1986: AAA/AA: 39%; A: 36%; BBB: 20%; HY: 5%
  - Market weights in Dec 2024: AAA/AA: 8%; A: 31%; BBB: 47%; HY: 13%

Factor Construction: Comparison to alternatives



Global credit factor:

- Tightens as negative returns are realized
- Remains elevated during the recovery
- Looks through “normal” return volatility

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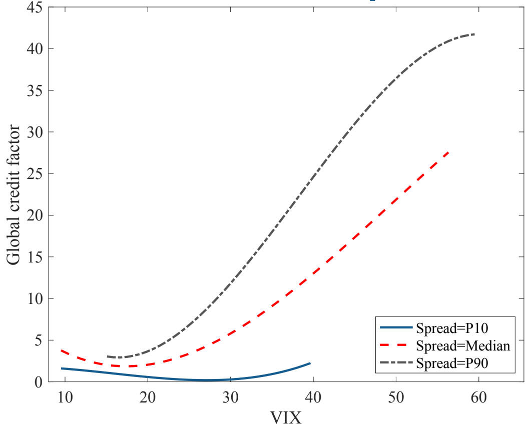
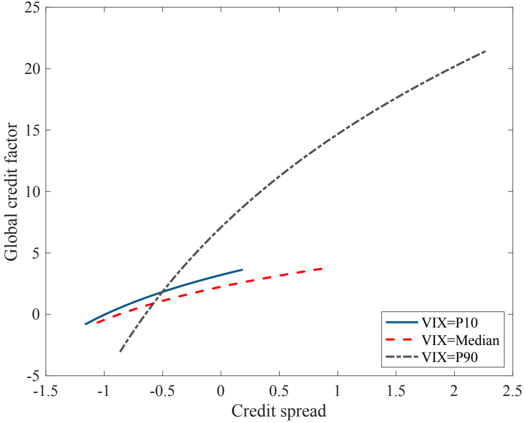
Global credit factor and predictors





- Flat in VIX for VIX below median (18)
- For VIX above median, slope increases in credit spread
- Same slope in credit spread for VIX below median

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Global credit factor as a pricing factor

Consider: equilibrium pricing kernel with affine prices of risk

$$\lambda_t = \lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)$$

- Expected returns:

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

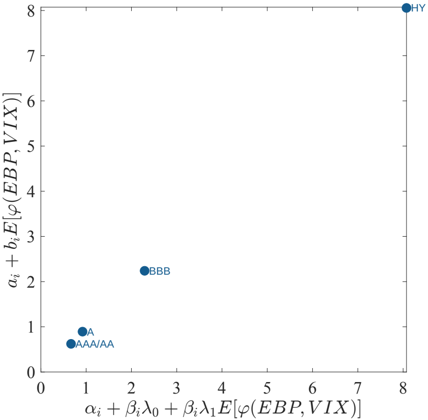
- Following Adrian et al. (2015), restricted return dynamics:

$$\begin{aligned} rx_{i,t+h} &= \alpha_{i,h} + \beta_{i,h}\left(\lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)\right) + \beta_{i,h} u_{t+h} + \epsilon_{i,t+h} \\ u_{t+h} &= \varphi\left(cs_{t+h}, \mathrm{VIX}_{t+h}\right) - \mathbb{E}_t\left[\varphi\left(cs_{t+h}, \mathrm{VIX}_{t+h}\right)\right] \end{aligned}$$

$\Rightarrow$ dynamic asset pricing restriction

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

Global credit factor in the cross-section



Affine price of risk: $\lambda_t = \lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)$

$\Rightarrow$ dynamic asset pricing restriction

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

Test 1: Target portfolios for factor construction

- Predicted returns from SRRR and DAPM line up

$\Rightarrow$ cross-sectional asset pricing restriction satisfied

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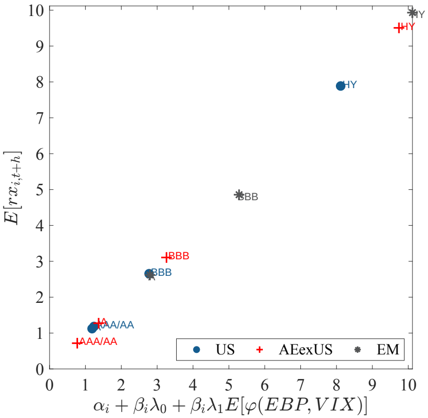
Global credit factor in the cross-section



Affine price of risk: $\lambda_t = \lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)$

$\Rightarrow$ dynamic asset pricing restriction

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

Test 2: Other country-level portfolios

- Predicted returns from DAPM line up with average realized returns

$\Rightarrow$ cross-sectional asset pricing restriction satisfied

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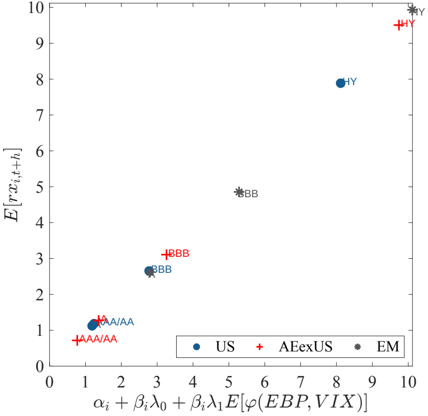
Global credit factor in the cross-section



Affine price of risk: $\lambda_t = \lambda_0 + \lambda_1 \varphi\left(cs_t, \mathrm{VIX}_t\right)$

$\Rightarrow$ dynamic asset pricing restriction

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

Test 2: Other country-level portfolios

- Predicted returns from DAPM line up with average realized returns

$\Rightarrow$ cross-sectional asset pricing restriction satisfied

$\Rightarrow$ $\varphi\left(cs_t, \mathrm{VIX}_t\right)$ captures time series variation in the global price of credit risk

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Portfolio-level risk premia

	(1) World	(2) U. S.	(3) AE, ex U. S.	(4) EM
GCC	0.63***	0.60***	0.72***	0.63***
BBB × GCC	-0.30***	-0.27***	-0.43***	-0.12
A × GCC	-0.45***	-0.42***	-0.56***	-0.25*
AAA/AA × GCC	-0.52***	-0.45***	-0.65***	
Total R^2	30.1	27.7	39.7	25.2
N. of obs	1,872	1,872	1,296	967

- At the portfolio level, R^2 is significantly higher

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Portfolio-level risk premia

	(1) World	(2) U. S.	(3) AE, ex U. S.	(4) EM
Total R^2	30.1	27.7	39.7	25.2
Time-series R^2	19.9	20.0	22.1	23.9
Cross-sectional R^2	3.3	2.7	4.3	0.7
Market-timing R^2	7.0	5.1	13.2	0.6
N. of obs	1,872	1,872	1,296	967

- At the portfolio level, R^2 is significantly higher
- Mostly driven by an increase in the time series R^2

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Other asset classes

		Regions		
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM
GCC	0.71***	0.60***	0.68***	0.78***
Equity × GCC	0.10	-0.17	-0.04	0.38
BBB × GCC	-0.42***	-0.27***	-0.44***	-0.39***
A × GCC	-0.53***	-0.42***	-0.55***	-0.44***
AAA/AA × GCC	-0.62***	-0.45***	-0.60***	0.00
Sovereign × GCC	-0.46***	-0.49***	-0.44***	-0.43***
Total R^2	6.6	11.3	7.0	6.9
N. of obs	59,255	2,808	40,722	15,725
N. bonds				

- Sovereign and equity returns also exposed to the GCC
- Cross-rating ordering preserved within bonds
- Equity loadings flatter, sovereign loadings strongly negative

Robustness: alternative standard errors

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

- Coefficients identical across SE specifications; only standard errors change
- Significance preserved under single- and two-way clustering, Driscoll-Kraay, Newey-West, and wild bootstrap

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Risk premia by rating

	(1) AAA/AA	(2) A	(3) BBB	(4) HY
GCC	0.17***	0.21***	0.36***	0.64***
AE, ex U. S. × GCC	-0.12***	-0.04***	-0.05***	0.10***
EM × GCC		0.11***	0.16***	0.23***
Total R^2	4.9	9.8	9.8	8.5
N. of obs	222,390	725,570	943,706	485,138
N. bonds	4,739	14,670	18,869	12,181

- EM bonds more exposed to GCC across credit ratings
- Safe AE, ex U. S.bonds less exposed than U. S.bonds; high yield bonds more exposed

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Risk premia by rating

	(1) AAA/AA	(2) A	(3) BBB	(4) HY
Total R^2	4.9	9.8	9.8	8.5
Time-series R^2	4.5	9.7	9.6	8.5
Cross-sectional R^2	-0.0	0.0	0.0	0.0
Market-timing R^2	0.3	0.0	0.1	-0.0
N. of obs	222,390	725,570	943,706	485,138
N. bonds	4,739	14,670	18,869	12,181

- EM bonds more exposed to GCC across credit ratings
- Safe AE, ex U. S.bonds less exposed than U. S.bonds; high yield bonds more exposed
- Little contribution from cross-country differences to overall R^2

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Risk premia with other characteristics

	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
GCC	-0.31***	-0.33***	-0.21***	-0.27***	-0.34***	-0.12***
Spread × GCC	0.09***	0.09***	0.07***	0.07***	0.09***	0.04***
Duration × GCC	0.04***	0.04***	0.02***	0.04***	0.04***	0.01***
Return vol × GCC	0.01***	0.01***	0.22***	0.25***	0.01***	0.28***
Total R^2	16.2	16.4	19.0	21.1	16.7	16.5
N. of obs	2,338,014	1,426,914	786,206	124,894	1,779,044	558,970
N. bonds	40,102	24,618	14,239	2,428	30,143	9,959

- Exposure higher for riskier bonds

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Risk premia with other characteristics

		Regions			Currencies	
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
Total R^2	16.2	16.4	19.0	21.1	16.7	16.5
Time-series R^2	2.4	2.8	1.9	5.9	2.9	2.3
Cross-sectional R^2	2.4	2.2	3.3	2.8	2.3	2.7
Market-timing R^2	11.4	11.4	13.9	12.3	11.4	11.5
N. of obs	2,338,014	1,426,914	786,206	124,894	1,779,044	558,970
N. bonds	40,102	24,618	14,239	2,428	30,143	9,959

- Exposure higher for riskier bonds
- Majority R^2 contribution from market timing R^2
  - Future returns higher when GCC tightens at the same time as bond-level exposure rises

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Risk premia with factors targeting other portfolios

	(1) Baseline	(2) U. S. portfolios	(3) AE ex U. S. portfolios	(4) EM portfolios
FCI	0.68***	1.37***	0.89***	5.98***
BBB × FCI	-0.32***	-0.67***	-0.43***	-2.78***
A × FCI	-0.48***	-0.98***	-0.64***	-4.23***
AAA/AA × FCI	-0.58***	-1.18***	-0.77***	-5.17***
Total R^2	9.4	9.4	9.6	8.6
N. of obs	2,376,804	2,376,804	2,376,804	2,376,804
N. bonds	40,103	40,103	40,103	40,103

- Factors targeting alternative portfolios perform similarly

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Risk premia with factors targeting other portfolios

	(1) Baseline	(2) U.S. portfolios	(3) AE ex U.S. portfolios	(4) EM portfolios
Total R^2	9.4	9.4	9.6	8.6
Time-series R^2	7.1	6.9	7.2	6.5
Cross-sectional R^2	0.8	0.9	0.8	0.7
Market-timing R^2	1.5	1.5	1.6	1.4
N. of obs	2,376,804	2,376,804	2,376,804	2,376,804
N. bonds	40,103	40,103	40,103	40,103

- Factors targeting alternative portfolios perform similarly

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Risk premia with factor using European predictors

		Regions			Currencies	
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
Global credit	0.50***	0.49***	0.51***	0.62***	0.51***	0.43***
BBB × Global credit	-0.22***	-0.20***	-0.27***	-0.24***	-0.20***	-0.24***
A × Global credit	-0.35***	-0.32***	-0.38***	-0.38***	-0.33***	-0.32***
AAA/AA × Global credit	-0.42***	-0.35***	-0.47***		-0.38***	-0.38***
Total R^2	10.0	10.1	9.4	13.2	10.3	9.2
N. of obs	2,119,444	1,201,655	790,840	126,949	1,554,782	564,662
N. bonds	37,119	21,638	14,222	2,432	27,172	9,947

- Factor constructed with European predictors performs similarly

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Risk premia with factor using European predictors

		Regions			Currencies	
	(1) Full sample	(2) U. S.	(3) AE, ex U. S.	(4) EM	(5) USD	(6) Non-USD
Total R^2	10.0	10.1	9.4	13.2	10.3	9.2
Time-series R^2	7.9	8.3	7.1	11.8	8.6	7.0
Cross-sectional R^2	0.6	0.5	0.7	0.4	0.5	0.7
Market-timing R^2	1.5	1.3	1.6	1.0	1.2	1.5
N. of obs	2,119,444	1,201,655	790,840	126,949	1,554,782	564,662
N. bonds	37,119	21,638	14,222	2,432	27,172	9,947

- Factor constructed with European predictors performs similarly

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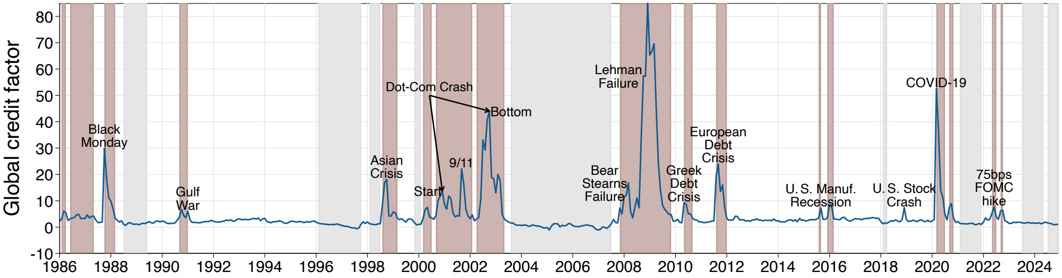
Global credit factor



- Loose (gray): T1 and reaches Q1
- Tight (red): T3 and reaches Q3

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Contributions from EBP and VIX: Tight vs. Loose

	Tight			Loose		
	(1) GCC	(2) $\varphi(VIX)$	(3) $\varphi_1(EBP) + \varphi_2(VIX)$	(4) GCC	(5) $\varphi(VIX)$	(6) $\varphi_1(EBP) + \varphi_2(VIX)$
FCI	0.66***	0.85***	0.72***	2.86***	-0.92***	-0.52***
BBB × FCI	-0.31***	-0.41***	-0.35***	-1.53***	0.13**	0.48***
A × FCI	-0.46***	-0.60***	-0.52***	-2.18***	0.45***	0.56***
AAA/AA × FCI	-0.56***	-0.74***	-0.62***	-2.41***	0.65***	0.63***
Total R^2	10.6	10.2	10.0	1.9	0.8	0.7
N. of obs	571,046	571,046	571,046	604,677	604,677	604,677
N. bonds	34,970	34,970	34,970	31,740	31,740	31,740

- VIX only factor performs well in tight periods

Contributions from EBP and VIX: Tight vs. Loose

	Tight			Loose		
	(1)	(2)	(3)	(4)	(5)	(6)
	GCC	$\varphi(VIX)$	$\varphi_1(EBP) + \varphi_2(VIX)$	GCC	$\varphi(VIX)$	$\varphi_1(EBP) + \varphi_2(VIX)$
FCI	0.66^{***}	0.85^{***}	0.72^{***}	2.86^{***}	-0.92^{***}	-0.52^{***}
BBB $\times$ FCI	-0.31^{***}	-0.41^{***}	-0.35^{***}	-1.53^{***}	0.13^{**}	0.48^{***}
A $\times$ FCI	-0.46^{***}	-0.60^{***}	-0.52^{***}	-2.18^{***}	0.45^{***}	0.56^{***}
AAA/AA $\times$ FCI	-0.56^{***}	-0.74^{***}	-0.62^{***}	-2.41^{***}	0.65^{***}	0.63^{***}
Total R^2	10.6	10.2	10.0	1.9	0.8	0.7
N. of obs	571,046	571,046	571,046	604,677	604,677	604,677
N. bonds	34,970	34,970	34,970	31,740	31,740	31,740

- GCC outperforms particularly during loose credit conditions
- EBP contribution allows GCC to "look-through" VIX volatility during calm periods

Contributions from EBP and VIX: Tight vs. Loose

	Tight			Loose		
	(1)	(2)	(3)	(4)	(5)	(6)
	GCC	$\varphi(VIX)$	$\varphi_1(EBP) + \varphi_2(VIX)$	GCC	$\varphi(VIX)$	$\varphi_1(EBP) + \varphi_2(VIX)$
Total R^2	10.6	10.2	10.0	1.9	0.8	0.7
Time-series R^2	7.0	6.6	6.1	1.2	0.7	-0.2
Cross-sectional R^2	2.1	2.1	2.4	0.5	0.1	1.1
Market-timing R^2	1.5	1.5	1.4	0.2	-0.0	-0.2
N. of obs	571,046	571,046	571,046	604,677	604,677	604,677
N. bonds	34,970	34,970	34,970	31,740	31,740	31,740

- GCC outperforms particularly during loose credit conditions
- EBP contribution allows GCC to "look-through" VIX volatility during calm periods
- No TS predictability by VIX factor during loose credit conditions (-42% correlation with GCC)
- GCC retains cross-sectional R^2 during loose periods

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Correlation with standard GFC proxies

- Low correlation with other used factors
- Correlations somewhat increase in the post-crisis period

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Recap: Risk premia due to global credit cycle

What are the risk sources that are priced by the global credit factor?

- Corporate bonds $\Rightarrow$ credit risk
- Bonds with differential maturity $\Rightarrow$ duration risk
- Bonds denominated in different currencies $\Rightarrow$ exchange rate risk

Recap: Risk premia due to global credit cycle

What are the risk sources that are priced by the global credit factor?

- Corporate bonds $\Rightarrow$ credit risk
- Bonds with differential maturity $\Rightarrow$ duration risk
- Bonds denominated in different currencies $\Rightarrow$ exchange rate risk

Empirical strategies

1. Decompose returns into different components
2. Use bonds of firms with multiple issue to isolate return variation

Bond-level sources of risk

Similar to van Binsbergen et al. (2025), decompose returns

$$rx_{i,t+h} = cr_{i,t+h} + fx_{i,t+h} + dr_{i,t+h}$$

- Credit risk: return difference between corporate bond and same duration and currency sovereign bond:

$$cr_{i,t+h} \equiv r^{c}_{i,t+h} - r^{c}_{DM,t+h}$$

- Currency curve differential: return difference between bond's currency sovereign bond and Treasury:

$$fxr_{i,t+h} \equiv r^{c}_{DM,t+h} + s^{c}_{t+h} - r^{tsy}_{DM,t+h}$$

- Duration risk: return difference between duration-matched Treasury and 3m T-bill:

$$dr_{i,t+h} \equiv r^{tsy}_{DM,t+h} - r^{tsy}_{3m,t+h}$$

Bond-level sources of risk

	(1) Total	(2) Credit risk	(3) Currency diff	(4) Duration risk
GCC	0.79***	0.68***	0.20***	0.09***
BBB $\times$ GCC	-0.29***	-0.32***	-0.01	0.01***
A $\times$ GCC	-0.43***	-0.48***	-0.03***	0.02***
AAA/AA $\times$ GCC	-0.52***	-0.58***	-0.11***	0.04***
Total R^2	9.0	9.4	3.3	0.0
N. of obs	2,376,804	2,376,804	568,906	2,376,804
N. bonds	40,103	40,103	9,959	40,103

- Credit risk loading decreases with credit quality
- Duration risk *increases* with credit quality
- Overall predictability from predictability of credit risk

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Bond-level sources of risk

	(1) Total	(2) Credit risk	(3) Currency diff	(4) Duration risk
Total R^2	9.0	9.4	3.3	0.0
Time-series R^2	7.9	7.1	3.4	-0.0
Cross-sectional R^2	0.3	0.8	-0.0	0.0
Market-timing R^2	0.8	1.5	-0.0	-0.0
N. of obs	2,376,804	2,376,804	568,906	2,376,804
N. bonds	40,103	40,103	9,959	40,103

- Credit risk loading decreases with credit quality
- Duration risk *increases* with credit quality
- Overall predictability from predictability of credit risk

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Are bonds in different currencies differentially exposed?

Approach: use multi-currency issuers, with at least one USD bond

$$rx_{i,t+h} = \alpha_t + \alpha_f + \alpha_{f,t} + \alpha_b \mathbb{1}_{USD} + \beta_r \text{GCC}_t \times \mathbb{1}_{USD} + \epsilon_{i,t+h}$$

- Differential exposure within the same firm-month

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Are bonds in different currencies differentially exposed?

Approach: use multi-currency issuers, with at least one USD bond

$$rx_{i,t+h} = \alpha_t + \alpha_f + \alpha_{f,t} + \alpha_b \mathbb{1}_{USD} + \beta_r \text{GCC}_t \times \mathbb{1}_{USD} + \epsilon_{i,t+h}$$

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

- Columns: bonds denominated in stated currency
- USD bonds have lower average returns but greater exposure to the global credit cycle

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Is the USD exposure differential due to exchange rate volatility?

Approach: use multi-currency issuers, with at least one USD bond

$$rx^{\mathcal{H}}_{i,t+h} = \alpha_t + \alpha_f + \alpha_{f,t} + \alpha_b \mathbb{1}_{USD} + \beta_r \text{GCC}_t \times \mathbb{1}_{USD} + \epsilon_{i,t+h}$$

	(1) Full sample	(2) EUR	(3) GBP	(4) CAD	(5) JPY	(6) AUD
USD	-0.21***	-0.10	-0.27	-0.47***	-0.29	-0.82***
USD × GCC	0.10***	0.11***	0.02	0.14***	0.17***	0.16***
W/in adj. R^2	0.7	0.8	0.0	1.1	3.7	0.7
N. of obs	651,603	452,473	163,391	170,261	42,947	74,854
N. firms	523	398	153	115	46	67

- Columns: bonds denominated in stated currency
- Lower but still substantial differential in exposure to the global credit cycle relative to USD bonds

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Are bonds in local (to issuer) currency differentially exposed?

Approach: use multi-currency issuers, with at least one local and one foreign bond

$$rx_{i,t+h} = \alpha_t + \alpha_f + \alpha_{f,t} + \alpha_b \mathbb{1}_{Lcl} + \beta_r \text{GCC}_t \times \mathbb{1}_{Lcl} + \epsilon_{i,t+h}$$

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

- Columns: firm local currency
- Local currency returns less exposed to global credit cycle, outside the U. S.and UK

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Is the local currency exposure differential due to exchange rate volatility?

Approach: use multi-currency issuers, with at least one local and one foreign bond

$$rx^{\mathcal{H}}_{i,t+h} = \alpha_t + \alpha_f + \alpha_{f,t} + \alpha_b \mathbb{1}_{Lcl} + \beta_r \mathrm{GCC}_t \times \mathbb{1}_{Lcl} + \epsilon_{i,t+h}$$

	(1) USD	(2) EUR	(3) GBP	(4) CAD	(5) JPY	(6) AUD
Local	-0.22**	0.16	0.46*	0.29**	-0.48*	0.59***
Local × GCC	0.05***	-0.16***	0.00	-0.13***	-0.07***	-0.03
W/in adj. R^2	0.1	2.1	0.0	1.1	3.1	0.2
N. of obs	266,653	140,605	55,224	73,896	27,307	11,506
N. firms	224	122	77	60	21	25

- Columns: firm local currency
- Local currency returns less exposed to global credit cycle, outside the U. S.

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Firm-month currency pairs: Counts

	USD	EUR	GBP	CAD	JPY	AUD
USD		39,706	14,304	11,285	3,818	5,221
EUR	39,706		14,898	4,391	2,359	4,440
GBP	14,304	14,898		2,263	1,218	1,854
CAD	11,285	4,391	2,263		839	2,289
JPY	3,818	2,359	1,218	839		648
AUD	5,221	4,440	1,854	2,289	648	

- Conditional on having a bond in currency X (columns), how many firm-months also have a bond in currency Y (rows)

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Firm-month currency pairs: Percent

	USD	EUR	GBP	CAD	JPY	AUD
USD		60%	41%	54%	43%	36%
EUR	53%		43%	21%	27%	31%
GBP	19%	23%		11%	14%	13%
CAD	15%	7%	7%		9%	16%
JPY	5%	4%	4%	4%		4%
AUD	7%	7%	5%	11%	7%	

- Conditional on having a bond in currency X (columns), what percent of firm-months also have a bond in currency Y (rows)

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Bond-level spread changes in tightenings

How do spreads move with GCC tightenings?

	(1) Full sample	(2) US	(3) AE, ex US	(4) EM
Tight GCC	96.56***	93.52***	93.13***	126.42***
BBB × Tight GCC	-55.34***	-53.95***	-53.40***	-61.14***
A × Tight GCC	-72.70***	-71.06***	-67.58***	-100.29***
AAA/AA × Tight GCC	-78.21***	-75.92***	-73.72***	
Adj. R^2	0.09	0.08	0.10	0.10
N. of obs	1,872,818	1,137,315	628,533	106,970

- Tight GCC ⇒ large widenings in spreads

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Bond-level spread changes in tightenings: horizons

How do spreads move around GCC tightenings?

	(1) $\Delta S_{t-3,t-1}$	(2) $\Delta S_{t-2,t-1}$	(3) $\Delta S_{t-1,t}$	(4) $\Delta S_{t-1,t+3}$	(5) $\Delta S_{t-1,t+6}$
Tight GCC	-6.22***	-20.30***	96.56***	75.28***	47.99***
BBB × Tight GCC	-2.25***	12.42***	-55.34***	-52.90***	-33.04***
A × Tight GCC	3.36***	16.22***	-72.70***	-63.55***	-39.94***
AAA/AA × Tight GCC	6.19***	19.50***	-78.21***	-64.25***	-39.62***
Adj. R^2	0.01	0.01	0.09	0.01	0.00
N. of obs	1,800,082	1,835,589	1,872,818	1,757,593	1,651,811

- Spreads contract leading up to GCC tightenings
- Spreads expand and stay elevated for over 3 months for HY bonds

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Firm-level EDF changes in tightenings

How do EDFs move with GCC tightenings?

	(1) Full sample	(2) U.S.	(3) AE, ex U.S.	(4) EM
Tight GCC	39.24***	42.27***	36.45***	29.18***
BBB × Tight GCC	-17.02***	-21.85***	-10.71**	-12.39**
A × Tight GCC	-28.56***	-29.65***	-27.49***	-23.61***
AAA/AA × Tight GCC	-28.95***	-34.46***	-23.67***	
Adj. R^2	0.00	0.00	0.01	0.01
N. of obs	150,506	81,721	53,698	15,087

- Tight GCC $\Rightarrow$ increases in EDFs
- Sensitivity increases with bond risk

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Firm-level EDF changes in tightenings: horizons

How do EDFs move around GCC tightenings?

	(1) $\frac{\Delta EDF_{t-3,t-1}}{EDF_{t-1}}$	(2) $\frac{\Delta EDF_{t-2,t-1}}{EDF_{t-1}}$	(3) $\frac{\Delta EDF_{t-1,t}}{EDF_{t-1}}$	(4) $\frac{\Delta EDF_{t-1,t+3}}{EDF_{t-1}}$	(5) $\frac{\Delta EDF_{t-1,t+6}}{EDF_{t-1}}$
Tight GCC	-10.60***	-8.73***	39.24***	44.80***	53.59***
BBB × Tight GCC	0.40	2.31**	-17.02***	-0.67	-8.33
A × Tight GCC	-2.57	0.83	-28.56***	-22.98***	-20.94
AAA/AA × Tight GCC	2.39	2.57**	-28.95***	-28.59***	-34.26**
Adj. R^2	0.00	0.00	0.00	0.00	0.00
N. of obs	150,105	150,338	150,506	149,840	148,450

- EDFs contract leading up to GCC tightenings
- EDFs expand and stay elevated for over 6 months for HY bonds

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The role of global intermediaries

So far: Tight relationship between global credit cycle and credit conditions faced by firms

The role of global intermediaries

So far: Tight relationship between global credit cycle and credit conditions faced by firms

Potential mechanism: global portfolio rebalancing

- Study relationship between mutual fund returns and the global credit cycle
- Study relationship between client flows into mutual funds and the global credit cycle
- Consider differential sensitivity of flows by
  - Fund asset class: government, IG fixed income, HY fixed income, Broad fixed income
  - Investment geographical focus: global, by region, and country-specific
  - Fund type: MFs vs ETFs

Tight GCC $\Rightarrow$ higher future global fund returns

$$Rx_{i,t+1} = \alpha + \beta \text{GCC}_t + \beta_r \text{GCC}_t \times \mathbb{1}_{i,r,t} + \zeta X_{i,t} + \epsilon_{i,t}$$

	(1) All ex U. S.	(2) Europe	(3) LATAM	(4) Asia	(5) U. S.	(6) Global
GCC	0.48***	0.67***	0.32	0.72***	0.36***	0.40***
All quality × GCC	-0.03	-0.25***	-0.04	-0.34***	-0.07**	0.05**
Investment grade × GCC	-0.12***	-0.20***	0.12	-0.53***	-0.15***	-0.06**
Government × GCC	-0.21***	-0.42***	-0.02	-0.44***	-0.32***	-0.19***
Adj. R^2	2.5	1.8	1.0	2.3	4.0	3.2
N. of obs	641,520	205,545	7,129	101,849	221,891	290,122
N. of funds	10,585	3,366	93	2,587	2,729	4,313

- Higher future global fund returns when global credit conditions deteriorate $\Rightarrow$ GCC movements reduce scope for diversification
- Across all regions/portfolios, except LATAM

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Tight GCC ⇒ higher future global fund returns

$$Rx_{i,t+1} = \alpha + \beta \mathrm{GCC}_t + \beta_r \mathrm{GCC}_t \times \mathbb{1}_{i,r,t} + \zeta X_{i,t} + \epsilon_{i,t}$$

	All ex U. S.		Europe		LATAM		Asia		U. S..		Global	
	(1) GCC	(2) VIX	(3) GCC	(4) VIX	(5) GCC	(6) VIX	(7) GCC	(8) VIX	(9) GCC	(10) VIX	(11) GCC	(12) VIX
FCI	0.48***	0.63***	0.67***	0.89***	0.32	0.60*	0.72***	0.76***	0.36***	0.54***	0.40***	0.61***
All quality × FCI	-0.03	-0.08***	-0.25***	-0.28***	-0.04	0.11	-0.34***	-0.22**	-0.07**	-0.27***	0.05**	-0.01
Investment grade × FCI	-0.12***	-0.27***	-0.20***	-0.41***	0.12	0.19	-0.53***	-0.45***	-0.15***	-0.32***	-0.06**	-0.19***
Government × FCI	-0.21***	-0.45***	-0.42***	-0.67***	-0.02	-0.06	-0.44***	-0.45***	-0.32***	-0.52***	-0.19***	-0.37***
Adj. R^2	2.5	0.8	1.8	0.4	1.0	1.2	2.3	0.9	4.0	2.3	3.2	1.6
N. of obs	641,520	641,520	205,545	228,670	7,129	7,862	101,849	116,112	221,891	221,891	290,122	290,122
N. of funds	10,585	10,585	3,366	3,372	93	93	2,587	2,588	2,729	2,729	4,313	4,313

- GCC outperforms VIX uniformly across all regions

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Tight GCC $\Rightarrow$ global fund investor reallocation

$$\frac{flows_{i,t}}{AUM_{i,t-1}} = \alpha + \beta GCC_t + \beta_r GCC_t \times \mathbb{1}_{i,r,t} + \zeta X_{i,t} + \epsilon_{i,t}$$

- Lower inflows when global credit conditions deteriorate
- Larger impact for high yield corporate bond funds
- No impact on dedicated U. S.funds

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Fund characteristics affect transmission

$$\frac{flows_{i,t}}{AUM_{i,t-1}} = \alpha + \beta \mathrm{GCC}_t + \beta_r \mathrm{GCC}_t \times \mathbb{1}_{i,r,t} + \zeta X_{i,t} + \epsilon_{i,t}$$

- Investors outside U. S.more sensitive, especially for high yield funds

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Fund characteristics affect transmission

$$\frac{flows_{i,t}}{AUM_{i,t-1}} = \alpha + \beta \text{GCC}_t + \beta_r \text{GCC}_t \times \mathbb{1}_{i,r,t} + \zeta X_{i,t} + \epsilon_{i,t}$$

- Investors outside U. S.more sensitive, especially for high yield funds
- ETF investors more sensitive

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Fund characteristics affect transmission

$$\frac{flows_{i,t}}{AUM_{i,t-1}} = \alpha + \beta GCC_t + \beta_r GCC_t \times \mathbb{1}_{i,r,t} + \zeta X_{i,t} + \epsilon_{i,t}$$

- Investors outside U. S.more sensitive, especially for high yield funds
- ETF investors more sensitive
- Investors into short-term funds more sensitive

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References I

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