Corporate Credit Risk and Capital Flows in Emerging Market Economies *

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Abstract

Foreign-currency denominated international bonds have become an increasingly popular financing instrument for many emerging market (EM) firms over the past decade. Credit risks that are associated with such securities could simultaneously serve as an attracting and a repelling factor to capital from abroad. Using the universe of corporate bonds issued by non-financial firms in 27 EM countries and 11 tax havens, I show that credit spreads on corporate bonds can explain international capital flows. Importantly, they do so above and beyond well-known drivers of capital flows such as global risk, US monetary policy, and EM sovereign risk. I exploit idiosyncratic shocks to large bond issuers to construct granular instrumental variables (GIVs) to identify the causal effect of domestic corporate credit risk on capital flows. In a static country panel framework, I find robust evidence that EM corporate credit risk serves as an attractor of international capital flows. The results of a dynamic panel local projections exercise further suggest that the build-up of corporate credit risk over time can unleash capital flow reversals, deteriorate the terms of trade, lower output, and raise unemployment. My findings thus reconcile the empirical and theoretical literature on push and pull factors of international capital flows.

Keywords: Capital flows, portfolio flows, corporate credit risk, excess bond premium, sudden stops, emerging markets, granular instrumental variables
JEL Classification: E44, F32, F34, F44, G15, G32, G33

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1 Introduction

Foreign-currency denominated corporate bond issuance has surged to unprecedented levels in emerging market economies (EMEs) over the past decade (see panel (a) Figure 1). This has attracted large capital inflows into emerging debt markets, raising concerns about a potential sudden reversal, or "sudden stop", of capital flows in response to either external shocks or growing corporate leverage and instability in the domestic financial system.[1] The latter could eventually lead to a reassessment and repricing of credit risk by international bond investors. A sudden tightening of credit conditions in international debt markets could not only increase the risk of insolvency of EM corporates. It could also precipitate a drop in the exchange rate which would further exacerbate the funding situation for firms holding unhedged foreign currency debt.[2]

It is therefore important to understand whether, in addition to acting as a "pull factor" of international capital, corporate credit risk can also unleash capital flow reversals, thus reinforcing domestic business cycles (Mendoza, 2010). Using a unique and rich cross-country panel of EM firms and their corporate bonds, I show that corporate credit risk can serve as a driver of capital flows into and out of EMEs. Importantly, this causal relationship obtains after controlling for the presence of strong global forces that have been found to be leading "push factors" of capital flows. My paper thus contributes to our understanding of the *domestic* origins of financial instabilities and business cycle fluctuations in EMEs. These domestic factors offer a complementary explanation to the Global Financial Cycle (Rey, 2015) known to be a pivotal motor of international capital flows.[3]

Identifying the causal relationship between the price of risk and international capital flows is notoriously challenging. The riskiness of corporate debt is determined, apart from factors fundamental to a firm, by the availability of credit. EMEs are exceptionally exposed to foreign investors' willingness to invest in domestic debt markets. This vulnerability demands a risk premium which is determined by foreign demand for EM debt. Credit risk is therefore endogenous to capital flows.[4] Yet at the same time, it is precisely this premium, along with positive (negative) prospects of economic growth, that attract (deter) foreign capital. Added to that are global factors, unrelated to a domestic economy's fundamentals, that may confound the relationship between the domestic business cycle and international capital flows. Global risk (Forbes & Warnock, 2012; Fratzscher, 2012), subsumed under the so-called Global Financial Cycle (Rey, 2015), US monetary policy (Bruno & Shin, 2015; Ghosh et al., 2014; Jordà et al., 2019; Miranda-Agrippino & Rey, 2020), and global interest rates (Akinci, 2013) feature prominently among such factors. Panel (b) of Figure 1 illustrates this point. Corporate credit spreads, corporate fundamentals, and global risk endogenously comove over the sample period.

One may imagine an ideal setting in which one observes both the demand for corporate

[1]Concerns for EMEs' hidden debt risk (Avdjiev et al., 2014; Das et al., 2020) have been fuelled most recently by the global Covid-19 pandemic. Both anecdotal evidence and data point towards worsening corporate leverage and currency mismatch (Forni & Turner, 2021).

[2]Evidence that EM firms do not perfectly hedge their foreign currency exposure is rather anecdotal.

[3]I do not hypothesize ex-ante that domestic credit risk could be a more powerful trigger of capital flow reversals than sovereign credit risk or external factors, or even a trigger at all. Instead, I investigate whether corporate credit risk can serve as an additional driver of changes in capital flows above and beyond what sovereign and global risk can account for.

[4]The remainder of this paper will focus on the fast-moving component of capital flows, i.e. portfolio flows that are more "fickle" with respect to changes in risk.

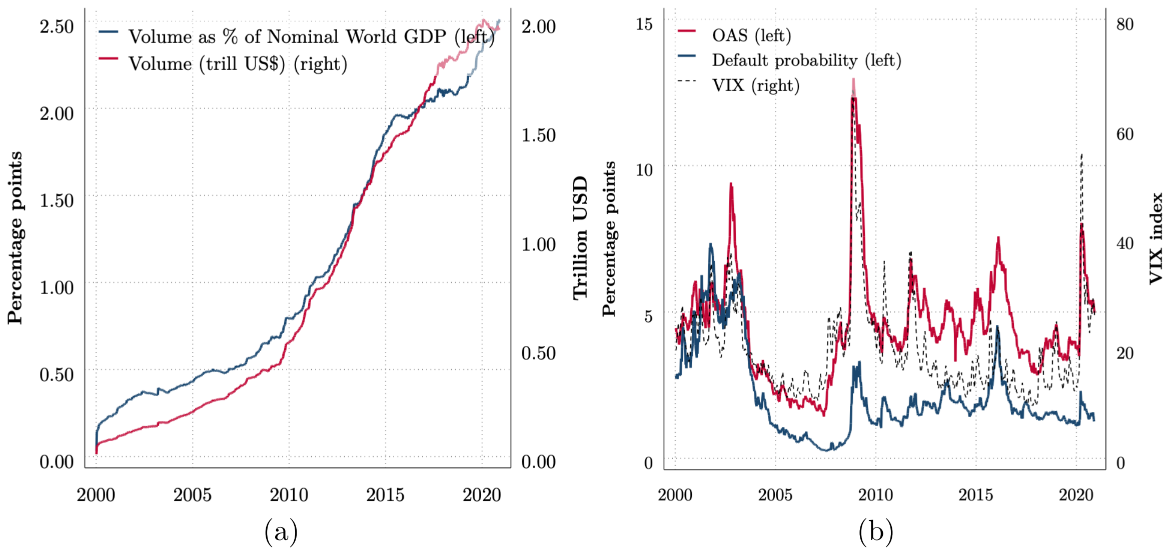


Figure 1: Corporate bond volume, credit spreads, fundamental default probability, and global risk (VIX)

Note: The left panel shows the sum total of notional USD-volume of corporate bonds issued by non-financial firms in my wider sample of 43 EMEs and traded on the secondary market at a given point in time. The secondary market traded volume is broadly representative of the primary market issuance. The right panel shows the weekly option-adjusted corporate bond spread (OAS) and Moody's expected default frequency – a measure of the probability of default – over a 1-year horizon, averaged across firms across countries. The VIX is the CBOE volatility index, smoothed over a 30-day rolling window.

debt by international investors as well as the supply of debt by domestic firms and its price. A high-frequency financial shock that is exogenous to both of these components as well as to global factors could be used to cleanly identify elasticities. Absent such a laboratory, the available data does not allow me to distinguish demand from supply. I therefore remain agnostic about the supply of corporate debt. Instead, I focus on how differences in the size of corporate borrowers can be exploited to extract information from granular prices – credit spreads – about their aggregate impact for identification.

To that end, I make three contributions to our understanding of the possible direction of causality between credit risk and capital flows. First, I collect a rich, cross-country microeconomic dataset spanning the universe of EM corporate bonds. I restrict my attention to USD-denominated corporate bonds issued by non-financial firms incorporated in 27 EMEs and 11 tax havens and traded in international secondary markets over the period from January 2000 to November 2020. I match bond-level data with issuer-level data on firm fundamentals as well as (high-frequency) country-level data on institutional investors' portfolio flows.[5] Using the matched sample of around 3,200 bonds, I decompose the weekly time-series of credit spreads into several risk components. This decomposition allows me to extract idiosyncratic, firm-specific shocks that are orthogonal to firm- and country fundamentals as well as to global risk. It is the compensation that investors demand in excess of any expected losses for bearing a firm's default risk. I find that, when aggregated across EMEs, this aggregate shock component strongly positively covaries with the "excess bond premium" (EBP) estimated by Gilchrist and

[5]Mutual funds' portfolio flows account for the lion's share of flows into EM debt markets. They are a suitable indicator for capital flow activity alongside low-frequency macroeconomic measures of gross capital flows. See Koepke and Paetzold (2020) for a comparison of measures of capital and portfolio flows and their characteristics.

Zakrajšek (2012) for the US over the period from 2000 up until 2009. However, this strong correlation falls from 60% to 22% for the period from 2010 up until the Covid-19 crisis. This observation warrants confidence that the firm-specific shocks to credit spreads in EMEs are not simply driven by a common global factor that is not captured by my spread model.

Second, with this observation in mind, I exploit the full heterogeneity in bond and firm characteristics to make statements about the granular effects of bond issuers' credit risk onto macroeconomic outcomes.[6] Having obtained idiosyncratic shocks to firms' credit risk, I construct "granular instrumental variables" (GIVs) (Gabaix & Koijen, 2020) that allow me to overcome the problem of endogeneity between credit risk and capital flows. The intuition behind GIV is that shifts in credit risk that are idiosyncratic to "big players" such as large borrowers can affect macroeconomic outcomes in a meaningful way. Since corporate bond issuers in EMEs are generally large corporations found to have systemic impact (Alfaro et al., 2019; Calomiris et al., 2022; Grigoli et al., 2021), I argue that aggregate fluctuations may have granular origins (Gabaix, 2011) in large corporate bond issuers. Firms' idiosyncratic shocks can then identify that credit risk – when stripped of all confounding effects of country-specific and global risk – can indeed drive capital flows into and out of the economy. From an asset pricing perspective, firm-specific risk cannot be fully diversified away in a granular economy characterized by a fat-tailed firm-size distribution. It bears a common component with systematic risk (Herskovic et al., 2020) and hence influences international investors' perception of economy-wide risk. This property, not captured by traditional asset pricing theory in which firms are atomistic, strengthens the validity of the instrument in affecting aggregate credit risk.

In simple terms, the GIV summarizes any variation in credit risk of particularly large firms that is not explained by the *average* firm. The GIV thereby also controls for sovereign risk under the assumption that a large firm is equally exposed to sovereign risk as the average firm. To the best of my knowledge, my paper is the first to study the *causal* effect of corporate credit risk on capital flows while controlling for potential spillovers from the sovereign bond market and external factors. Other studies (Akinci, 2013; Caballero et al., 2019) analyze the ability of aggregate credit spreads to predict future economic activity in EMEs. However, their methodologies rely on assumptions on the causal ordering of shocks in structural VAR frameworks.[7]

Third, unlike previous papers, I extend the sample of corporate bonds to also cover bonds issued by offshore subsidiaries in tax havens. Recent compelling evidence by Coppola et al. (2021) and Avdjiev et al. (2014) suggests that EM corporates have issued a sizeable fraction of their foreign-currency denominated debt via offshore subsidiaries in tax havens over the past decade. To the extent that not all of these funds are channelled into real activity, offshore issuance of bonds may pose underestimated risks to financial stability. Neglecting offshore bonds could bias the effect of credit risk on capital flows as both credit risk of the subsidiary firm and portfolio flows into and out of tax havens would not be captured.

My findings support the hypothesis that credit risk is indeed a relevant factor that explains capital flows. The results of the instrumented country panel regressions yield a strong

[6]While others embark on similar endeavors with respect to studying corporate bond spreads in EMEs (e.g. Caballero et al., 2019; Cavallo & Valenzuela, 2009), they either *aggregate* micro-measures across firms to study macroeconomic outcomes, or they study how macroeconomic factors affect microeconomic measures pertaining to corporate bonds.

[7]Statistically speaking, these frameworks test for Granger causality in the sense that X *predicts* Y. This is not to be mistaken with a true "cause-and-effect" relationship that the GIV approach attempts to uncover by instrumenting an exogenous relationship.

relationship, both in terms of significance and magnitude, controlling for other domestic and global factors. The direction of the effect in the baseline model indicates that a rise in credit risk *attracts* international capital and therefore raises net capital inflows. This observation is in line with the literature on "pull factors" of international capital flows which suggests that domestic factors attract capital inflows in good times. The relationship holds up to a set of robustness checks.

The positive association between credit risk and capital flows begs the question whether the effect could be asymmetric depending on the state of the economy as well as the degree of leverage and currency mismatch on corporate balance sheets (Kalemli-Özcan et al., 2021). Specifically, corporate credit risk could strike precisely when firms are the most vulnerable to a funding cost reversal, for example when firms cannot meet obligations in foreign currency by liquidating assets in local currency (Chui et al., 2014). To shed light on whether currency mismatch could pivot this relationship, I interact the credit risk measure with large real effective exchange rate depreciations. The results provide tentative evidence that international investors are more likely to retract capital if they expect firms to not be able to meet their funding needs due to rising currency mismatch and leverage.

Theories of sudden stops argue that it is the very *build-up* of domestic credit risk over time that can trigger capital flow reversals. I therefore further analyze my hypothesis in a panel local projections framework with instrumental variables (panel IV-LP) following Jordà (2005).[8] This method allows me to investigate the dynamic response of capital flows and other monthly indicators of real economic activity to accumulated credit risk over a longer horizon. Identification again relies on the GIV. The impulse responses highlight that credit risk, when built up over time, can unleash powerful adverse dynamics onto the real economy. Net capital flows decrease, the terms of trade deteriorate, industrial production falls by 6.6 percentage points, and the unemployment rate rises by up to 1.3 percentage points over a two-year horizon in response to a 100 basis point exogenous widening of credit spreads. Hence, while the static regression setting can capture the positive relationship between credit risk and capital inflows, the dynamic panel IV-LP setting uncovers the adverse feedback that prolongued domestic financial imbalances in the non-financial sector inflict on capital outflows and the wider economy. A prolonged build-up of credit risk therefore amplifies business cycle fluctuations.

Finally and more generally, my paper adds to a growing research agenda on the granular corporate origins of macroeconomic fluctuations in EMEs. While a vast body of research on capital flow volatility in EMEs has focused on the sovereign nexus (Aguiar & Gopinath, 2006; Arellano, 2008; Mendoza & Yue, 2012; Yue, 2010), this paper explores the corporate nexus (Bianchi, 2011; Mendoza, 2010). Historically, capital flow reversals have often occurred alongside sovereign default on foreign-currency denominated bonds.[9] Since the Global Financial Crisis (GFC), governments in EMEs have therefore tried to remedy problems associated with currency mismatch by issuing relatively more local currency debt (see Figure 8 in Appendix A) (Carstens & Shin, 2019).[10] At the same time, international appetite for EM corporate bonds has been fuelled by ultra-low interest rates in advanced economies (Calomiris et al., 2022). It is for these reasons that nowadays one may attribute an increasing role to EM corporate debt

[8] See also Jordà et al. (2015) and Ramey and Zubairy (2018).

[9] Examples of recent sovereign defaults include Barbados (2018), Jamaica (2013, 2010), Nicaragua (2008, 2003), Argentina (2001), Turkey (1999), Russia (1998).

[10] As illustrated in Figure 8 in Appendix A, the non-financial corporate (NFC) sector still holds substantially more foreign currency debt relative to local currency debt than the government sector. See also Caballero et al. (2019) for a breakdown of bond debt into domestic and external debt based on more granular data.

markets as a source of financial instability and business cycle fluctuations. Much about the domestic sources and mechanisms of macro-financial risks in EM debt markets as well as their triggers (Avdjiev et al., 2014) remains to be understood and explained. Amidst the strain on corporate balance sheets and global investor wariness induced by the Covid-19 pandemic, my paper adds to our understanding of how one specific source of risk – corporate default – may contribute to overall macroeconomic and financial instability. Knowledge thereof can guide policy makers in designing appropriate preemptive policies (e.g. capital controls, macroprudential policies, taxes) and reactive policies (e.g. foreign reserve interventions, corporate relief programs) capable of easing the strain on the economy (Basu et al., 2020).

This paper proceeds as follows. Section 2 places the paper into the existing literature. Section 3 details the data and presents descriptive statistics. Section 4 discusses the methodological issues related to potential endogeneity between corporate risk and capital flows. Section 5 explains the basic intuition of the GIV approach and outlines the identification strategy. Section 6 presents results of the static and dynamic regression models. Section 7 outlines robustness checks. Finally, Section 8 concludes.

2 Related Literature

This paper relates to several strands of literature. The endogenous relationship between credit risk and capital flows builds on theoretical work on sudden stops by Mendoza (2010) and Bianchi (2011). Mendoza (2010) explains the occurrence of deep recessions after sudden stops through the build-up of leverage during expansions. Sudden stops are only triggered in high-leverage states in which agents' collateral constraint binds. Because credit constraints link bond issuance to market-determined prices, firms overborrow in good times (Bianchi, 2011). Agents cannot insure against Fisherian debt-deflation dynamics, or fire sale spirals (Caballero & Simsek, 2020) triggered by exogenous shocks. This explains why capital flows into EMEs are so "fickle" (Caballero & Simsek, 2020). These credit market frictions are the fulcrum of my hypothesis whereby high credit risk in bond markets, due to leverage and currency mismatch, unleashes capital outflows.

In recent years, corporate spreads have received increasing attention as a predictor of business cycle fluctuations. Gilchrist and Zakrajšek (2012) are among the first to comprehensively document the high information content of corporate bond spreads for aggregate outcomes in the context of the US economy. They show that the aggregated residual component of credit spreads – after accounting for firms' fundamental default risk – can serve as a significant and robust predictor of business cycle fluctuations. To the best of my knowledge, I am the first to apply a similar bottom-up approach of disentangling credit risk to a rich panel of EMEs in an open-economy context. Several papers investigate the macroeconomic effects of corporate credit spreads in Western Europe (De Santis, 2016; Gilchrist & Mojon, 2018), and of sovereign credit spreads (Akinci, 2013) and corporate credit spreads (Caballero et al., 2019) on business cycle fluctuations in emerging markets, albeit in a less granular fashion. I contribute to this strand of literature in two ways. The common denominator of existing studies is that they construct *aggregate* indicators of credit spreads and risk premia rather than studying the *granularity* of their underlying data. Instead, I explicitly exploit the heterogeneity in credit spreads and volume of debt across borrowers for identification. Moreover, while other researchers only establish the predictive power of credit spreads, I go one step further by identifying the *causal* link between credit spreads and changes in aggregate capital flows. Both of these extensions exploit the richness of the data across borrowers and countries. Hence, they allow me to study the information content of credit spreads at the firm level and at a higher frequency.

Another strand of literature seeks explanations for the recent surges in capital inflows into emerging debt markets. Chang et al. (2017) show theoretically that a fall in the world interest rate – as observed over the past decade – leads EME firms to pivot from bank financing to bond financing as the former becomes relatively more expensive when there is an equity shortfall.[11] Calomiris et al. (2022) document that the surge in bond issuance since the GFC has been driven in part by the issuance of large USD-denominated corporate bonds and by global investors' search for yield in riskier asset markets. Two factors have increased both demand for and supply of large bonds. First, bonds with a volume of at least USD 500 are index-eligible and hence highly desired by institutional investors.[12] Second, institutional investors have been attracted by both the highly liquid nature of these index traded bonds and their role in facilitating benchmark trading. Evidence by Raddatz et al. (2017) find that inclusion of companies into benchmark bond and equity indices affects mutual funds' country allocations and hence portfolio flows into these markets as well as exchange rates. Despite these scale effects, I consider both index-eligible and smaller-denomination bonds to exploit the full heterogeneity in the size distribution of corporate borrowers for identification.

Several papers shed light on the granular origins of credit risk in EM corporates. Asis et al. (2021) find a positive distress risk premium in EM equities that is driven by global factors such as US monetary policy and global liquidity risk. Similarly, Cavallo and Valenzuela (2009) find in a sample of EM bonds that macroeconomic variables as well as global factors drive variation in spreads. This certainly poses concerns about endogeneity in our context which I address in my identification strategy. Alfaro et al. (2019) document that corporate default risk is positively correlated with firm leverage and firm size in EMEs in the post-GFC period. Importantly, they find that idiosyncratic shocks to the sales growth of large firms positively correlate with GDP growth. This finding indicates systemic importance of large firms. These granular origins of aggregate fluctuations (Gabaix, 2011) build the backbone of my identification strategy.

The notion that "large players" – be it firms, sectors, or countries – may affect aggregate outcomes is exploited for identification in recent work by Gabaix and Koijen (2020). In their "granular instrumental variable" (GIV) approach, they formalize the idea of using idiosyncratic shocks to large players to purge off common shocks that may affect aggregate variables. This allows them to clearly identify the causal effect of these players on aggregate outcomes. GIVs have been adopted most recently in several papers in international macroeconomics and finance. Camanho et al. (2022) use GIVs constructed through idiosyncratic shocks to large mutual funds' portfolio rebalancing to identify the elasticity of supply of foreign exchange. Aldasoro et al. (2020b) exploit idiosyncratic shocks to country-level cross-border bank flows to identify the causal effect of bank inflows on domestic macro-financial conditions. Galaasen et al. (2020) show, using GIVs, that idiosyncratic loan-level risk is not diversified away through aggregation in banks' portfolios and can spill over to other borrowers via banks' balance sheets. Kwak (2021) constructs GIVs to identify spillovers from the corporate into the sovereign bond market in the Euro area during the European sovereign debt crisis.

[11] Bank credit and bond financing may however be imperfect substitutes as they serve different short-term and long-term financing needs.

[12] This institutional feature has enticed large corporates to issue more external debt at the expense of hoarding large amounts of cash.

Recent comprehensive cross-country evidence by Coppola et al. (2021) suggests that capital flows into offshore tax havens can be a sizeable share of nationality-based external debt. Avdjiev et al. (2014) document that repatriation of funds from offshore subsidiaries to domestic firms can occur via three main channels: as within-company flows, between-company flows, and as corporate deposits. Not all of these flows may translate into real activity but instead may represent financial operations. Measuring debt by residency rather than by nationality of the issuer's ultimate parent can therefore mask important origins of risks to financial and macroeconomic stability. I hence take a more holistic approach by considering internationally traded bonds that are issued both by domestic firms and by offshore subsidiaries of EM parent companies.

Research on the link between corporate and sovereign risk is still in its infancy. It is well known that sovereign credit risk premia endogenously comove with the USD exchange rate as global investors make portfolio choices based on dollar returns (Hofmann et al., 2020). Corporate borrowers are more insulated from such currency movements as they mostly borrow in hard currencies. However, there may exist spillovers from sovereign into corporate bond markets via at least two channels: the banking sector and state ownership of corporations. Using Italian firm-level data, Moretti (2020) finds that banks with higher sovereign debt holdings exhibit higher loan losses in their corporate debt portfolios. Broner et al. (2021) and Pandolfi and Williams (2020) find positive spillovers from EM sovereigns to government-related and financial firms through higher growth in income, employment, and dividends relative to tradable firms. By contrast, an equivalent case for reverse causality can be made through the impact of changes in tax revenues on sovereigns, as evidenced by Kwak (2021) for the European sovereign debt crisis of 2008-2012. I argue below that the GIV approach to identification controls for these confounding effects by exploiting firm-specific shocks that are uncorrelated with common shocks to a country's sovereign risk.

3 Data

Since the GFC, a large share of investment and expenditures by EM corporates has been financed through the issuance of internationally traded corporate bonds denominated in foreign currency. This paper analyzes credit risk in a panel representing the *universe* of USD-denominated corporate bonds across a panel of firms from several EMEs.[13] To this end, I obtain and match a rich dataset at four different levels of granularity: bond-, firm-, country-, and global-level.

Countries The set of EMEs selected into the sample is justified on the grounds of two criteria. First, I select countries included by leading global equity and bond index providers whose benchmark indices are closely tracked by global investors. Second, I include additional countries classified on the grounds of determinants of economic development such as GDP per capita, exports of diversified goods and services, and integration into the global financial system. My sample therefore comprises most of the countries included in the MSCI Emerging Market Index and the JP Morgan Corporate Emerging Market Bond Index suite, as well as several additional countries classified as "Emerging Market and Middle-Income Economies" by the International Monetary Fund (2021). Table A.1 in Appendix A provides a detailed list of

[13] I leave it to future research to complement data on the universe of *USD-denominated* bonds with data on the universe of *local* currency bonds.

classifications.

Bond spreads and characteristics. I retrieve time-series as well as cross-sectional data on bond characteristics from Bloomberg.[14] I limit the sample to bonds that are (i) active or matured, traded any day between 1 January 2000 and 1 December 2020, (ii) denominated in USD, (iii) issued by non-financial firms, (iv) issued by *onshore* issuers in one of 43 EMEs or by *offshore* subsidiaries in one of 11 tax havens, (v) subject to a fixed coupon schedule, and (vi) have a remaining term to maturity of at least one year. The criteria in (i)–(iv) yield a sample of 6,006 bonds spanning 43 EMEs for which the time-series of credit spreads is reliably available. Filters (v)–(vi) will be applied to the sample in the estimation.

The limited bond coverage across EMEs before 2000 restricts the sample period to 2000-2021. I limit my analysis to only USD-denominated bonds. Since 2008, the bulk of new issuances of corporate bonds has been denominated in foreign currency.[15] EM corporates tend to prefer issuing debt in foreign currency – as opposed to sovereigns – since these markets are usually more liquid and hence more attractive for international investors. The liquidity of USD-denominated bond markets allows me to obtain reliable time series of credit spreads on bonds that are frequently traded. Moreover, focusing on USD-denominated bonds limits the influence of currency mismatch faced by international investors' as a confounding latent factor in the analysis.

Following recent evidence by Coppola et al. (2021) on the systematic obfuscation of large-scale bond issuance through foreign subsidiaries in tax havens, I also collect information on bonds issued by firms domiciled in tax havens whose next-of-kin parent company is incorporated in an EME.[16] I select eleven tax havens following Coppola et al. (2021) that exhibit at least five bonds issued on behalf of firms with parents incorporated in EMEs across the sample period. These tax havens include the Bahamas, Bermuda, British Virgin Islands, Cayman Islands, Curacao, Hong Kong, Ireland, Jersey, Luxembourg, Netherlands, and Panama. Table A.2 in Appendix A presents an overview of the number and cumulative notional volume of bonds in the sample, split between onshore and offshore issuance. Appendix C.2 provides additional information on bond characteristics in the cross-section of onshore-offshore issuances.

To obtain a reliable measure of credit risk for the sample of bonds, I obtain week-end option-adjusted spreads (OAS) and option-adjusted effective duration from Bloomberg. In most basic terms, an OAS is the spread over an issuer's spot rate curve, i.e. the theoretical yield on a zero-coupon Treasury security.[17] Equivalently, the option-adjusted effective duration is the sensitivity of the bond's yield to a shift in the entire yield curve. OAS have the advantage of harmonizing yields across bonds of various different cash flow characteristics, particularly

[14] While there are other commercial databases available (e.g. Thomson Reuters Datastream, Cbonds, Morningstar), Bloomberg offers a broad global coverage of corporate bonds and relevant pricing sources as well as meta data on the issuing company and parent company. This warrants confidence that the resulting sample is representative and indeed spans the universe of corporate bonds in EMs.

[15] More than 60 % of issuances have been denominated in USD (Caballero et al., 2019; Calomiris et al., 2022).

[16] The share of bonds issued via tax havens is sizeable for some countries, including Brazil, Russia, and China.

[17] Formally, let $r^j_{k,t}$ and r_t denote the yield curves of bond k of firm j with maturity M and of the safe asset, respectively. An OAS $S^j_{k,t} = r^j_{k,t} - r_t$ is the solution to

$$\underbrace{p_{k,t}}_{\text{bid price}} = \sum_{n=1}^{N} \underbrace{\prod(n)}_{\text{Pr. of } n^{th} \text{ path}} \sum_{\tau=t}^{M} \frac{\overbrace{C_{k,\tau}(n)}^{\text{cash flow}}}{1 + r_\tau + r_{k,t}}$$

Table 1: Corporate bonds – Summary statistics

	Mean	SD	Min	Median	Max
No. of bonds per firm/week	7.64	8.37	1.00	4.00	41.00
Bond volume (mil)	649.70	498.46	5.00	500.00	4,115.28
Maturity at issue (years)	11.70	7.83	1.50	10.00	50.00
Term to maturity (years)	7.36	6.67	0.50	5.50	42.55
S&P Issuer Rating	BBB-		D	BBB-	AAA
OAS spread (bsp)	401.95	581.23	-16,786.50	262.67	19,064.08
Duration (years)	4.92	3.45	-0.02	4.19	22.12
Coupon rate (%)	6.42	2.28	0.00	6.25	13.75
Callable bonds (%)	0.33	0.47			

Note: Sample period: 2000/01/07 – 2020/11/27; Bond-week observations=1,084,333; Number of bonds=4,668; Number of firms = 1,281; Number of countries=30. The sample statistics are based on trimmed data.

across heterogeneous countries.[18] They take into account embedded options in bonds such as early redemption and hence make spreads more comparable.

Table 1 presents summary statistics for the sample of bonds. Overall, the distribution of bond characteristics exhibits considerable heterogeneity. The median firm has four bonds outstanding at a given point in time with a considerable positive skew towards a few firms with a large set of bonds outstanding. The distribution of notional bond volume is similarly skewed, ranging from USD 5 million to USD 4.1 billion. The median bond volume centers on the threshold of USD 500 million at which bonds become eligible for inclusion in leading emerging market bond indices. Note that the tails of the distribution of OAS spreads are quite long, owing to the computation of the model-based measure.[19] A sizeable fraction of 33% of bonds feature an embedded call option.

The firms in my sample cover the full spectrum of issuer credit ratings ranging from defaulting issuers with a D-rating to high-quality AAA-rated issuers. The median rating is just above the cut-off from investment-grade to high-yield rating where many firms tend to cluster (Acharya et al., 2021). Figure 2 presents a fairly bell-shaped distribution of S&P issuer ratings for the firms in the sample. The sample of EME credit ratings therefore appears fairly representative of the global distribution of ratings. Note however that a considerable right tail of bonds is in default (D-rating). Moreover, Figure 2 shows that credit spreads are much larger and more volatile in the worst high-yield rating categories as expected.

Firm fundamentals. To employ an adequate measure of expected default of the bond issuer, I follow the literature and obtain daily series of expected default frequencies (EDFs) of publicly listed firms from Moody's KMV CreditEdge database.[20] The calculation of the EDF takes a

[18] See for example Caballero et al. (2019) and Cavallo and Valenzuela (2009) who use OAS in a similar cross-country context and Anderson and Cesa-Bianchi (2020) who use OAS in a US context.

[19] In other words, the OAS is not the observed spread that investors incur. Instead it is a theoretical measure of credit risk once the embedded option is taken into account. Hence the possibility of negative OAS.

[20] The bulk of the literature relies on measures derived from some variant of the Merton model, which has been subject to vast criticism (Bharath & Shumway, 2008). Other model-free measures such as option-implied default risk can be constructed (Culp et al., 2018), yet they tend to be more demanding in terms of the

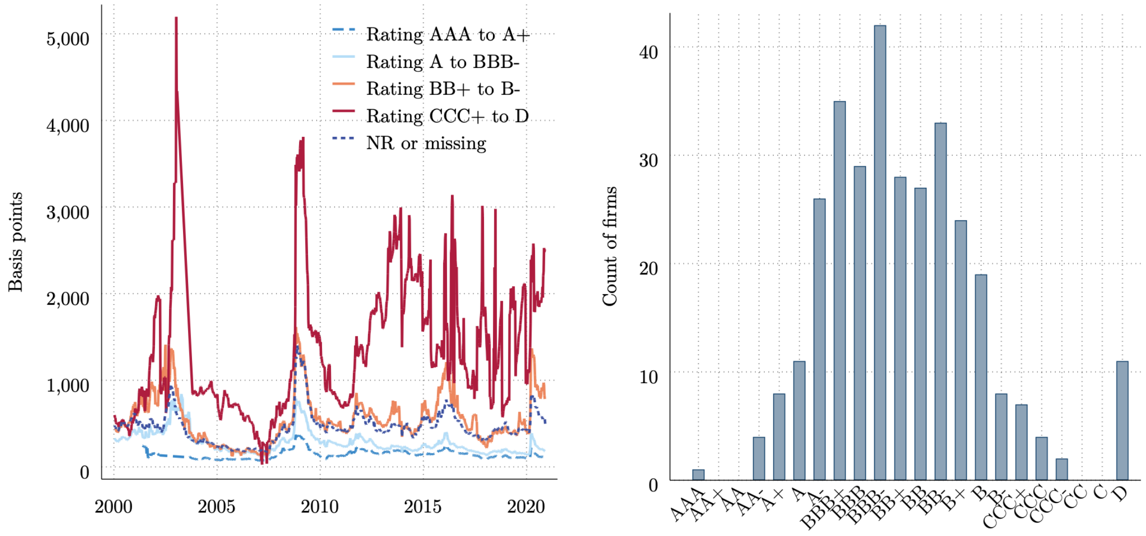


Figure 2: Credit spreads by rating category and the distribution of ratings

Note: The left panel shows the arithmetic average of the option-adjusted spread (OAS) series for a given selection of rating categories of the S&P issuer rating. The right panel shows the frequency of average S&P ratings of firms computed over the sample period. Data availability of issuer ratings limits the bonds and firms underlying these statistics to a subset of the sample.

firm's market value of assets, its asset volatility, and leverage as inputs in a proprietary Merton-type model. It then converts the resulting *distance to default* into a probability of default over a 12-month period. It is therefore a timely market-based measure of credit risk based on observable information.[21]

In addition to the expected default data, I obtain quarterly balance sheet information from Bloomberg. Table 2 reports information on the distribution of firm size and key financial indicators. The median firm faces a probability of default over a one-year horizon, as implied by Moody's EDF measure, of 0.43% and an Altman's Z-score of 1.9.[22] Note that the median Z-score is just above the threshold of 1.8 which is commonly referred to as the score below which a company is close to bankruptcy. Equally striking is the degree of leverage that the median firm takes up, with a right skew towards excessively large multiples of debt to equity. Profitability as indicated by the 12-month trailing earnings per share similarly exhibits a very large variance and right skew. The median-sized firm comprises about USD 2.3 billion in total assets and has a market capitalization of USD 1.1 billion. Unsurprisingly, EM corporations are also quite large by measures of equity and sales, in line with stylized facts documented by Alfaro et al. (2019).

Bond information is then matched with firm identifiers from Moody's KMV in a three-

granularity and coverage of data.

[21] Let V be the market value of assets, σ_V be the asset volatility, and D be the default point. Then, in an abuse of notation, the distance to default, DD, is roughly defined as:

$$DD = \frac{V - D}{V \cdot \sigma_V}$$

[22] As an indicator of whether a firm is close to becoming insolvent, Altman's Z-score is computed by Bloomberg based on leverage, liquidity, profitability, solvency, and activity characteristics obtained from balance sheet information.

Table 2: EM corporations – Summary statistics

	Mean	SD	P25	Median	P75
EDF 1-Year (%)	1.997	4.504	0.086	0.430	1.814
Altman's Z-score	2.340	2.707	1.172	1.902	2.920
Debt/Equity	1.46e+05	3.334e+06	49.195	86.957	149.796
Earnings per share (bn)	3.045	136.702	0.000	0.000	0.000
Total assets (bn)	8.349	19.557	0.751	2.311	7.495
Market capitalization (bn)	5.161	24.139	0.215	1.069	4.137
Equity (bn)	4.315	11.318	0.422	1.349	4.166
Sales (bn)	5.151	13.359	0.325	1.042	3.797

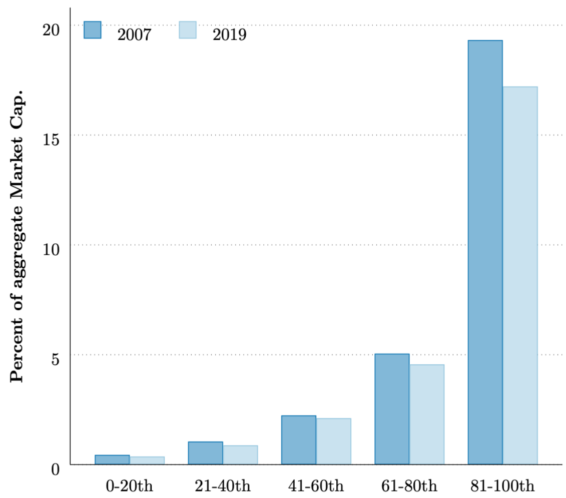
Note: Sample period: 2000/01/07 – 2020/11/27; Firm-week observations=204,331; Number of firms = 692; Number of countries=27. The sample statistics are based on winsorized data at the top and bottom 1% within a given country. If a given company is privately held by a publicly traded parent company, the balance sheet information of the parent company is used for the computation of statistics.

step procedure: (i) matching by (unique) Bloomberg ID and ISIN of the issuer, jointly and individually, (ii) matching by unique Bloomberg ID and ISIN of the parent company, and (iii) matching by equity ticker symbol of subsidiary and parent company, respectively, using a matching algorithm outlined in Appendix B. The matched sample comprises 1,346 firms in 30 countries.

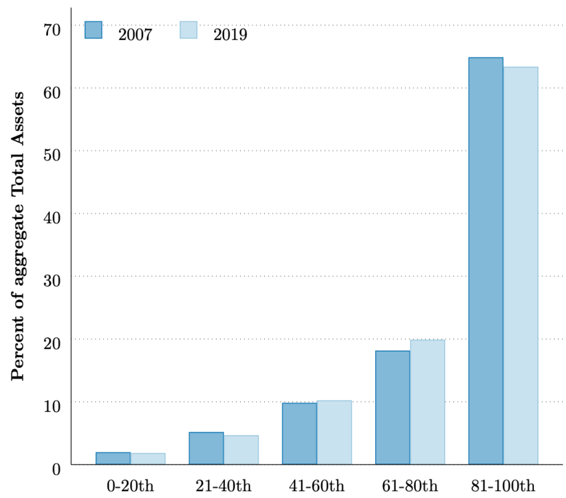
As we shall see in Section 5, one necessary condition for the GIV to be a valid instrument is that the distribution of firm size is sufficiently "granular". That is to say that activity must be concentrated in a handful of particularly large firms. If all firms were uniformly of the same size – as is the conventional assumption in representative agent frameworks – the lack of "large firm shocks" with systemic impact would compromise the relevance of the instrument. Figure 3 shows the share of firms in a country's aggregate equity market capitalization (panel (a)) and their relative share of total assets (panel (b)) across the firm-size distribution. The figure suggests that the largest 20$^{\text{th}}$ percentile of firms, as measured both by market capitalization and by total assets, takes up a much larger share of aggregate market capitalization than smaller firms.[23] Comparing the shares in 2007 versus 2019 further suggests that this "granularity" is relatively stable over time.

A further condition for the GIV to be a "strong" instrument is that the variable to be instrumented – the credit spread – exhibits sufficient heterogeneity across the size distribution of firms. That is, larger firms in the market for debt must clearly distinguish themselves from smaller firms in the degree of credit risk. Figure 4 provides confidence that this condition is met. It shows the distribution of the level of OAS (top panel) as well as the volatility in the time-series of OAS (bottom panel) for each firm according to its place in the size distribution, measured

[23] Caution is warranted in interpreting absolute numbers in Figure 3 as the data used to compute these statistics comes from two different sources. I obtain annual data on a country's aggregate stock market capitalization from the IIF. By contrast, weekly data on market capitalization of the firms included in my sample comes from Bloomberg. Since my sample only comprises listed companies with substantial USD-denominated bond issuance in international debt markets, other public companies that do not issue in these markets are not captured in the firm size distribution in the figure. Moreover, listed *financial firms* such as banks are excluded from my sample. Thus, while the largest 20% of firms take up only about 20% of total market capitalization, among the subset of these firms in the total population of listed firms they likely have a larger market share.



(a) Market Capitalization



(b) Total Assets

Figure 3: Concentration of shares across the firm size distribution over time

Note: The figures plot the concentration of equity market capitalization (panel (a)) and total assets (panel (b)) across the size distribution of non-financial firms. The quantiles are computed based on a firm's position in the *sample* distribution within a country, not in the *population* distribution. The shares (in %) are computed as the average share of a firm's market capitalization in the total market capitalization of a country (data source: IIF) and the average share of a firm's total assets in the sum of total assets *in the sample*, respectively, over the reference years 2007 and 2019. The statistics are averaged across 15 and 18 countries, respectively.

by (the logarithm of) total assets. As indicated by the non-parametrically fitted relationship between credit risk and firm size, large firms tend to exhibit smaller and less volatile credit spreads on average. They also issue bonds larger in volume than their peers, denoted by the larger size of circles. These observations suggest that there is sufficient heterogeneity across the firm-size distribution to exploit variation in firm-specific shocks to credit risk

Figure 4 also distinguishes between bonds that have been issued onshore or offshore via a subsidiary. Simple eye-balling does not yield any substantial difference between the risk-size relationship. Yet, the non-parametrically fitted relationship suggests that bonds issued offshore tend to demand a slightly higher and more volatile credit spread, especially for firms smaller than the median firm.

Capital and portfolio flows. Country-level data on net capital flows comes from two sources.[24] As the closest high-frequency proxy to inflows and outflows to and from international bond markets, I obtain portfolio "country-flow data" from EPFR Global's proprietary database.[25] EPFR Global collects and aggregates weekly data on portfolio investment flows from a large sample of global institutional investors covering more than 14,000 equity funds and 7,000 bond funds with more than USD 42 trillion assets under management. Country coverage is determined by funds' mandate to invest in a specific geographical location. Aggregate portfolio flows are calculated based on changes in country allocations of funds. As argued by

[24]The desire to have a high-frequency measure of capital flows restricts the choice of variables to those that measure *net* capital flows. Data on *gross* debt portfolio flows starting in 09/2002 are only available at a quarterly frequency from the IMF Balance of Payments statistics.

[25]I focus on debt portfolio flows to isolate direct effects of credit risks in corporate bond markets onto portfolio flows into these markets. Forbes and Warnock (2014) document that most episodes of extreme capital flows around the world are debt- rather than equity-led.

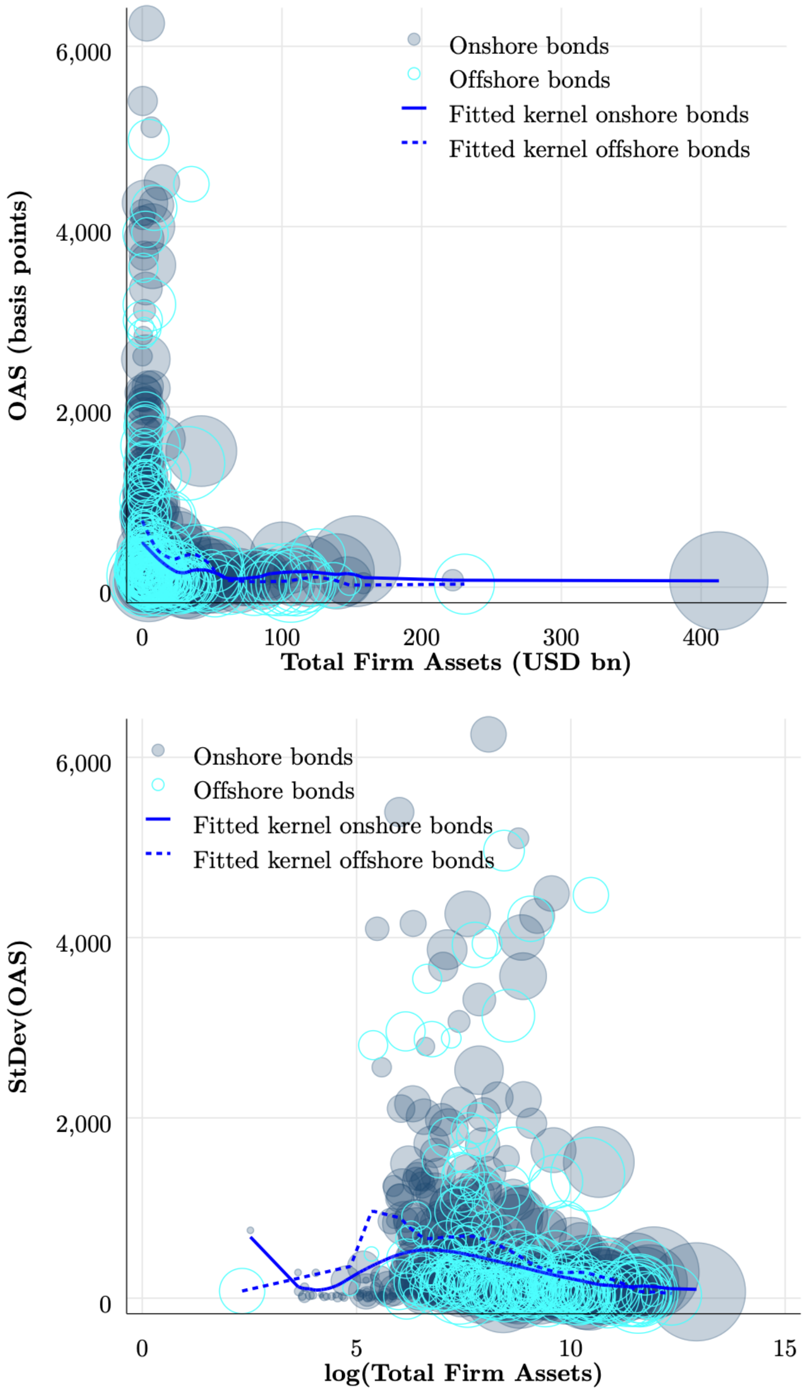


Figure 4: Heterogeneity in credit spreads and in volatility across the firm-size distribution

Note: The top panel presents the average option-adjusted spread (OAS) observed for each firm over the sample period for a given firm size as measured by total assets. The average OAS are computed for both onshore and offshore issuances. The observations are weighted by the average volume of bonds of a given firm, with larger circles indicating greater notional USD-volume. The bottom panel presents the volatility in the time-series of OAS of each firm over the sample period across the firm size distribution, scaled by the logarithm of total assets. Both plots include the fitted line of a non-parametric Kernel regression for both onshore and offshore issuances.

Chari et al. (2020), EPFR's country flows are free from valuation effects and represent real quantities precisely because they are computed based on aggregate re-allocations at the fund level.

The EPFR data spans 32 EMEs in my sample. The flow measure is disaggregated into allocations to bond and equity markets which is a clear advantage compared to other flow measures for the purpose of my analysis. It conveniently controls for confounding effects between bond and equity markets which aggregate portfolio flow measures cannot account for. The data however comes with several caveats. For one, the time series of country flows only starts in 2004 whilst bond and firm data is available from 2000. Moreover, for some smaller EMEs, the time series starts only in the second half of the sample. This is only partially problematic because some countries do not exhibit bond coverage as early as 2000 (see Table A.2 in Appendix A). Finally, EPFR data represents *net* flows as opposed to *gross* flows. That is, changes in liabilities are netted against changed in assets.

The Institute of International Finance (IIF) offers an alternative to EPFR bond flows with its measure of debt portfolio flows. It covers 25 EMEs at a weekly frequency starting in 2005 and at a monthly frequency as early as 2000 for some countries.[26] To maximize the coverage along both the time and country dimension as well as exploit the highest frequency available in the static country regression, I use weekly EPFR flows in my baseline regression model to identify the causal effect at the weekly frequency. However, I use the monthly IIF flows in the dynamic local projections analysis when estimating impulse responses of monthly indicators of macroeconomic activity, given its longer series at the monthly frequency.

In addition to country-level portfolio and capital flows, I also obtain country-level index series of the JP Morgan suite of Emerging Market Bond Indices (EMBI) and the Corporate Emerging Market Bond Indices (CEMBI). The EMBI comprises public debt securities at the municipal and federal level. It serves as a suitable proxy for sovereign risk at the country level to account for residual spillovers into corporate bond markets. As its corporate equivalent, the CEMBI includes a large portfolio of USD-denominated and internationally traded corporate bonds with a volume of at least USD 500 million. It is therefore a relevant benchmark index relative to which to assess the variation in OAS spreads in a given country.

Global factors. Finally, I obtain time-series on global factors from Bloomberg and FRED, including the Chicago Board Options Exchange's volatility index (VIX), the 10-year US Treasury yield, and the US Baa spread. All of these measures have been frequently used as a proxy for the Global Financial Cycle.[27] Specifically, the VIX is widely used as a measure of global risk aversion (Di Giovanni et al., 2022). Shocks to the US Baa spread are found by Akinci (2013) to account for a considerable share of variation in economic activity in EMEs.

[26] In a horserace, Koepke and Paetzold (2020) show that IIF and EPFR data have significant predictive content for portfolio flows based on the IMF's Balance of Payments Statistics (BoPS).

[27] Additional measures could include the first principal component of capital flows across countries (Cerutti et al., 2019), a monthly indicator derived from global risky asset prices (Miranda-Agrippino & Rey, 2020), or a measure of global "flights-to-safety" that capture the co-movement between risky and safe asset returns across developed markets (Ahmed et al., 2021). I focus on those indicators of global risk that are readily available at a weekly frequency.

4 Discussion of Endogeneity

In light of the link between the Global Financial Cycle and the domestic financial cycle in EMEs (Aldasoro et al., 2020a), valid concerns about endogeneity arise. It is broadly agreed that global developments have come to predominantly steer short- to medium-term changes in the current account and exchange rates in EMEs. Yet, domestic developments have been found to impact – rather than just to react to – capital flows as well, and thus need to be considered with equal importance.

The key challenge to identifying the causal effect of credit risk on capital flows involves overcoming the potential risk of reverse causality. On the one hand, as this paper argues, a causal nexus may be drawn from credit spreads to capital flows when the underlying risk that is priced by international investors stems from the default risk of an investment. Positive, yet compressed credit spreads attract capital from abroad in good times. These inflows fuel corporate leverage but also maturity mismatch on firms' balance sheets as firms borrow in foreign currency. As fundamental default risk crosses the threshold of investors' risk tolerance, risk is repriced, capital flows halt or reverse, and the exchange rate depreciates by the uncovered interest rate parity (UIP) condition. Additional currency mismatch further feeds into firms' default risk which increases credit spreads. A feedback loop may arise in which higher credit spreads not only bring capital flows to a halt but also trigger their reversal as international investors reassess their risk exposure in these markets.

On the other hand, a case can be made that it is in fact capital flows that determine credit spreads in EM bond markets. The influx of cheap financing in good times compresses credit spreads as funding is abundant and firms find it easy to refinance their debt. As a result, the domestic currency appreciates. When global external factors trigger capital outflows, funding falls short of investment needs, the domestic economy contracts, and the local currency depreciates. The resulting currency mismatch and dry-up of liquidity increase risk premia demanded by investors. The direction of causality may thus run from capital flows via the exchange rate to corporate credit spreads. Quantities may be driving prices rather than the reverse. The question as to which direction of causality prevails is deeply rooted in the debate about whether the Global Financial Cycle is the dominant force, above and beyond domestic financial developments, that determines business cycle fluctuations in EMEs (Rey, 2015).

The existing literature circumvents the problem of endogeneity by addressing the *predictive* rather than the *causal* effect of credit spreads on domestic economic activity. Statistically speaking, these frameworks test for Granger causality in the sense that X *predicts* Y. This is not to be mistaken for a true "cause-and-effect" relationship that the GIV approach attempts to uncover by using an exogenous relationship as instrument. Akinci (2013) and Caballero et al. (2019) follow the approach of Gilchrist and Zakrajšek (2012) by using structural VAR models to analyze whether sovereign and corporate credit spreads can forecast domestic economic activity. These approaches however have two features that make them ill-suited for the purpose of my analysis. First, they rely on assumptions about the recursive ordering of key macroeconomic and financial variables in the structural VAR model to identify the effect of spreads on macroeconomic aggregates. The validity of these assumptions relies on macroeconomic variables being more slow-moving than financial variables. Hence, the former lag behind the latter. This arguably plausible assumption is exploited for identification. Second, they employ low-frequency data at the quarterly level. Both of these features would not be able to address the faster-moving nature of capital flows that I examine. Capital flows – to the extent that they are portfolio flows – and credit risk may react to each other in a nearly simultaneous manner. It would therefore be fatal to draw strong assumptions on the recursive ordering of these variables in a structural VAR approach. While quarterly data is suitable to predict business cycle movements, short-term fluctuations in capital flows would be smoothed out if the data were measured at a quarterly frequency. It is for these reasons that I employ a more granular approach to identification which exploits the full heterogeneity in credit spreads across firms and across countries at a weekly frequency to overcome endogeneity.

5 Identification of the Causal Effect

The purpose of the empirical analysis is to present a novel way to identify the causal effect of credit spreads on international capital flows, or more precisely, on the change in the stock of international capital invested in the domestic corporate bond market. To that end, I exploit firm-specific shocks to heterogeneous firms which borrow in international debt markets. These shocks allow me to construct a measure that picks up exogenous variation specific to large borrowers relative to variation of the *average* borrower. Intuitively, this measure is purged of any shocks that affect all firms, and hence the average firm. This section first outlines the basic intuition of GIVs (Gabaix & Koijen, 2020) under some simplifying assumptions and subsequently applies the approach to overcome the issue of endogeneity between credit risk and capital flows.

5.1 Understanding Granular Instrumental Variables (GIV)

The idea that aggregate outcomes have granular origins through the activities of a limited number of large entities – where entities are broadly defined – serves as a natural starting point for the construction of instruments for identification of causal links. Such instruments exploit entity-specific events that are orthogonal to what is happening to "everyone else" (Gabaix, 2011). In basic terms, the GIV is a summary statistic of idiosyncratic shocks to large players such as firms, industries, or countries. It is a construct of differences between size-weighted and unweighted aggregates of these firm-specific shocks. If we can credibly believe that shocks to large firms are truly idiosyncratic to these firms and hence exogenous, we can sum over all of these shocks to obtain an "aggregate exogenous shock" at a given point in time. Yet, it may still be the case that some systematic latent factor affects all of these firms in the same way. We therefore do not simply sum over the firm-specific shocks but instead take the difference of the sum of size-weighted individual shocks to the shocks faced by the *average* firm. If latent common factors affect all firms roughly equally, this will purge the summary statistic of any systematic components.

Importantly, firms must be sufficiently large – otherwise their shocks will simply be averaged out. This heterogeneity in the size distribution of firms at the micro-level can be exploited for identification of macro-elasticities. Hence, a key condition for the validity of GIVs is that these large players account for a sizeable share of economic activity such that they can plausibly affect aggregate outcomes. Corporate bond markets in EMEs are dominated by a handful of large corporations that are able to access international funding (see Figure 3 and Alfaro et al. (2019)). Moreover, credit risk is distributed heterogeneously across the firm-size distribution (see Figure 4). This condition is therefore likely to be met.

To convey the basic intuition in reduced form, suppose we want to identify the elasticity α of some country-specific endogenous macro variable F_t to domestic firms' aggregate credit spread S_t. Let F_t be the net capital flow to this country such that,

$$F_t = \alpha S_t + \epsilon_t \tag{1}$$

where ϵ_t denotes an aggregate shock to country c.[28] Suppose that the aggregate credit spread – for example the spread on a country-level corporate bond index – is a weighted average of the credit spread $s_{j,t}$ of individual firms j, i.e. $S_t = \sum_j s_{j,t} \cdot w_j$. The weights w_j are the contribution to, or share of, each individual firm j's spread in the country's aggregate measure.[29] The share can represent, for example, the weight on each bond in the country's benchmark bond index, discussed below. For now, we operate under the strong assumption that individual credit spreads $s_{j,t}$ have the same sensitivity to a common shock η_t across all firms,

$$s_{j,t} = \lambda \eta_t + u_{j,t} \tag{2}$$

where λ denotes the loading on the common shock. For ease of exposition, assume $\lambda = 1$ and that the loading is time-invariant. We may also think of a vector of common shocks $\boldsymbol{\eta}_t$ and loadings Λ which will be useful for illustration in the application. Importantly, $u_{j,t}$ is the unobserved, idiosyncratic shock to an individual firm j that affects the firm's observed credit spread. We assume that the idiosyncratic shock is orthogonal to both the common shock to firms η_t and the aggregate country-level shock ϵ_t, i.e. $E[u_{j,t}\eta_t] = E[u_{j,t}\epsilon_t] = 0$. How shall we conceive of these shocks? Take the example of Brazilian firms. We may think of η_t as a negative funding shock in debt markets which hits all firms' funding conditions equally and ϵ_t as domestic macroeconomic news. In addition, there may be idiosyncratic reasons that induce, say, Telekom Brazil to reduce the riskiness of its debt in excess of what would be expected based on the common shock alone. This "idiosyncratic reason", for example stemming from a change in management, is unlikely to be correlated with the common shock η_t and the aggregate shock ϵ_t. Yet, because Telekom Brazil is a large player in the Brazilian corporate sector, idiosyncratic changes in its credit risk may have aggregate effects.

The key issue with identification in this setting is that we cannot recover α in (1) directly with OLS because it is likely that the aggregate shock to the economy and the shock common to all firms are correlated, i.e. $E[\epsilon_t \eta_t] \neq 0$. We therefore require an instrument z_t for the aggregate credit spread S_t in (1). This instrument can be constructed by taking the difference in the *share-weighted* sum of credit spreads and the *equally-weighted*, or unweighted, sum of credit spreads across the firm distribution. Let $\bar{S}_t$ be the equally-weighted (weighted by $1/N$) sum of spreads in a given country. The GIV is then given by,

[28] I henceforth omit country subscripts for notational convenience.

[29] For simplicity, suppose for now that weight w_j is time-invariant. I will later relax this assumption.

$$
\begin{aligned}
z_t = S_t - \bar{S}_t &= \sum_j \Big(w_j s_{j,t} - \frac{1}{N} s_{j,t} \Big) \qquad (3) \\
&= \sum_j \Big((\lambda \eta_t + u_{j,t}) w_j - (\lambda \eta_t + u_{j,t}) \frac{1}{N} \Big) \\
&= \sum_j u_{j,t} \Big(w_j - \frac{1}{N} \Big) \\
&= u_t - \bar{u}_t \qquad (4)
\end{aligned}
$$

In other words, the GIV is the difference between the share-weighted and the equally-weighted sums of idiosyncratic shocks, $u_t - \bar{u}_t$. The GIV hence exploits the heterogeneity in shares of firm j's credit spread in the aggregate credit spread. Intuitively, z_t picks up the variation in the share-weighted series of firm shocks relative to average shocks that is due to "granular" issuers. The definition of the instrument in (4) shows that the instrument would simply be zero and hence invalid if there was no heterogeneity in the size distribution of borrowers, i.e. $w_j = 1/N \quad \forall j$ where $\sum_j w_j = 1$.[30] It is therefore crucial that bond issuers within a given country in the cross-country panel are sufficiently heterogeneous in size.[31]

Why is z_t a suitable instrument? Importantly, the GIV satisfies the exogeneity condition required for identification, $E[z_t \epsilon_t] = E[z_t \eta_t] = 0$ as long as the exclusion restriction $E[u_{j,t} \eta_t] = E[u_{j,t} \epsilon_t] = 0$ holds. That is, the instrument is valid if we can reasonably assume that firm-specific shocks are uncorrelated with common shocks. Moreover, idiosyncratic shocks to credit spreads must affect the macroeconomic variable of interest, F_t, only through changes in aggregate credit risk, S_t, such that they are hence orthogonal to unobserved aggregate shocks ϵ_t. I discuss these conditions in Section 7. Note also that the GIV is a relevant instrument $E[z_t F_t] = E[(S_t - \bar{S}_t) F_t] \neq 0$ by (1) and (3).[32] The strength of the GIV is that it is purged of the effect of the common shock η_t that affect credit spreads in (4). It can hence be used to identify a causal effect. To the extent that the common shock may also represent the impact of sovereign spreads on corporate spreads, the GIV also eliminates any confounding spillovers from sovereign bond markets into corporate bond markets.[33]

Lastly, we may wonder why idiosyncratic risk $u_{j,t}$ should matter in the aggregate if a savvy investor could simply diversify this risk. Why should such seemingly diversifiable firm-specific risk influence how investors perceive economy-wide risk? Note that it is not obvious that firm-specific shocks are fully diversifiable by investors. Traditional asset pricing theory assumes that firms are atomistic, and hence the impact of their risk vanishes in the aggregate under the central limit theorem. This is not the case in a granular economy where the distribution of firm-size is fat-tailed. By the granular hypothesis (Gabaix, 2011), firm shocks represent non-diversifiable "grains" rather than atoms of economic and financial activity. These grains can drive aggregate fluctuations and transmit to all other agents. Empirical evidence gives

[30] Alfaro et al. (2019) provide important evidence that the idiosyncratic shocks of large firms in EMEs do have systemic impact such that $w_j \neq 1/N$.

[31] By implication, several countries with one a handful of large firms borrowing in international debt markets need to be dropped from the sample.

[32] The moment condition $E[(F_t - \alpha S_t) z_t] = 0$ implied by the exogeneity assumption $E[u_{j,t} \epsilon_t] = 0$ then serves to identify the elasticity $\alpha = \frac{E[F_t z_t]}{E[S_t z_t]}$.

[33] These spillovers are arguably common to all firms except for state-owned enterprises with explicit or implicit government guarantees. I control for this possibility in my estimation.

ample reason to believe that firm-level risk matters in the aggregate. Galaasen et al. (2020) show that idiosyncratic credit risk of granular borrowers survives aggregation in banks' loan portfolios. Carvalho and Gabaix (2013) demonstrate that fundamental volatility, made up of an aggregate of purely idiosyncratic firm-level shocks, accounts for macroeconomic volatility observed over the past half-century. Herskovic et al. (2020) show that the dispersion of the firm-size distribution constitutes a common factor in individual firm volatilities that is priced by investors. In light of the stark evidence of granularity, a more recent body of work studies asset pricing in granular economies for equities (Abolghasemi et al., 2020) and corporate bonds (Abolghasemi, 2021).[34] These models account for the fact that firm-specific risk of large firms affects systematic risk through a common component (Herskovic et al., 2016). It is thus likely that idiosyncratic risk of large corporate borrowers influences international investors' perception of economy-wide, systematic risk.

5.2 Application of GIV to Capital Flows

Country-level regression model. Equipped with the simple intuition of GIVs, I apply the stylized example of a country-specific macroeconomic variable F_t in (1) to the context of capital flows across a panel of EM countries. I postulate that changes in international investors' capital allocations, i.e. (net) capital flows $F_{c,t}$, in a given country c at time t are linearly related to a country's aggregate credit spread $S_{c,t}$ as well as a set of country-specific and global controls $\boldsymbol{X}_{c,t}$,

$$F_{c,t} = \alpha S_{c,t} + \beta \boldsymbol{X}_{c,t} + \epsilon_{c,t} \tag{5}$$

where $\epsilon_{c,t}$ denotes the aggregate shock to country c. Let $S_{c,t} = \sum_j w_{j,c,t-1}\, s_{j,c,t}$ where weights on firm j's credit spread are lagged by one period.[35]

As before, the challenge is to identify and estimate α, i.e. the elasticity of capital flows with respect to a change in the price of risk. I hypothesize that in normal times $\alpha = \alpha^{in} > 0$. That is, when the domestic economy goes through tranquil episodes, a widening of credit spreads attracts foreign capital. However, I expect that $\alpha = \alpha^{out} < 0$ when currency mismatch on corporate balance sheets and default risk endogenously interact to induce international investors to retract capital.[36] To estimate α, I instrument the credit spread $S_{c,t}$ with the GIV, i.e. a summary statistic of exogenous firm-specific shocks. How do we obtain these idiosyncratic shocks from the information content of corporate bonds?

Decomposing credit spreads to extract idiosyncratic shocks. The term credit risk subsumes various forms of risk that generate a wedge between the return on the risky security and the risk-free return on a safe asset of equivalent maturity, i.e. the credit spread. To understand which features intrinsic to the debt instrument and borrower as well as systematic

[34] In these extensions of the conditional CAPM, a firm's market beta depends on the firm's weight in the economy.

[35] Weights may be endogenous themselves. Although not a remedy, lagging the weights is a way to address this issue.

[36] I remain agnostic about the precise definition of states of the economy as these states are themselves endogenously determined by the interplay of domestic credit risk and capital flows. For example, the notion of *risk-on* and *risk-off* episodes relates to episodes of capital flows that are driven by global factors. It would be misleading to search for causal effects of credit risk precisely during times when global factors prevail.

market characteristics drive credit risk, Gilchrist and Zakrajšek (2012) decompose US corporate bond spreads into a fundamental counter-cyclical component of expected default and a cyclical expectations-driven residual component. They denote the latter as the "excess bond premium". International evidence by Akinci (2013) suggests that credit spreads are driven by risk aversion of global investors as much as they are driven by domestic factors affecting corporate financial vulnerability.

Combining these insights, I decompose credit spreads into several risk factors to extract idiosyncratic bond-level shocks. Specifically, an individual firm j's credit spread $s_{j,c,t}[k]$ in country c paid on bond k is assumed to be linearly related to a measure of the firm's default risk $D_{j,c,t}$, a vector of bond characteristics capturing the bond's liquidity risk $\boldsymbol{X}_{j,c,t}[k]$, a vector of country risk characteristics $\boldsymbol{Z}_{c,t}$, and a vector of global risk measures $\boldsymbol{G}_t$,

$$s_{j,c,t}[k] = a_c + \Lambda^j D_{j,c,t} + \Lambda^k \boldsymbol{X}_{j,c,t}[k] + \Lambda^c \boldsymbol{Z}_{c,t} + \Lambda^g \boldsymbol{G}_t + u_{j,c,t}[k] \tag{6}$$

where $u_{j,c,t}[k]$ is the "pricing error" of bond k. $(\Lambda^j, \Lambda^k, \Lambda^c, \Lambda^g)$ represent the "factor loadings" on the firm (j), bond (k), country (c), and global (g) risk premia, respectively. a_c denotes country fixed effects. I explicitly account for the default risk premium at the firm-level by using a measure of a firm's probability of default (Gilchrist et al., 2009; Gilchrist & Zakrajšek, 2012). This premium captures *expected* default risk based on firm fundamentals. The model in (6) is the analogue to the model in (2) with $\lambda\eta_t$ representing the vector of common risk factors $\boldsymbol{\eta}_t$ and their loadings Λ. However, the model in (6) is defined at the individual bond level. To obtain a measure of the credit spread and idiosyncratic shock at the firm level, I take the share-weighted average of credit spreads and idiosyncratic shocks of firm j from the estimation of (6) across outstanding bonds,

$$s_{j,c,t} = \sum_k w_{j,c,t}[k]\, s_{j,c,t}[k] \qquad \text{and} \qquad \hat{u}_{j,c,t} = \sum_k w_{j,c,t}[k]\, \hat{u}_{j,c,t}[k] \tag{7}$$

where the weight $w_{j,c,t}[k]$ on each individual bond k is defined by its face value $V_{j,c,t}[k]$ relative to the total volume of bonds of firm j outstanding at time t, $w_{j,c,t}[k] = V_{j,c,t}[k] / \sum_k V_{j,c,t}[k]$.

The fact that the spread model in (6) ommits a currency risk premium should not be a cause for concern. I only include hard-currency denominated bonds in the sample. Since international investors mainly finance their investments through USD debt, they do not face currency risk. One may argue that there is still implicit currency risk involved with lending to firms which face currency mismatch on their balance sheet. I argue that such a currency risk premium would be subsumed under the default risk component. The ultimate consequence for a firm facing currency mismatch is that it will not be able to liquidate sufficient assets in local currency to repay foreign currency debt and hence default on its obligations.

How ought one interpret the persistent occurrence of idiosyncratic shocks, or in other words "pricing errors", in the time series of corporate spreads? It is not too difficult to think of examples of firm-specific surprises that may not be priced by investors into the expected default component: sales receipts falling far short of a company's forecast due to product faultiness; the unanticipated costs of a corporate lawsuit; damage to a local production facility due to a fire or natural disaster; the death of a CEO; an unexpectedly high exposure to a regulatory change.[37] What is important is that these shocks represent unexpected changes in a firm's outlook that are not priced in yet.[38] Or alternatively, as Gabaix and Koijen (2020) argue, idiosyncratic shocks may represent any unexpected changes in a firm's *sensitivity* – its "loading" – to a common shock.

Constructing the optimal GIV. Having obtained the idiosyncratic shocks $\hat{u}_{j,c,t}$ at the firm-level, I next construct the GIV analogous to (4),

$$z_{c,t} = \sum_j w_{j,c,t-1} \hat{u}_{j,c,t} - \frac{1}{N_{c,t}} \sum_j \hat{u}_{j,c,t} \tag{8}$$

where $w_{j,c,t}$ is the share of firm j in the country aggregate (or the size of the firm relative to its peers) and $N_{c,t}$ is the total number of issuing firms in a given country. Both may vary over time. The baseline specification considers a firm's "external debt at risk" relative to a country's aggregate external debt issued by non-financial corporations.[39] Thus, the weight captures the expected dollar loss on the face value of debt for a risk-neutral investor. Then, $z_{c,t}$ is a valid instrument constructed by idiosyncratic shocks. Specifically, the instrument is valid if the exclusion restriction holds, $E[u_{j,c,t}[k]\epsilon_{c,t}] = 0$.

How can we be sure that the shocks $\hat{u}_{j,c,t}[k]$ are truly idiosyncratic? There may be factors not captured by the spread model in (6) after all. Ideally, one would use principal component analysis (PCA) as a non-parametric approach to separating common shocks from idiosyncratic shocks (see for example Gabaix and Koijen (2020) and Aldasoro et al. (2020b)). This approach would have the advantage of not imposing assumptions on the structure of endogenous relationships while allowing for reverse causality. However, the unbalanced nature of the bond-firm-country panel does not allow for PCA without sacrificing sample size and thus statistical power. Alternatively, one may think of saturating the spread model with a host of bond, firm, sector, and country fixed effects. Depending on the interaction with time fixed effects, one would quickly run into the curse of dimensionality, given that spreads are recorded at weekly frequency. By contrast, using the specification in (6) allows us to give economic meaning to the various components of credit risk. It thus appeals to risk premia that the literature has found to be important.

Estimation through instrumentation. Once the GIV is obtained, the estimation proceeds with two-stage least squares. First, I run a regression of the aggregate credit spread onto the GIV and a set of controls $\boldsymbol{X}_{c,t}$ at the country-level c,

$$S_{c,t} = \gamma^z z_{c,t} + \beta^s \boldsymbol{X}_{c,t} + \nu_{c,t} \tag{9}$$

where $\nu_{c,t}$ is an unobserved error. $\nu_{c,t}$ is most likely correlated with the aggregate shock $\epsilon_{c,t}$

[37] Engljähringer and Stracca (2020) combine an econometric and narrative approach to compile a database of idiosyncratic shocks (events) of car manufacturers and global banks. They find that these shocks significantly affect firm's equity valuations, also within the respective sector, in the the short-term.

[38] From a *behavioral* perspective, these pricing errors may capture deviations from full information rational expectations (FIRE) of international investors.

[39] The idea follows from the model of sovereign spillovers proposed by Gabaix and Koijen (2020) where "shares" of sovereign debt are computed based on a country's "debt at risk". Camanho et al. (2022) use as a weight an investment fund's market capitalization relative to their respective country aggregate.

in (5). This is remedied through the instrument z_t which is uncorrelated with the aggregate shock by construction. The predicted $\hat{S}_{c,t}$ from the first stage are then used as an independent variable in the second stage to estimate the regression model in (5) with OLS,

$$F_{c,t} = \alpha \hat{S}_{c,t} + \beta^f \boldsymbol{X}_{c,t} + \epsilon_{c,t} \tag{10}$$

where $\boldsymbol{X}_{c,t}$ also includes country fixed effects. The coefficient α is just identified as long as the exclusion restriction $E[u_{j,c,t}\epsilon_{c,t}] = 0$ holds such that the instrument is valid $E[z_{c,t}\epsilon_{c,t}] = 0$

Summary of estimation procedure. The step-wise estimation procedure can be summarized as follows:

1. Decompose credit spreads $s_{j,c,t}[k]$ into risk components using (6) to purge the idiosyncratic shocks off common factors.
2. Aggregate idiosyncratic shocks at the firm level $\hat{u}_{j,c,t}$ using (7).
3. Construct optimal GIVs at the country level using (8).
4. Estimate 1^{st} stage: regress $S_{c,t}$ onto $z_{c,t}$ using (9).
5. Estimate 2^{nd} stage: regress $F_{c,t}$ on the instrumented changes in credit spread $\hat{S}_{c,t}$ using (10).

6 Results

6.1 Extraction of Idiosyncratic Shocks

As a first step in my identification strategy, I estimate the corporate spread model in (6) to decompose credit spreads into its risk components and idiosyncratic shocks. Following Gilchrist and Zakrajšek (2012), I regress bond k's credit spread $s_{j,c,t}[k]$ on a set of bond-specific characteristics that include the bond's modified option-adjusted duration, the amount issued (in USD), the fixed coupon rate, the age of the issue, as well as an indicator variable for bonds with underlying call options, $CALL_j[k]$.[40] In addition, the firm-specific probability of default $EDF_{j,c,t}$ captures market-based changes in investors' expectations about firm fundamentals. The spread model is further augmented by the CBOE volatility index, VIX_t, and the 10-year US Treasury yield, $UST10Y_t$, to account for spillovers of US monetary policy and changes in global risk aversion following work by Miranda-Agrippino and Rey (2020).

I also include country as well as industry fixed effects to control for any factors specific to a country or industry. In line with Cameron et al. (2011), standard errors are clustered along countries (c), industries, firms (j), and time (t). The BICS Level 1 industry classification summarizes government-related entities in one single industry. Including industry fixed effects based on this classification system therefore controls for spillover effects from the sovereign to the corporate bond market via state-owned enterprises.[41]

[40] I refrain from using a log-transformation as used by Gilchrist and Zakrajšek (2012) since it reduces the sample size as negative OAS values are excluded. Moreover, estimating the spread model in levels lends itself to a natural interpretation of the relevant factor loadings.

[41] This provides an additional backstop to the GIV which removes common sovereign exposure that is captured by η_t.

Table 3: Credit spread decomposition: extracting idiosyncratic shocks to credit spreads

	(1) Est.	SE	(2) Est.	SE
$\text{EDF}_{j,t}$	72.014***	9.817	48.810***	9.795
$\text{Duration}_{j,t}[k]$	-3.139	3.147	0.161	3.107
$\text{Coupon}_{j}[k]$	62.099***	14.138	50.867***	15.257
$\text{Age}_{j,t}[k]$	-0.190***	0.063	-0.198***	0.068
$\text{Volume}_{j}[k]$	-28.698*	15.930	11.295	19.669
$\text{CALL}_{j}[k]$	134.326***	28.429	256.717***	83.603
VIX_{t}	6.882***	1.476	6.842***	1.658
UST10Y_{t}	-87.075***	16.939	-55.421***	16.565
$\text{Government-Related}_{j}$	-101.081	73.469	-108.121*	58.591
$\text{EDF}_{j,t}$ x $\text{CALL}_{j}[k]$			49.123**	19.705
$\text{Duration}_{j,t}[k]$ x $\text{CALL}_{j}[k]$			-14.559**	5.341
$\text{Coupon}_{j}[k]$ x $\text{CALL}_{j}[k]$			7.193	16.705
$\text{Age}_{j,t}[k]$ x $\text{CALL}_{j}[k]$			0.299	0.310
$\text{Volume}_{j}[k]$ x $\text{CALL}_{j}[k]$			-186.343***	36.660
VIX_{t} x $\text{CALL}_{j}[k]$			1.948	1.690
UST10Y_{t} x $\text{CALL}_{j}[k]$			-68.304***	18.307
Country & Industry FE	YES		YES	
Observations	550,394		550,394	
Adjusted R^2	0.375		0.407	

Note: This table reports the baseline results of the corporate spread decomposition in (6). The sample period covers 2000/01/07 – 2020/11/27. The dependent variable is the option-adjusted spread (OAS). Standard errors are clustered in the country, industry, firm, and time dimension following Cameron et al. (2011). Daily expected default frequencies (EDFs) at the 1-year horizon are converted into weekly averages. The indicator variable $CALL_j[k]$ is one for bonds with any type of underlying call option. The VIX_t is the CBOE volatility index. The $USD10Y_t$ is the 10-year US Treasury yield. Industry fixed effects are based on the BICS industry level 1 classification system. The country subscript c is suppressed to preserve space.

The baseline results presented in column (1) of Table 3 indicate that both bond- and firm-specific factors as well as global risk affect spreads both in terms of magnitude and significance of the estimated coefficients. Consider an increase in the probability of default of an average firm by one percentage point, e.g. an increase in the EDF credit measure from 10 to 11.[42] The estimated coefficient translates into an increase in the OAS by 72 basis points at the margin. As expected, higher expected default risk commands a higher risk premium to compensate for potential default losses. Moreover, corporate spreads significantly increase when global risk rises, i.e. when the VIX increases, and when US Treasury yields fall.

In a separate robustness check (not reported), I also account for the possible impact

[42] Moody's computes the EDF measure as a daily series which I aggregate to a weekly frequency. While the main inputs of the EDF model are quarterly balance sheet metrics – notably leverage – the key high-frequency component entering the EDF calculation is asset volatility. In a separate robustness check (not reported), I therefore include firms' equity volatility $EVOL_{j,t}$ as a regressor. The results remain unchanged, suggesting that the EDF carries information about the probability of default of a firm beyond the volatility in its equity returns. This corroborates the idea that the EDF serves as a sufficient statistic for a firm's solvency.

of oil price shocks on oil-exporting EMEs in the sample.[43] I therefore control for the spot oil price and the expected oil prices as measured by the 12-month Brent Crude Oil futures price, respectively. Neither of them comes out as economically and statistically significant, nor do they change the baseline results. Note also that government-related firms appear to pay a significantly lower credit spread by virtue of e.g. ringfencing or implicit or explicit guarantees by the state. While this finding is not statistically significant, it does not alleviate our initial concern about confounding effects and potential endogeneity due to the corporate-sovereign nexus. It still commands greater rigor with respect to the robustness of the GIV as outlined in Section 7.

What is the role of optionality in the underlying bond? The OAS, by definition, controls for the impact of the option to redeem the bond early on the riskiness of the bond to the bondholder. As such, OAS should correctly adjust for the cost of callable bonds being more sensitive to interest rate changes and the benefits of being less sensitive to default risk. Nevertheless, optionality may carry certain latent attributes that affect the desirability of holding callable bonds (Duffee, 1998; Gilchrist & Zakrajšek, 2012). To ensure that such features do not drive the results, I interact the regressors with the $CALL_j[k]$ variable. Augmenting the baseline model by these interaction terms changes the magnitude of coefficients but does not significantly affect the direction and significance of the coefficients of interest in column (2) of Table 3. Callable bonds do demand a significantly higher credit spread at the margin, yet they do not significantly weaken the power of expected default risk of a firm in explaining observed credit risk. In addition, callable bonds are significantly more sensitive to interest rate changes as suggested by the interaction with the bond's duration and the US yield curve.

Given the richness of risk factors that the spread model in (6) controls for, it is important to ensure that the remaining variation, i.e. the idiosyncratic shocks $\hat{u}_{j,c,t}[k]$, account for sufficient variation in credit spreads. If the bond-, firm- and country-level risk factors already absorbed most of the variation in spreads, the shocks $\hat{u}_{j,c,t}[k]$ would likely suffer from lack of relevance in explaining spreads, thus invalidating the GIV. Table 4 presents the variance decomposition of credit spreads based on the baseline specification in column (1) of Table 3. While default risk as captured by the $EDF_{j,c,t}$ takes up the largest share of almost 20% of the variance, the bulk of variation in spreads of around 70% is still left unexplained. This unexplained variation is arguably idiosyncratic firm risk captured by $\hat{u}_{j,c,t}[k]$. Interestingly, global risk as captured by the VIX_t and $UST10Y_t$ account for only a small fraction of 2.7% of variation in spreads. This finding stands in stark contrast to evidence in the literature that attributes a strong role to global factors in affecting asset prices around the world (Miranda-Agrippino & Rey, 2020).[44]

For comparison, the variance decomposition for the sample of EMEs is juxtaposed with the variance decomposition of an equivalent spread model applied to US corporate bonds by Chitu et al. (2022) that follows the established methodology of Gilchrist and Zakrajšek (2012). The statistics are broadly in line with those for the US. This provides reassurance that the spread model in (6) is an adequate representation of systematic risk factors that explain credit spreads.

[43] Recent evidence by Miranda-Agrippino and Rey (2022) suggests that two global factors drive about a third of the variation in gross capital flows and that the second of these global factors in capital flows is highly correlated with oil prices.

[44] One may wonder whether the small variance share of global risk in credit spreads in the baseline specification in Table 3 may be attributable to collinearity between the $EDF_{j,c,t}$ and the VIX_t and $UST10Y_t$, respectively. However, the pairwise correlations of default risk with global risk factors at the firm level are only 0.04 and

Table 4: Variance decomposition of corporate spreads

	Variance in %	
	EMEs	US
$\text{EDF}_{j,t}$	19.81	22.69
$\text{Duration}_{j,t}[k]$	0.03	1.55
$\text{Coupon}_{j}[k]$	5.23	8.62
$\text{Age}_{j,t}[k]$	0.30	0.12
$\text{Volume}_{j}[k]$	0.04	0.05
VIX_{t}	0.81	
UST10Y_{t}	1.88	
Country FE	2.13	
Industry FE	0.55	1.27

Note: The first column shows the variance decomposition of the estimated model in (6) for the sample of EM bonds. The second column shows the variance decomposition for an equivalent estimation for a sample of US bonds taken from Chitu et al. (2022). The US estimates are based on a panel of bonds issued by S&P 500 firms spanning 01/2000–05/2021 following the methodology by Gilchrist and Zakrajšek (2012).

6.2 Aggregation

Having obtained the idiosyncratic shocks $\hat{u}_{j,c,t}[k] = s_{j,c,t}[k] - \hat{s}_{j,c,t}[k]$ from estimating the second specification in Table 3, I aggregate the shocks at the firm-level as in (7) to construct the GIV for each country. I compute the GIV, $z_{c,t}$, for country c using the weights defined as $w_{j,c,t} = D_{j,c,t}/\sum_j D_{j,c,t}$. The total nominal bond debt volume, $D_{j,c,t}$, of firm j in country c is set in relation to the total bond debt volume of a given country. The weights are therefore time-varying.[45] The GIV is computed as in (8).

While there exists considerable heterogeneity in credit spreads, and hence firm-level shocks, across countries, it is nevertheless instructive to examine how these shocks behave at the aggregate level. The simple arithmetic average of idiosyncratic shocks of all firms across all countries in the sample is computed as,

$$\hat{U}_t^{EM} = \frac{1}{N_t} \sum_c \sum_j \sum_k \hat{u}_{j,c,t}[k] \tag{11}$$

where N_t is the number of bond-firm-country observations in week t. Figure 5 plots the resulting indicator, $\hat{U}_t^{EM}$, along with the excess bond premium (EBP) found by Gilchrist and Zakrajšek (2012) for the US.[46]

The EBP in EMEs strongly comoves with the EBP estimated by Gilchrist and Zakrajšek

-0.02, respectively. Even at the aggregate country level, the pairwise correlations are only very small at 0.13 and -0.02, respectively.

[45] Gabaix and Koijen (2020) argue that the conditions for the validity of the GIV still hold under the assumption of time-varying, rather than fixed, weights.

[46] To ensure comparability with the baseline model by Gilchrist and Zakrajšek (2012), I run a separate estimation of the spread model in (6) with all variables except the EDF in logs. Then, the idiosyncratic shocks at the

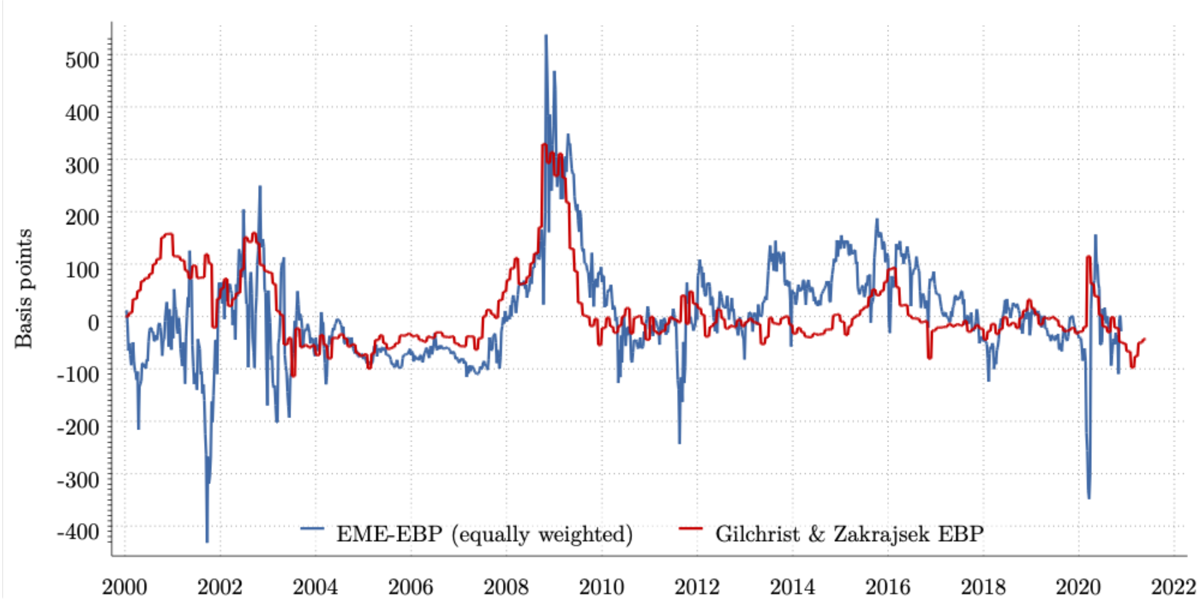


Figure 5: The Excess Bond Premium of Emerging Market Economies and the EBP of Gilchrist and Zakrajšek (2012).

Note: The excess bond premium (EBP) for emerging market economies is computed as the arithmetic average of residuals from the decomposition of the log of option-adjusted credit spreads (OAS) following closely the model in (6) and Gilchrist and Zakrajšek (2012). The EBP is based on an unbalanced panel of 27 EMEs. The EBP estimated by Gilchrist and Zakrajšek (2012) for the US is publicly available via the Federal Reserve. Countries include AE, AR, BR, CL, CN, CO, CZ, DO, HU, ID, IL, IN, KR, KZ, MX, MY, PE, PH, QA, RU, SA, SG, TH, TR, TW, VE, and ZA.

(2012) around major crises episodes. However, the correlation vanishes after the GFC up until the Covid-19 crisis. While the pairwise correlation over the sample period from 01/2000 to 12/2009 is a striking 0.60, it drops to only 0.22 over the period from 01/2010 to 12/2019. This is further underpinned when computing the pairwise correlation over a rolling 10-year window (see Figure 13 in Appendix D). This observation suggests that a common factor, e.g. a global factor, may have driven both the EBP in the US and in EMEs up until the GFC. However, in recent years there seems to have been a disconnect, giving room to other determinants. This finding provides confidence that the firm-specific shocks obtained from the granular spread decomposition are not simply an artefact of the sentiment of global investors that affects both corporate bond markets in advanced and emerging economies.

Gilchrist and Zakrajšek (2012) provide an alternative explanation for the driving force behind variation in the EBP in the US: the effective risk-bearing capacity of financial intermediaries. They find evidence that financial intermediaries' ability to provide funding liquidity may constrain the supply of credit (Brunnermeier & Pedersen, 2009). Both primary dealers, security broker-dealers, and large banks on the sell-side as well as institutional investors such

firm-level are computed by first obtaining the level prediction,

$$\hat{s}_{j,c,t}[k] = \exp\left[\hat{a}_c + \hat{\Lambda}^j EDF_{j,c,t} + \hat{\Lambda}^k \boldsymbol{X}_{j,c,t}[k] + \hat{\Lambda}^g \boldsymbol{G}_t + \hat{\epsilon}_{j,c,t}[k] + \frac{\hat{\sigma}^2}{2}\right]$$

where $\hat{\epsilon}_{j,c,t}[k]$ is the unexplained variation in the *log*-credit spread, $(\hat{\alpha}, \hat{\Lambda}^j, \hat{\Lambda}^k, \hat{\Lambda}^g)$ denote pooled OLS estimates and $\hat{\sigma}^2$ is the estimated error variance. Given the level prediction, we can then compute the level-error term as $\hat{u}_{j,c,t}[k] = s_{j,c,t}[k] - \hat{s}_{j,c,t}[k]$, and aggregate across all bonds.

as large banks, insurance companies, and pension funds on the buy-side may be capital constrained. The high correlation of the US- and EME-EBPs up to and including the GFC suggests that liquidity frictions of financial intermediaries may account for variation in the EME-EBP. Yet, the lack of correlation between the two EBPs over the second half of the sample period sheds doubt on US-based financial intermediaries being the primary driver. Structural shifts in the global architecture of global banks and institutional investors (the "pipes" of global capital flows) could pose a further source of variation. Moreover, global commodity cycles and EM firms' exposure to those cycles could play a role. I leave it to future research and data availability to tackle this important yet non-trivial empirical exercise.

6.3 Country-Level Estimation

Equipped with the GIV, I estimate the capital flow model in (10) with two-stage least squares, instrumenting the aggregate corporate spread by the GIV. The dependent variable is the EPFR bond portfolio flow measure (in millions) resulting from changes in funds' country allocations. The estimation period is restricted to January 2004 to November 2020 because the earliest available data for bond fund flows starts in 2004. Using EPFR flows further restricts the estimation sample to 16 countries. I include a set of controls that are assumed to affect the flow of capital into and out of an economy.[47] The monetary policy rate $MPR_{c,t}$ and the 10-year government bond yield $GOV10Y_{c,t}$ of a given country form the block of higher-frequency domestic "pull factors" that, along with the corporate spread, affect the attractiveness of investing in the domestic economy in the short- and medium-term. The VIX_t and $UST10Y_t$ form the block of global "push factors" that act as a summary statistic for global risk. Finally, I also include country fixed effects.

Table 5 presents two sets of results. The first column contains the estimated coefficients of a fixed effects panel regression estimated with OLS. The second column contains the second-stage results of the model in (10) estimated with the credit spread, $\hat{S}_{c,t}$, as instrumented by the GIV, $z_{c,t}$. In the OLS regression, global factors clearly dominate. Rising global market volatility, i.e. risk aversion, and rising US yields result in net capital outflows. Domestic factors have virtually no significant impact, neither positive nor negative, on capital flows. This finding is in line with the literature on push factors that attribute a dominant role to global risk (Akinci, 2013; Bruno & Shin, 2015; Forbes & Warnock, 2012; Fratzscher, 2012; Ghosh et al., 2014; Miranda-Agrippino & Rey, 2020).

However, once the corporate credit spread is instrumented using the GIV, there is a significant positive response of portfolio flows to a widening of credit spreads. The direction of the effect suggests that credit risk has an attracting effect on capital from abroad. Not only does the GIV enter the first stage regression with a highly statistically significant coefficient, but also the F-statistic and χ^s-statistic of the Sanderson and Windmeijer (2016) first-stage F-tests for weak instruments and underidentification, respectively, are very high. They indicate that the GIV does not suffer from instrument weakness. Interestingly, US monetary policy seems to lose its clout on capital flows once the credit spread measure is instrumented. Since I control for the 10-year US yield in the previous step, this should not be driven by the correlation between credit spreads and US yields.[48]

[47] The chosen set of controls is limited by the availability of long high-frequency time series for the large sample of countries at hand.

[48] Caution is in place not to make any statements about which factors are the most powerful in affecting capital

Table 5: The effect of credit spreads instrumented by the GIV on bond portfolio flows

	(1) OLS		(2) IV	
	Est.	SE	Est.	SE
$S_{c,t}$	-0.003	0.003	0.039***	0.015
$MPR_{c,t}$	-0.005	0.007	-0.000	0.007
$GOV10Y_{c,t}$	-0.006	0.012	-0.030**	0.015
VIX_t	-0.224***	0.040	-0.246***	0.041
$UST10Y_t$	-0.070***	0.008	-0.026	0.016
Country FE	YES		YES	
Observations	9,569		9,569	
Adj. R^2	0.049		0.030	
F-Statistic			371.290	
χ^2 Statistic			372.185	

Note: The first column reports the results of a regression of the EPFR bond portfolio flow measure onto the option-adjusted spread $S_{c,t}$ of country c, the monetary policy rate $MPR_{c,t}$, the 10-year sovereign yield $GOV10Y_{c,t}$, the CBOE volatility index VIX_t, and the 10-Year US Treasury yield $UST10Y_t$, estimated with OLS. The second column reports the second-stage results of this specification whereby the credit spread $S_{c,t}$ is instrumented by the GIV, $z_{c,t}$. The unbalanced country panel model is estimated with country fixed effects and an indicator for the GFC and the Covid-19 crisis (not reported). Standard errors are robust with respect to serial correlation and cross-dependence. The table reports the F-statistic and χ^2-statistic of the Sanderson and Windmeijer (2016) first-stage F-test for weak instruments and underidentification, respectively.

What may explain the downward bias in the OLS estimate? The coefficient on the credit spread $S_{c,t}$ switches from being insignificant and negative (but close to zero) in the OLS regression to being significant and positive in the instrumented regression. The downward bias in the OLS estimate likely results from the positive correlation between credit spreads and global risk factors during downturns. Specifically, global risk-off episodes are characterized by spikes in the VIX and in credit spreads as well as capital outflows. This dominating effect pushes the OLS estimate into negative territory when leaving the spread $S_{c,t}$ uninstrumented. The fact that the OLS coefficient on $S_{c,t}$ is close to zero is precisely an indication that there may be asymmetric forces of the widening and tightening of spreads on inflows and outflows at play that, when not instrumented, net each other out. Absent a valid exogenous instrument, global factors therefore dominate.

One may argue that the GIV does not only affect capital flows through credit spreads but also through the stance of monetary policy or through sovereign yields. Such a relationship would violate the exclusion restriction and turn the instrument invalid. This could potentially also explain why the OLS estimates of $MPR_{c,t}$ and $GOV10Y_{c,t}$ are both insignificant. I argue that the effect of the GIV via the monetary policy stance of a country can be ruled out on the grounds of the high frequency nature of this analysis. Because monetary policy makers meet infrequently, monetary policy is sluggish to react to shocks emanating from the corporate sector or shocks affecting credit risk in capital markets within a one-week window. Moreover, to the extent that the spread decomposition in model (6) already controls for spillovers from

movements. Instead, the results indicate that domestic factors matter even *after* controlling for global push factors.

sovereign bond markets onto state-owned enterprises, a possible effect of the GIV on sovereign yields should not be a cause for concern.

Notably, the direction of the effect of $\hat{S}_{c,t}$ on $F_{c,t}$ is positive. A widening of corporate spreads hence leads to net capital inflows, all else equal. This finding supports the idea that a higher level of credit risk (in good times) attracts capital from international investors in search for yield. Yet, taken symmetrically, it cannot be reconciled with the hypothesis that countries experience net capital outflows when credit risk rises to precariously high levels. Such a reversal could for example occur when firms face difficulties meeting financial obligations because the foreign currency value of their liabilities cannot be covered by the value of cash flows and liquidatable assets. Absent granular data on gross capital flows, it is not possible to disentangle the contribution of capital inflows vs. outflows to this effect.

To shed light on the possible *reversal* of capital flows in response to a widening of spreads, I augment the baseline model by interacting the spread with an indicator for large currency depreciations. The idea is that default risk, when exacerbated by rising currency mismatch, induces international investors to reprice risks in domestic bond markets and to retract. Because exchange rate movements are endogenous to capital flows, it is problematic to include the percentage change in the exchange rate as a regressor. Instead, let $\mathbb{1}_{c,t}^{FX}$ be an indicator that takes the value of one if the bilateral real effective exchange rate is more than two standard deviations higher than the mean exchange rate at a given point in time. Both the standard deviation and mean are computed over a 2-year rolling window.

Reiterating (9)-(10), the augmented model takes the following first and second stage form,

$$\begin{aligned} S_{c,t} &= \gamma^s z_{c,t} + \beta^s X_{c,t} + \nu_{c,t}^s \\ S_{c,t} \times \mathbb{1}_{c,t}^{FX} &= \gamma^i z_{c,t} \times \mathbb{1}_{c,t}^{FX} + \beta^i X_{c,t} + \nu_{c,t}^i \end{aligned} \tag{12}$$

where the spread $S_{c,t}$ and the spread interaction term $S_{c,t} \times \mathbb{1}_{c,t}^{FX}$ are both instrumented in the first stage. The second stage is then given by,

$$F_{c,t} = \alpha^s \hat{S}_{c,t} + \alpha^i \hat{S}_{c,t} \times \mathbb{1}_{c,t}^{FX} + \alpha^f \mathbb{1}_{c,t}^{FX} + \beta X_{c,t} + \epsilon_{c,t} \tag{13}$$

Table 6 presents the results of this augmented specification for both the OLS and the instrumented estimation. The estimates on the instrumented interaction term suggest that a widening of credit spreads still attracts net capital inflows, potentially even during periods of high currency mismatch. However, during episodes of large real currency depreciations, net capital flows tend to fall. This contractionary effect on capital flows is similar in magnitude to the expansionary effect on the level of the spread, $S_{c,t}$. The indicator variable for real FX depreciations is only modestly significant and positive. A positive effect of real FX depreciations on net capital flows could point towards the trade channel of external adjustment. When a country's currency depreciates in real terms, the effect stimulates expected exports. Greater expected opportunities for growth may in turn attract capital. However, this evidence is rather tentative and the following exercises show that it partly lacks robustness.

The results of the model with asymmetric effects also shed light on the previous suspicion that the close to nil estimate in the baseline OLS specification in Table 5 may result

Table 6: Asymmetries in the effect of credit spreads on bond portfolio flows during large real exchange rate depreciations

	(1) OLS		(2) IV	
	Est.	SE	Est.	SE
$S_{c,t}$	-0.002	0.003	0.044**	0.017
$S_{c,t}$ x $\mathbb{1}^{FX}_{c,t}$	0.024**	0.012	-0.041**	0.020
$\mathbb{1}^{FX}_{c,t}$	-3.785	6.817	16.317*	9.027
$\text{MPR}_{c,t}$	0.001	0.007	0.001	0.007
$\text{GOV10Y}_{c,t}$	-0.024**	0.012	-0.036***	0.013
VIX_t	-0.231***	0.041	-0.251***	0.043
US10Y_t	-4.147***	0.680	-1.856*	1.013
Country FE	YES		YES	
Observations	9,569		9,569	
Adj. R^2	0.049		0.026	
F-Statistic			310.996	
χ^2 Statistic			311.811	

Note: The first column reports the results of a regression of the EPFR bond portfolio flow measure onto the option-adjusted spread $S_{c,t}$ of country c interacted with an indicator variable for large currency depreciations, $\mathbb{1}^{FX}_{c,t}$, as well as the monetary policy rate $MPR_{c,t}$, the 10-year sovereign yield $GOV10Y_{c,t}$, the CBOE volatility index VIX_t, and the 10-Year US Treasury yield $UST10Y_t$, estimated with OLS. The second column reports the second-stage results of this specification whereby the credit spread $S_{c,t}$ and its interaction term are instrumented by the GIV, $z_{c,t}$. The indicator variable for large currency depreciations is defined by the bilateral effective FX rate based on the consumer price index. The unbalanced country panel model is estimated with country fixed effects and an indicator for the GFC and the Covid-19 crisis (not reported). Standard errors are robust with respect to serial correlation and cross-dependence. The table reports the F-statistic and χ^2-statistic of the Sanderson and Windmeijer (2016) first-stage F-test for weak instruments and underidentification, respectively.

from widening and tightening of spreads just cancelling each other out. This is corroborated through the interaction terms with the indicator variable for large currency depreciations. The coefficient on $S_{c,t}$ rises from 0.039 in column (2) of Table 5 to 0.044 in the GIV regression in column (2) of Table 6. This suggests that previously the effect was muted when not allowing for asymmetries.

Overall, the results make a strong case for domestic credit risk acting as a "pull factor" on international capital. They substantiate the claim that domestic credit risk can have a *causal* effect on capital flows above and beyond the driving forces of the Global Financial Cycle and global risks. The results also yield some suggestive evidence on the role of heightened credit risk as a repelling factor of international capital.

6.4 Dynamic Responses to Credit Risk

Having established a causal link between credit risk and capital flows, it is instructive to examine how the system given by (9) and (10) behaves in response to shocks to aggregate credit risk.[49] Even more so, the wider implications for the real economy need to be examined. To that end, I formulate a dynamic model using Jordà (2005)'s local projection method with instrumental variables in a panel context (panel IV-LP) (Jordà et al., 2015).[50]

Local projections have two advantages in the context of my analysis. First, they can accommodate potential non-linearities arising from the asymmetric effect of credit risk shocks on capital flows. For example, local projections can account for different time-varying states of *tightening versus widening* of credit spreads or capital *surges versus retrenchment* reminiscent of risk-on and risk-off episodes. Second and more generally, local projections are parametrically less intensive and less prone to model misspecification than standard VAR techniques. They impose little structure on the data generating process.

Mendoza (2010) and Bianchi (2011) suggest that the build-up of leverage during expansions is at the heart of capital flow reversals that occur in high-leverage states. I am therefore interested in the *cumulative* response of capital flows to the *build-up* of credit risk over a horizon from t to $t+h$. Let $\sum_{j=0}^{h} y_{c,t+j}$ denote the sum of the outcome variable of interest from t to $t+h$. The panel IV-LP method is a series of panel regressions for each horizon h,

$$\sum_{j=0}^{h} y_{c,t+j} = \beta_h \sum_{j=0}^{h} \hat{S}_{c,t+j} + \phi_{c,h}(L)\boldsymbol{X}_{c,t-1} + \epsilon_{c,t+h} \qquad \text{for} \quad h = 0, ..., H \tag{14}$$

where $\hat{S}_{c,t}$ denotes cumulative credit risk, $\boldsymbol{X}_{c,t}$ is a vector of control variables that includes country fixed effects, and $\phi_{c,h}(L)$ denotes its polynomial lag operator. The coefficient β_h carries the interpretation of a multiplier along the lines of Ramey and Zubairy (2018) and leaning on the financial accelerator literature (Bernanke et al., 1999; Mendoza, 2010). In addition to its intuitive interpretation, one advantage of this specification is that it allows me to estimate the standard errors for the cumulative responses directly. This would not be possible if specified in levels (Ramey & Zubairy, 2018). The error term $\epsilon_{c,t+h}$ is known to suffer from serial correlation following successive leading of the dependent variable. Moreover, cross-panel correlation between countries cannot be ruled out. I therefore adjust standard errors such that they are robust to serial correlation and cross-panel heteroskedasticity (Driscoll & Kraay, 1998).

As before, the cumulative measure of credit risk is likely to suffer from endogeneity with respect to capital flows. By design, the local projections method is intended to provide a partial remedy to the problem of endogeneity. This is because the cumulative credit risk measures as well as the controls are pre-determined in the specification and should hence not be endogenous to future cumulative capital flows. This approach in itself however does not allow us to make *causal* statements. To identify the credit risk shock, I therefore instrument the cumulative credit spread $S_{c,t+j}$ by the GIV, $z_{c,t}$, through a first-stage panel regression,[51]

[49] I leave it to future research to augment the existing system by an additional structural relationship between capital flows, credit risk, and exchange rates to capture the full feedback loop.

[50] Alternatively, one can estimate a standard (panel) VAR model with a recursive ordering of financial and macroeconomic variables (Caballero et al., 2019; Gilchrist & Zakrajšek, 2012).

[51] While the cumulative credit spread does not have a natural interpretation of an accumulating stock variable, I interpret it as the sum of risk premia, and hence the build-up of risk over time.

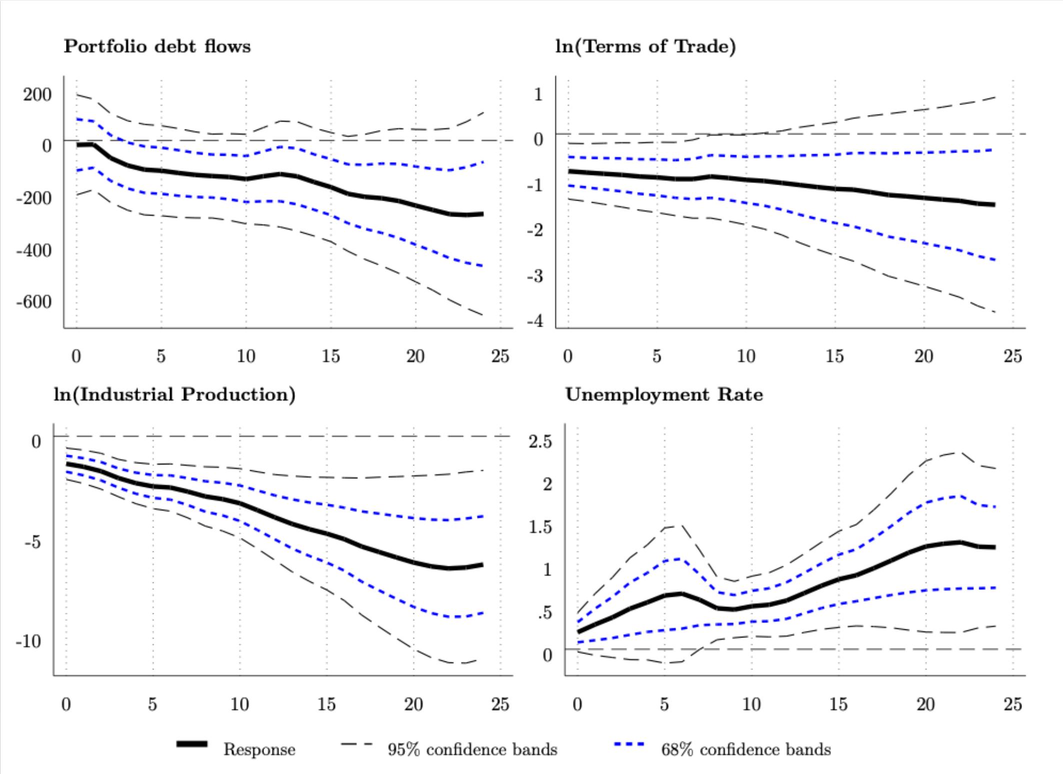


Figure 6: Impulse responses with respect to a credit risk shock

Note: The four panels show the impulse responses with respect to a 100 basis point increase in the average country-level option-adjusted credit spread in an unbalanced panel of countries. The impulse responses are estimated using a panel local projections framework whereby the credit spread is instrumented by the granular instrumental variable (GIV). Standard errors are robust with respect to serial correlation and cross-dependence. Portfolio debt flows are measured in millions and converted to reflect end-of-month changes. The monthly terms of trade and industrial production indices are measured in logs. The monthly unemployment rate is measured in percentage points. The x-axis indicates months after the shock.

$$\sum_{j=0}^{h} S_{c,t+j} = \gamma_{c,h} z_{c,t} + \phi_{c,h}(L)\boldsymbol{X}_{c,t} + \nu_{c,t+h} \tag{15}$$

which again includes a vector of control variables that also contains country fixed effects. The fitted spread $\hat{S}_{c,t}$ is then used in the second stage panel IV-LP in (14). I thus extract exogenous variation in credit spreads that can build up over time to act upon macroeconomic outcomes.

To exploit the full sample length, I use the monthly measure of net debt portfolio flows by the IIF rather than the weekly measure of net bond market portfolio flows by EPFR for this exercise. The IIF series starts as early as January 2000 for some countries while the EPFR measure starts only in 2004. Besides looking at the dynamic response of capital flows, I also estimate the panel IV-LP model in (14) for the terms of trade of a country, industrial production in the manufacturing sector, and the unemployment rate as measures of real economic activity. I limit my attention to these variables as they are available at monthly frequency for at least 14 (and up to 30) countries. The vector of controls $X_{c,t}$ comprises up to three lags of the domestic monetary policy rate, the domestic stock market index, the VIX, and the 2-year US Treasury yield.

Figure 6 presents the cumulative impulse responses of the key macroeconomic variables to a 100 basis point shock to the credit risk build-up in the average country-level OAS over a two-year horizon. Portfolio debt flows contract upon impact. The terms of trade – the ratio between the country's export prices and import prices – deteriorate so that a unit of exported goods can purchase less units of imported goods. This likely makes the economy more competitive in terms of exports but impinges on households' purchasing power with respect to imported goods, and hence overall consumption. Industrial production falls upon impact while the unemployment rate rises by 0.75 percentage points over the first 6 months. The results suggest that the prolonged build-up of financial imbalances in the non-financial corporate sector can unleash powerful and adverse dynamics for the real economy as argued by Mendoza (2010) and Bianchi (2011).

There may be concern that while the GIV proved to be a valid instrument for credit risk in the static analysis of capital flows, it may not be a valid instrument to identify the impact of credit risk onto the terms of trade and economic activity. Two points alleviate these concerns. First, additional tests on the first stage of the panel IV-LP regressions suggest that the GIV does not suffer from instrument weakness and is a significant explanatory variable also of the *cumulative* credit risk premium. Second, credit spreads are an arguably faster-moving variable than real economic activity. Their higher-frequency nature is also exploited in the causal orderings of VAR frameworks. It is therefore unlikely that, for example, high unemployment would cause a prolonged build-up of leverage and credit risk in the economy. If anything, the results suggest that the reverse is happening.

Nevertheless, future work should address – through additional higher-frequency data of real activity – whether there are other channels that may play a role. In addition, future research should investigate how the results may depend on the interplay between the state of the domestic vs. the state of the global economy. This could for example be evaluated along the lines of domestic tightening vs. widening of (i) credit, (ii) capital controls, or (iii) exchange rate conditions, as well as global risk-on and risk-off episodes. The latter case may prove an instructive laboratory to evaluate whether domestic effects of credit risk dissipate once the Global Financial Cycle comes to dominate.

7 Robustness and Discussion

The validity of the GIV relies on a number of strong assumptions. In an emerging market setting with many confounding factors at play, it is important to carefully examine both *instrument relevance* and *instrument exogeneity.* This section outlines some of the robust features of the results and proposes possibilities to strengthen the results which are left to future research.

Instrument relevance. Ideally, the GIV should be able to explain a large share of variation in aggregate credit risk such that $E[z_{c,t}S_{c,t}] \neq 0$. That is, it needs to be *relevant* in the data generating process underlying credit spreads. As the previous section outlines, first-stage estimates of the effect of the GIV onto credit spreads are highly significant, even after controlling for other exogenous regressors.[52] Additional tests indicate that the GIV does not suffer from instrument weakness. Moreover, the exogenous regressors – the monetary policy rate, the VIX,

[52] Since the spread decomposition separates variation in global risk factors from idiosyncratic shocks, the GIV should be exogenous to the regressors included in (10).

and the 10-Year US Treasury yield – should be truly exogenous with respect to the dependent variable. This is likely to hold true. The only cause for concern pertains to the endogenous relationship between capital flows and domestic sovereign risk. Irrespective of this relationship, the GIV should be exogenous with respect to sovereign yields. Constructing the GIV as the difference between share-weighted and equally-weighted firm shocks removes common factors – such as sovereign risk – that affect all firms alike. Moreover, the spread decomposition controls for state-ownership, thereby capturing spillovers from sovereign into corporate bond markets.

Instrument exogeneity. It is pivotal that the idiosyncratic shocks extracted in the spread model in (6) truly represent unexplained firm-specific variation in credit risk. The idiosyncratic shocks $u_{j,c,t}[k]$ must be orthogonal to the common shock $\eta_{c,t}$ and the aggregate shock $\epsilon_{c,t}$ that affects country c. If there was a reason to believe that $E[u_{j,c,t}[k]\,\eta_{c,t}] \neq 0$ or $E[u_{j,c,t}[k]\epsilon_{c,t}] \neq 0$, then the resulting GIV would be invalid. That is, the exogeneity condition would be violated. Gabaix and Koijen (2020) propose PCA on credit spreads at the bond-level as a possible way to improve the soundness of the exogeneity assumption. PCA may be a superior method in that it ensures that results are not driven by the structure imposed on credit spreads in (6), but the unbalanced panel in this analysis does not lend itself to PCA.

In the absence of PCA as a viable option, explicitly decomposing spreads is the second best approach to accounting for *systematic* sources of risk. I argue that the unexplained variation $\hat{u}_{j,c,t}[k]$ obtained from estimating the spread model in (6) indeed represents idiosyncratic, firm-specific risk. First, the liquidity risk premium arising from holding bonds is partly accounted for by using the option-adjusted spread in excess of US Treasury yields that are matched to each individual cash flow. Moreover, I only select bonds in my sample that are liquidly traded in international bond markets for the price to reveal sufficient information about the underlying risk of the security. Second, including the bond's duration as an explanatory variable controls for interest rate risk that arises when changes in interest rates change the value of the underlying coupon cash flows to investors. Third, I control for a firm's fundamental risk by including the EDF measure in the model. The EDF measure also picks up fundamental aggregate risk in the domestic economy as well as a country's growth prospects more generally through investors' valuation of expected cash flows. Fourth, I include industry and country fixed effects to account for any systematic sectoral and geographic variation. Fifth, the analysis is stripped of confounding effects of exchange rate risks since only USD-denominated bonds trading in international debt markets are selected. Arguably, this alleviates concerns about currency mismatch on international investors' balance sheets.[53] Finally, I control for global risk and global sentiment through leading indicators which the literature has found to adequately capture the Global Financial Cycle. Any remaining variation in corporate spreads must therefore capture risks that are non-systematic and specific to an individual firm.

Exclusion restriction. On a more subtle level, the validity of the exogeneity condition $E[z_{c,t}\,\epsilon_{c,t}] = 0$ relies on the question of whether the exclusion restriction $E[u_{j,c,t}[k]\,\epsilon_{c,t}] = 0$ holds. Is it reasonable to assume that idiosyncratic shocks to credit spreads affect capital flows, $F_{c,t}$, only through changes in aggregate credit risk, $S_{c,t}$, and are hence orthogonal to unobserved aggregate shocks $\epsilon_{c,t}$?[54] In other words, conditional on being exogenous with respect to both credit spreads and capital flows, does the effect of the GIV truly transmit via credit risk instead

[53] Due to a lack of granular data on the currency mismatch on corporate balance sheets, exchange rate risk premia arising from investors pricing in the currency mismatch of their investment cannot be captured.

[54] That is, the only reason why the GIV $z_{c,t}$ is correlated with $F_{c,t}$ is through the correlation between $z_{c,t}$ and $S_{c,t}$, i.e. $z_{c,t}$ has no independent effect on $F_{c,t}$.

of affecting capital flows directly? For example, the GIV as a summary statistic of weighted shocks to large firms could attract or repel capital from abroad because shocks to these firms may signal greater growth prospects to international investors. The question is whether this effect could materialize in the absence of any impact on observed credit spreads.

I propose two arguments to rule out a direct effect of the GIV onto capital flows. First, even in a scenario in which only a handful of large firms experience shocks, it is unlikely that the average international investor would observe these shocks precisely and make an explicit change to their asset allocation. ETFs and passive funds that only track a corporate spread index (e.g. the CEMBI) make up an ever growing share of the global fund industry. These funds do not make discretionary decisions but rather passively react to movements in the observed aggregated credit spread. Second, if not prices in financial markets were to reveal a change in a borrower's credit risk, then international investors would need to receive this information from a different source. For this to be possible, firm-specific news shocks would need to accumulate as private information to induce investors to change their capital allocation. Provided that financial markets are efficient, this is unlikely to happen. If anything, the rapid information transmissions of such news shocks would occur via financial markets and hence be reflected in observable credit risk measures.

Firm-level heterogeneity. Identification via GIV assumes existence of substantial heterogeneity across the size distribution of firms. If the size distribution is not sufficiently fat-tailed within a given country, the instrument will be invalid. As discussed in Section 3, Figure 3 suggests that heterogeneity obtains in the *sample* of non-financial firms when firm size is measured by both market capitalization and total assets. To underline that this observation is robust, additional data that spans the *population* of firms in the panel of countries could be used. That is, international bond issuers should be sufficiently "granular" also with respect to large bond issuers in local-currency markets and financial firms. This could be verified with balance sheet data with more comprehensive coverage e.g. from ORBIS.

An additional milder requirement is placed on the heterogeneity in the distribution of idiosyncratic shocks to corporate borrowers. If these shocks do not exhibit sufficient variation within a given country, the instrument will be weak. Considering the large size of my sample and the heterogeneity of industries across firms and countries, a sufficient level of heterogeneity in shocks is likely warranted. As verified in Figure 4, credit spreads are considerably heterogeneous across the size distribution of firms.

Time-varying weights in the GIV. The firm-specific weights $w_{j,c,t}$ used to compute the GIV are at the heart of the identification strategy. While the wrong set of weights does not invalidate the instrument, it does result in biased OLS estimates (Gabaix & Koijen, 2020). However, one threat to identification could stem from the weights being endogenous to the aggregate shock $\epsilon_{c,t}$. One way to mitigate, albeit not remedy, this issue is to lag the weights as in (8). Moreover, using weights based on different definitions of firm size could further strengthen the results. Thus, one could construct weights based on e.g. relative market capitalization, total book value of assets, or sales shares subject to comprehensive data availability.

The most promising, yet also hard to obtain, weights are index weights used in the construction of the CEMBI index commercialized by JP Morgan. The CEMBI index is a leading corporate bond index which serves as an important benchmark for mutual funds and other global investors. Using CEMBI index weights on bonds has two salient benefits. First, the spread between the country-specific CEMBI and the 10-year US Treasury yield is one of the most universally tracked high-frequency measures of *aggregate* corporate credit risk in EMEs. The weights on individual bonds included in the index therefore come closest to a measure of the relative share of a given issuer's credit risk in aggregate credit risk. Second, using CEMBI index weights would alleviate the concern in the GIV specification that company weights may be endogenous. Since the inclusion of bonds into the index is at the discretion of JP Morgan and since they generally lack transparency about index construction, their index weights are unlikely to correlate with unobserved idiosyncratic firm shocks that the spread model in (6) does not already account for. On the downside, using CEMBI weights would limit the sample to only a subset of bonds, firms, and hence countries as only bonds of a certain size ($\geq$ USD 500 million) are eligible for inclusion in the index.

Robustness of the credit spread measure. What if the aggregate OAS does not capture the key observable to which investors react? While OAS is a suitable measure to homogenize corporate spreads across various bond characteristics, it is model-based and hence suffers from potential shortcomings in the underlying model. To ensure that the results are free from model-bias, I run the baseline specification with the Z-spread (zero-volatility spread) as the dependent variable. The Z-spread is computed by discounting each dated cashflow on a bond by the US Treasury spot yield curve at each point of maturity. This comes closest to Gilchrist and Zakrajšek (2012)'s spread measure which is purged of "duration mismatch", except that they use the estimated yield curve of Gürkaynak et al. (2007) rather than the spot yield curve. Table E.1 in Appendix E repeats the results of Table 3 with the Z-spread as the dependent variable, albeit with fewer observations due to limited data availability.

The baseline results remain robust with respect to the choice of dependent variable. The measure of a firm's likelihood of default, the $EDF_{j,t}$, remains a significant explanatory variable of the credit spread, with the magnitude of the coefficient increasing in size. The effect however disappears when interacting $EDF_{j,t}$ with an indicator for callable bonds, $CALL_j[k]$. Note that the Z-spread does not account for any options embedded in the bond and hence may be a flawed measure of the underlying riskiness of the bond, hence diluting the effect of the $EDF_{j,t}$. This finding strengthens the case for using the OAS as the baseline measure of credit spreads in my analysis. Moreover, since the Z-spread is only scantly available, the sample size drops from 550,394 to 85,973 bond-week observations. It is for these reasons that the Z-spread can be ruled out as a reliable alternative to the OAS.

Spillovers from sovereign risk. Approximately half of all bonds in the sample are issued by government-related firms. Of these bonds, about 80% are issued by firms of which the ultimate owner is the government but which do not enjoy any explicit government guarantees for debt (see Figure 12 in Appendix A). This observation inevitably attributes greater relevance to the role of state-ownership as a potential confounder. State-ownership may lead to both spillovers from sovereign into corporate debt markets (Broner et al., 2021) and spillovers from corporate into sovereign debt markets (Kwak, 2021). The results of the baseline spread decomposition in Table 3 do not confer a significant role of government-related firms in driving a wedge in borrowing costs. Yet, it may be the case that sovereign risk only latently transmits via time-varying spillovers from sovereign bond markets.

To control for sovereign risk spillovers, I repeat the spread decomposition in (6) by interacting the indicator variable with a country's JP Morgan Emerging Market Bond Index, $EMBI_{c,t}$ x Gov-Related$_j$ (see Table E.2 in Appendix E). Neither do the interaction term and the individual variables $EMBI_{c,t}$ and Gov-Related$_j$ turn out significant, nor do they significantly affect the other estimates. Repeating the same test with the 10-year government yield Gov10Y$_{c,t}$ as a measure of sovereign risk – albeit with a smaller sample size due to limited data availability – yields similarly robust results.[55]

The insignificance of sovereign risk indicators and government-related firms is somewhat surprising, considering that previous studies have found significant spillovers across the corporate-sovereign nexus. It is worth noting that the corporate spread used in this analysis is the spread over the US risk-free rate, not the spread over the local government yield. As an additional robustness check, one may construct local credit spreads relative to domestic sovereign risk. However, given the requirements on the data to construct maturity-matched option-adjusted spreads from the bottom up, I leave this endeavor to future research.

Even if confounding effects from sovereign risk still persisted in the supposedly idiosyncratic firm shocks $u_{j,c,t}$ after estimating the spread model in (6), the very step of constructing the GIV in (8) should strip off common exposure to sovereign risk. Sovereign risk would thus be captured by the common shock $\eta_{c,t}$ and differenced out through the GIV. Even if sovereign risk remained as a latent factor, the inclusion of local government yields in the country-level regression model in (9) should provide an additional backstop in accounting for that remaining variation. Hopefully this convinces the reader that the empirical strategy controls for the corporate-sovereign nexus at three separate stages, thus capturing plausibly exogenous variation in corporate credit risk.

Robustness w.r.t sub-samples. To further strengthen the results and uncover potential latent channels at play, future checks should consider different sub-samples of bonds, firms, and countries, respectively. The obvious drawback of these sample splits is that they come at the expense of statistical power when the estimation is run on smaller samples that possibly exlude countries with less bond coverage. Notwithstanding, sub-samples could for example be split by (i) bonds issued onshore and offshore, (ii) bonds excluding those that were privately issued, and (iii) bonds issued by oil and gas-related companies to ensure that none of these issuer characteristics are driving the results. Similarly, different subsets of countries could be considered, in particular those with a fixed versus floating exchange rate. Evidence by Jordà et al. (2019) suggests that changes in global risk appetite induced by US monetary policy transmit more strongly to countries with a fixed exchange rate. The significant results for domestic pull factors obtained in this paper could thus be biased by the large presence of countries with a floating exchange rate in the sample. Additional checks could ensure that there are no distinct effects of domestic credit risk on capital flows for countries with a peg. By the same token, future robustness checks could control for the degree of capital account openness in a given country. The extent to which capital, more precisely portfolio flows, can enter and exit a country freely may be decisive in the asymmetric relationship between corporate credit risk and capital flows. The implicit assumption underlying this paper is that countries selected into the sample generally exhibit open capital accounts. To some extent, such effects should already be subsumed under the country fixed effects, unless they are strongly time-varying.

Gross capital flows. The importance of accounting for gross capital flows as opposed to net capital flows has been stressed by the literature in recent years (Avdjiev et al., 2018; Caballero & Simsek, 2020; Forbes & Warnock, 2012). The portfolio flow measure of EPFR used in the benchmark exercises cannot be obtained on a gross basis. This is because EPFR only observes mutual funds' country allocations and changes in these allocations. These flows do not capture

[55]The disadvantage of using the two proxies for sovereign risk is that both reduce the sample size and thus statistical power.

domestic capital retrenchment by domestic investors. To account for the potential dampening impact of repatriating funds domestically, it would be instructive to employ measures of gross capital flows obtained from the IMF's Balance of Payments Statistics. Importantly, these flows do not only represent portfolio flows but also other items captured in the current account.[56] The main caveat of using IMF data is that it is compiled only at quarterly frequency. I argue that the high frequency nature of data on corporate credit risk and portfolio flows is crucial for identification, as the granular origins of the causal relationship will likely wash out once aggregated to quarterly frequency. Thus, benefits of the identification approach must be weighed against the costs of missing the effects of capital retrenchment. I leave it to future work to explore if there is sufficient information content in credit risk to explain capital flows at quarterly frequency.

Further limitiations. In addition to those already mentioned above, there are several limitations of my analysis. For one, my empirical strategy does not explicitly control for shocks that could induce firms to substitute from bond financing to equity or bank credit, and vice-versa.[57] The scope of my analysis is limited to credit risk emanating from international corporate bond markets only. This is partially addressed by including only non-financial firms in the sample of issuers in order to avoid potential cross-dependencies between banks issuing bonds at the same time as lending to other bond issuers. This also partially decouples the analysis from the financial cycle by shifting the focus to the real economy. Moreover, some of the issuers could be subject to implicit or explicit government guarantees (e.g. by virtue of state ownership). This may lead to spillovers between sovereign and corporate risks. Accounting for government-related entities in the spread decomposition partly controls for such guarantees but does not capture latent, implicit guarantees. In the absence of detailed information on such cross-dependencies, the only possible remedy is to explicitly control for sovereign risk in the IV regression. Future research should explore the role of state-ownership of large corporations and potential spillovers more explicitly.

8 Conclusion

In conclusion, I show that corporate credit risk, when stripped of any systematic variation in risk that is fundamental to a firm, a country, and the global economy, can explain capital flows above and beyond what sovereign risk and external factors can account for. Using the universe of corporate bonds issued by non-financial firms in 27 EMEs and 11 tax havens, I identify the causal effect of credit risk on capital flows using Granular Instrumental Variables (GIV). I exploit variation in the size distribution of firms as well as idiosyncratic shocks to firms' credit spreads to construct exogenous instruments that pick up, in simple terms, the degree to which large firms differ from the average firm in their idiosyncratic credit risk. In country panel regressions, I show that net capital inflows have granular origins in the credit risk of large borrowers. Impulse responses obtained from instrumented panel local projections indicate that the prolonged build-up of credit risk in the domestic economy can unleash capital outflows, deteriorate the terms of trade, decrease output, and raise unemployment. It will be instructive to discipline a model to better capture the precise mechanism underlying this

[56] As discussed by Coppola et al. (2021), it should not matter in theory whether foreign investments are booked as portfolio or FDI flows.

[57] Bond financing differs from financing through bank credit in several important ways. One such difference is that the former is preferably used by firms for longer-term investments while the latter is used to cover short-term financing needs (e.g. through revolving lines of credit as a type of loan).

state-dependent causal relationship. I relegate this to future research. My findings contribute to our understanding of the domestic origins of sudden stops and balance of payments crises in EMEs. They offer a complementary explanation to the vast literature on the Global Financial Cycle (Rey, 2015) as a driver of international capital flows.

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A Data Overview

Table A.1: Classification of countries into emerging market economics (EMEs)

ISO	Country	MSCI EM index	JPM CEMBI index	IMF Fiscal Monitor	This sample
AR	Argentina		X	X	X
AZ	Azerbaijan		X	X	X
BH	Bahrain		X	X	X
BD	Bangladesh		X		X
BL	Belarus			X	X
BR	Brazil	X	X	X	X
BG	Bulgaria		X	X	X
BB	Barbados		X	X	X
CL	Chile	X	X	X	X
CN	China	X	X	X	X
CO	Colombia	X	X	X	X
CR	Costa Rica			X	X
HR	Croatia		X	X	X
CZ	Czech Republic	X	X		X
DO	Dominican Republic			X	X
EC	Ecuador			X	X
EG	Egypt	X	X	X	X
SV	El Salvador		X	X	X
GE	Georgia		X	X	X
GH	Ghana		X		X
GR	Greece	X		X	
GT	Guatemala		X	X	X
HK	Hong Kong		X		X
HU	Hungary	X	X	X	X
IN	India	X	X	X	X
ID	Indonesia	X	X	X	X
IQ	Iraq	X	X	X	X
IL	Israel		X		X
JM	Jamaica		X	X	X
JO	Jordan		X	X	X
KZ	Kazakhstan		X	X	X
KW	Kuwait	X	X	X	X
MO	Macao		X		X
MY	Malaysia	X	X	X	X
MX	Mexico	X	X	X	X
MA	Morocco		X	X	X
NG	Nigeria		X		
OM	Oman		X	X	
PA	Panama		X	X	
PY	Paraguay		X	X	X
PE	Peru	X	X	X	X
PH	Philippines	X	X	X	X
PL	Poland	X	X	X	X
QA	Qatar	X	X	X	X
RO	Romania			X	X
RU	Russian Federation		X	X	X
SA	Saudi Arabia	X	X	X	X
RS	Serbia			X	X
SG	Singapore		X		X
ZA	South Africa	X	X	X	X
KR	South Korea	X	X		X
TW	Taiwan	X	X		X
TH	Thailand	X	X	X	X
TT	Trinidad & Tobago		X	X	
TR	Turkey	X	X	X	X
UA	Ukraine		X	X	X
AE	United Arab Emirates	X	X	X	X
UY	Uruguay			X	X
VE	Venezuela			X	X
ZM	Zambia		X		

Note: The MSCI Emerging Markets Index is a composite indicator of equity market performance in global emerging markets based on market capitalization. Countries in this table reflect the index's 24 constituents as of March 2022. The JP Morgan Corporate Emerging Market Bond Index (CEMBI) is a suite of corporate bond indices for various segments of the corporate bond market. The index composition changes regularly. The above countries reflect those included in the CEMBI High-Yield + Index at any date since inception of the index in 2002. The IMF sample of countries includes 40 jurisdictions that are defined as "Emerging Market and Middle-Income Economies" in the Fiscal Monitor of the International Monetary Fund (2021). The last column refers to the initial set of countries for which bond data is obtained from Bloomberg.

Table A.2: Overview of number and volume of bonds by country

ISO	Country	Earliest Issue Date	**No. of bonds**		**Volume (US$ bn)**	
			Onshore	Offshore	Onshore	Offshore
AR	Argentina	1991-07-11	412	4	76.29	1.68
AZ	Azerbaijan	2012-02-09	7		8.25	
BL	Belarus	2014-03-18	2		0.01	
BR	Brazil	1993-10-06	269	334	88.36	296.90
BG	Bulgaria	2005-11-18	34		3.56	
CL	Chile	1993-12-08	294	23	149.22	13.07
CN	China	1998-04-15	225	750	50.06	442.11
CO	Colombia	1994-12-16	46	27	31.45	14.19
CR	Costa Rica	2003-12-10	19		3.71	
HR	Croatia	2002-04-03	22		7.47	
CZ	Czech Republic	1997-05-28	94	6	30.65	3.13
DO	Dom Rep	1998-01-28	70	8	5.07	1.66
EC	Ecuador	2010-10-22	11		1.32	
EG	Egypt			5		3.05
SV	El Salvador			8		2.82
GE	Georgia	2010-07-22	12		2.97	
HU	Hungary	2005-10-05	11	7	3.95	3.11
ID	India	1995-09-27	133	51	61.08	24.18
IN	Indonesia	1993-11-04	148	17	88.08	13.08
IL	Israel			33		43.22
JM	Jamaica	2006-11-16	9	18	2.02	14.07
KZ	Kazakhstan	2001-07-06	51	16	46.38	10.21
MY	Malaysia	1993-07-01	106	2	73.67	6.00
MX	Mexico	1981-04-13	784	29	587.28	10.40
PY	Paraguay	2011-03-03	57		2.27	
PE	Peru	1998-12-16	181	11	35.43	7.21
PH	Philippines	1993-11-15	57	12	14.63	3.64
PL	Poland	2014-03-27	3	13	0.58	5.67
QA	Qatar	1996-12-15	22	19	17.09	14.75
RO	Romania	2001-04-06	9	5	2.41	2.64
RU	Russian Federation	1998-03-19	9	320	2.38	245.54
SA	Saudi Arabia	2019-04-16	18	23	33.50	24.30
SG	Singapore	1997-06-25	224	16	88.43	9.09
ZA	South Africa	1985-02-28	76	8	32.63	4.42
KR	South Korea	1992-08-06	451	7	92.13	2.40
TW	Taiwan	1999-02-23	9	12	2.38	7.18
TH	Thailand	1993-09-17	68		24.82	
TR	Turkey	2010-11-10	63	6	26.06	1.46
UA	Ukraine	2003-03-19	4	19	2.66	10.82
AE	United Arab Emirates	2006-10-27	95	33	83.39	22.61
UY	Uruguay	2007-04-30	14		0.18	
VE	Venezuela	1992-03-17	38	5	85.11	1.07
VN	Vietnam			2		1.36

Note: This table lists the cumulative number and volume of bonds outstanding for both onshore and offshore firms incorporated in the sample of EMEs, cumulated across the sample period from January 2000 to November 2020.The earliest issue date of bonds refers to those bonds included in the sample, i.e. those with reliable pricing data as of January 2000. Hence, some countries only exhibit bonds as early as 2019. The availability of bond data and bond issuance is very heterogeneous across countries, both in terms of the number of bonds issued and the notional volume. Large economies such as Argentina, Brazil, China, Mexico, and Russia exhibit large cumulative numbers of bonds traded by domestic firms in the sample. Firms in smaller EMEs with less developed capital markets such as Azerbaijan, Belarus, Jamaica, Poland, and Ukraine exhibit fewer bonds.

B Bond-Firm Matching

To obtain the bond-firm-country panel, I match bonds retrieved from Bloomberg with information on default probabilities of firms from (i) Moody's CreditEdge and (ii) the Credit Research Initiative of the National University of Singapore (NUS-CRI). The NUS-CRI data is obtained for robustness.

A note on the NUS-CRI database The NUS-CRI provides monthly data on PDs and daily data on DTDs for all publicly listed companies across 66 countries, both EMEs and tax havens. The DTD measure of the NUS-CRI is calculated based on the Merton model just as the EDF measure of Moody's CreditEdge is calculated. However, the specific methodologies differ. Anecdotal evidence suggests a correlation of at least 80% among the two measures of expected default. The NUS-CRI database has several benefits over Moody's CreditEdge. It is free of charge, publicly accessible, and updated daily. One disadvantage of the NUS-CRI database is that it is only available with a one-year lag. Hence, the available time series cuts off on 27/12/2019, forgoing one additional year for the estimation. Just as Moody's CreditEdge, NUS-CRI links the companies in the dataset to unique company identifiers in Bloomberg. This aids bond-firm matching, albeit with caveats.[58].

Bond-firm matching The matching exercise is complicated by a number of issues. First, the Moody's and NUS-CRI databases use slightly different alphanumeric identifiers for firms that make an exact matching with the alphanumeric identifiers retrieved from Bloomberg difficult. When exact matches cannot be found, firms are then matched by regular expressions within the alphanumeric identifiers or by different numeric or character identifiers.

Second, more than a third of all bonds are issued via subsidiaries in tax havens, most of which are privately owned by the parent company and hence do not have a default probability assigned to them. These bonds must be matched with the default data of their parent companies via the company ticker or company name. Company names are often recorded inaccurately or with slightly deviating words. This makes matching across the different databases less accurate and more difficult, as the standard algorithms ("fuzzymatch" in R) do not pick up these relations.

Third, assigning a unique company identifier to a bond in Bloomberg is complicated by the fact that Bloomberg provides different identifiers depending on whether an identifier "field" is queried via the CUSIP of the bond or via the ticker symbol of the bond's issuer.[59] In the following, I therefore distinguish between (a) tickers and (b) ISINs, that refer to (i) the subsidiary and (ii) the parent company.

To tackle the above problems, I iteratively match bonds with firms starting with the first identifier in the below lists. Any bonds that were not matched exactly through that identifier are then attempted to be matched by the following identifier in the following iteration. I first attempt to match any identifiers at the subsidiary level before moving to the parent level, if possible. The following steps outline the chosen identifiers by which I iteratively match bonds

[58] Bloomberg currently does not support Moody's KMV identifiers to link bonds directly to firms in Moody's database

[59] For example, the fields in Bloomberg entitled "DEBT˙TO˙EQUITY˙FUNDAMENTALS˙TKR" and "ISSUER˙EQUITY˙TICKER" may yield different ticker symbols depending on how they are queried via the Bloomberg Excel-API.

to firms.

Firms in Moody's CreditEdge:

(i) Unique BB-ID (based on subsidiary-ticker) and subsidiary ISIN
(ii) Unique BB-ID (based on parent ISIN)
(iii) Subsidiary ISIN
(iv) Subsidiary ticker
(v) Parent ticker
(vi) Parent ISIN

This matching procedure yields 3,129 bonds matched with 833 firms in 40 countries of incorporation. Some of these matches may arguably be imperfect and further cross-validation is needed.

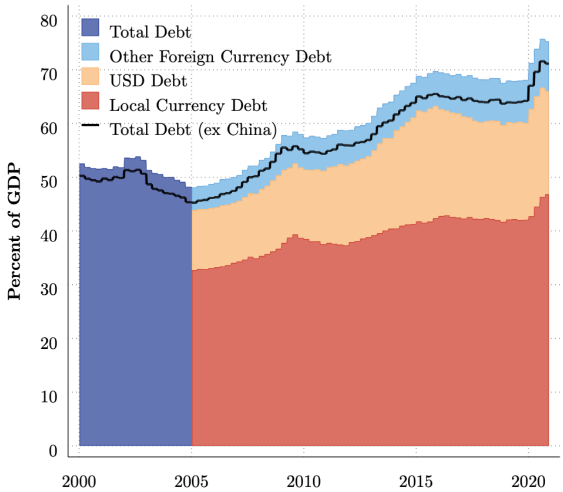
Firms in the NUS-CRI:

(i) Unique BB-ID (based on ticker-S) and subsidiary ISIN
(ii) Unique BB-ID (based on ticker-S)
(iii) Subsidiary ISIN
(iv) Substring of unique BB-ID
(v) Unique BB-ID (based on parent ISIN)
(vi) Parent ISIN
(vii) Subsidiary ticker and issuer name

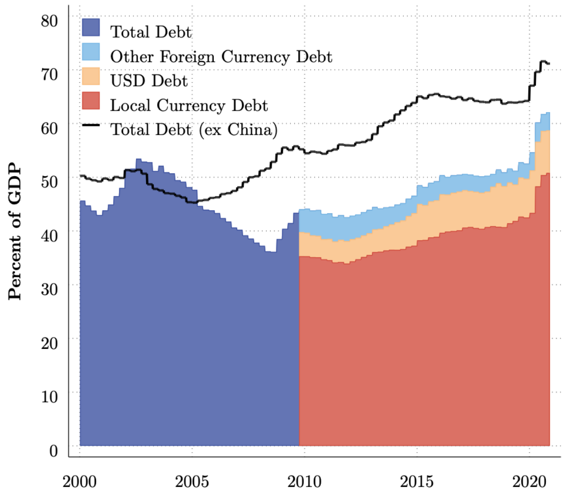
This matching procedure yields 3,184 bonds matched with 863 firms in 36 countries. The bond matches with NUS-CRI firms may be more reliable than the bond matches with Moody's firms but are subject to the same uncertainty surrounding the uniqueness of company identifiers in Bloomberg.

C Additional Descriptive Statistics

C.1 Time-Series Data



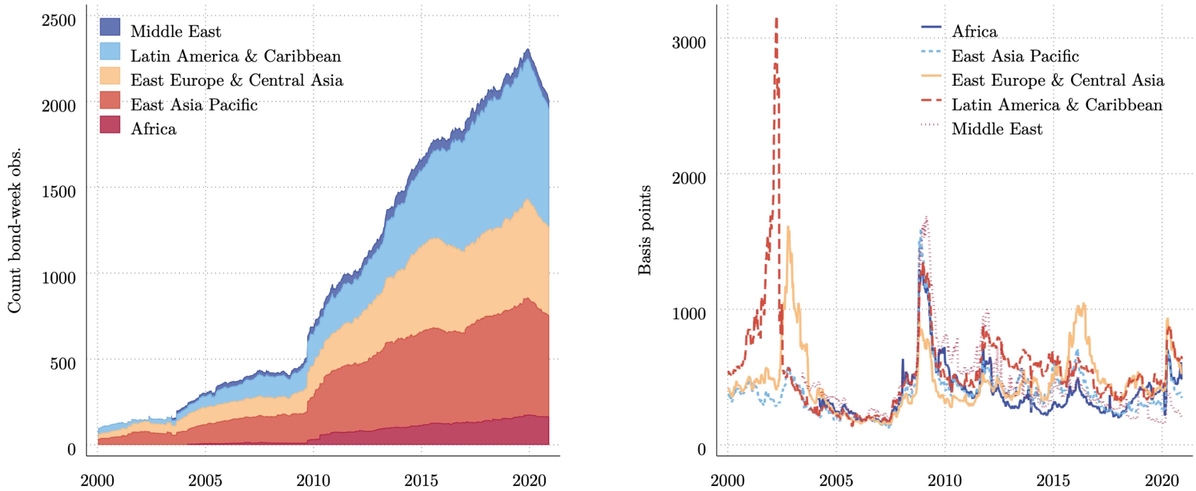
(a) Non-Financial Corporations



(b) Government

Figure 7: Decomposition of sectoral debt statistics into local and foreign currency debt

Note: This figure presents a decomposition of the average total stock of debt issued by non-financial corporations (NFCs, panel (a)) and the government (panel (b)) as a percentage of a country's GDP into its currency components. The aggregate debt levels are computed as a simple average across a sample of 22 EMEs. The black line presents the mean total debt level excluding China from this sample. The data is based on the quarterly global debt monitor of the Institute of International Finance (IIF). Details on the currency composition are available from Q1-2005 (NFC) and Q4-2009 (Government).



(a) No. of bond-week observations (b) Average credit spread

Figure 8: Regional differences in credit spreads and data coverage

Note: The graph in the left panel displays the count of bond-week observations of option-adjusted spreads (OAS) available for each region over the sample period. The the graph in right panel shows the simple arithmetic average of OAS for each region over the sample period. Both panels are based on the trimmed, unbalanced cross-country panel of bonds spanning 30 EMEs.

Table C.1: Credit spreads along the firm-size distribution

	Obs.	Mean	Median	SD	5th Pct.	95th Pct.
0-20th pctile	35,962	853.62	423.39	1,486.14	75.04	3,451.95
21-40th pctile	36,853	685.17	402.50	1,043.74	101.66	2,260.01
41-60th pctile	36,596	516.96	274.87	1,000.26	88.49	1,741.57
61-80th pctile	37,164	391.62	245.41	1,006.19	83.62	780.86
81-100th pctile	37,205	276.45	205.19	398.47	95.20	634.12
Missing	192,264	522.58	298.44	964.02	96.47	1,512.48
Total	376,044	532.33	291.78	1,013.37	90.86	1,605.95

Note: This table presents statistics of option-adjusted spreads (OAS) computed at different percentiles of the firm-size distribution. Credit spreads at the firm level are first computed as a simple average of spreads across all bonds $K_{j,t}$ of a given firm j at time t. The number of observations in the table refers to firm-week observations. Firm size is measured by total assets. Due to limited data availability on total assets, the bottom row also reports statistics for the sample of firms with missing information on total assets.

C.2 Cross-Sectional Data

This section presents a descriptive overview of the cross-section of 6,006 bonds in the untrimmed, unmatched sample of bonds selected as described in Section 3. Figures 9 to 12 split the composition of the sample according to various bond characteristics. They also offer a split between bonds issued by onshore firms in 43 EMEs and by offshore subsidiaries in 11 tax havens.

Unsurprisingly, BRICs countries such as Mexico, China, Brazil, and Russia experience the largest cumulative volume of bonds outstanding across the sample period (Figure 9). Offshore issuance of bonds takes up the lion's share of issuances by volume for the case of China, Brazil, and Russia. This is in line with evidence by Coppola et al. (2020) who find similar shares of debt issued offshore by these countries.[60] They highlight the risk and policy implications arising when portfolio flows into these offshore markets are masked as FDI flows. As becomes clear from Figure 9, ignoring offshore bonds would omit a significant share of portfolio flows into EM corporate balance sheets that could bias the analysis.

Figure 10 shows that roughly half of the cumulative volume of bonds is company guaranteed debt. About 40 % of bonds are senior unsecured debt. A larger fraction of senior unsecured debt is issued offshore than onshore. This once again points towards the riskiness of offshore issuance.

About two thirds of bonds in the sample are standard bonds that are held until maturity (Figure 10). The remaining third represents bonds with underlying option features.[61] This embedded optionality is accounted for in the option-adjusted spread (OAS) measure that I use in the estimation. Hence, the OAS allows for comparison between bonds with different cash flow characteristics and contingencies.

The bulk of bonds issued by non-financial firms in the sample have a maturity of 3, 5, 7, or 10 years (Figure 11). Only a handful of bonds have a 30 year tenure. The medium- to long-term nature of bond credit has implications for the severity of currency mismatch on firms' balance sheet. Currency mismatch and maturity mismatch may act to amplify each other if left unhedged. The sample also includes a number of perpetuities, which however will be excluded from the estimation because they exhibit different properties from standard bonds.

[60] Note that their comprehensive sample of debt securities also covers bonds issued by financial firms.

[61] A callable bond gives the issuer the right to redeem the bond before maturity, e.g. so as to benefit from favorable interest rate drops. A sinkable bond requires the issuer to adhere to a specified schedule when redeeming the bond early. Money is set aside in a sinking fund to avoid a large lump-sum payment at maturity.

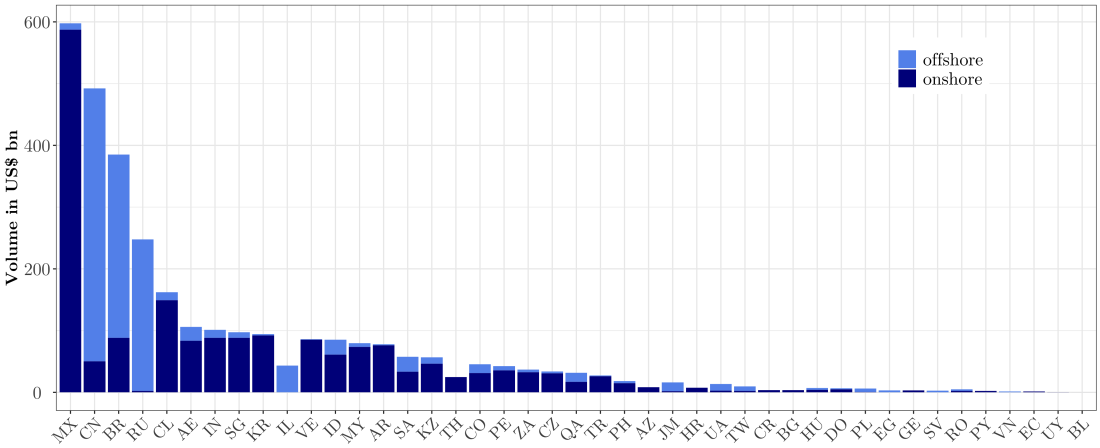


Figure 9: Volume of bonds outstanding split by country and onshore-offshore issuance

Note: This figure displays the cumulative notional volume of corporate bonds outstanding over the sample period 01/2000-11/2020, split by country and onshore-offshore issuance. Note that the volume at each point in time represents the cumulative face value of bonds but does not take into account early redemption or default. The bars are sorted according to the maximum notional volume from highest to lowest.

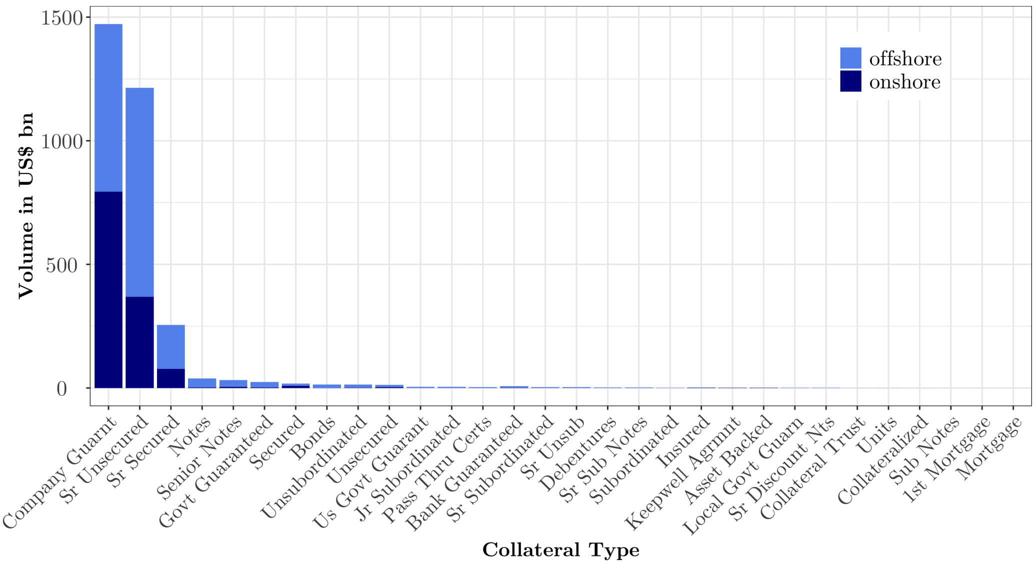


Figure 10: Volume of bonds of different collateral types split by onshore-offshore issuance

Note: This figure displays the cumulative notional volume of corporate bonds outstanding over the sample period 01/2000-11/2020, split by collateral type of bonds and onshore-offshore issuance. Note that the volume at each point in time represents the cumulative face value of bonds but does not take into account early redemption or default. The bars are sorted according to the maximum notional volume from highest to lowest.

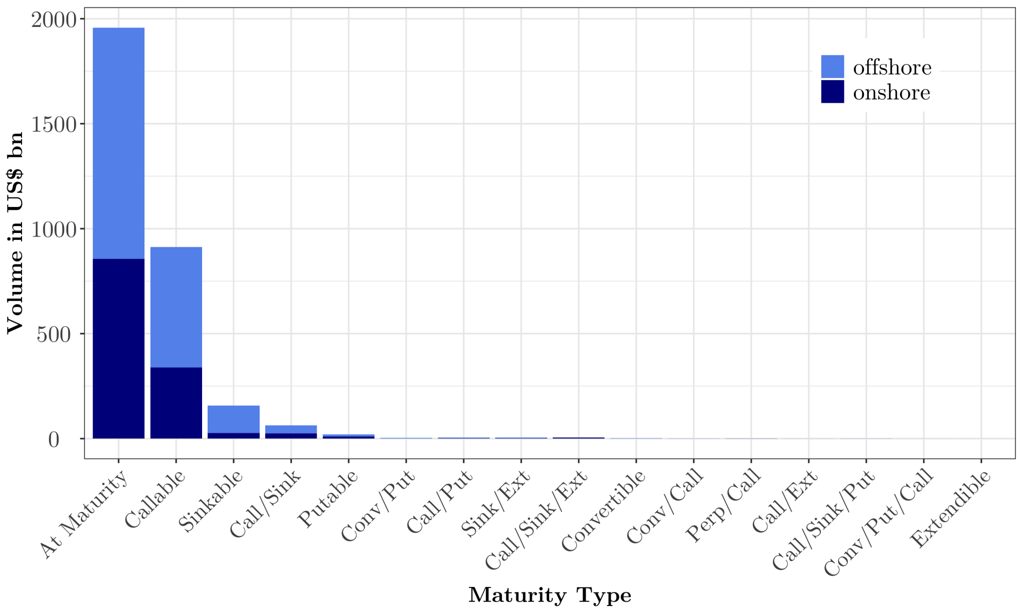


Figure 10: Volume of bonds of different maturity types split by onshore-offshore issuance.

Note: This figure displays the cumulative notional volume of corporate bonds outstanding over the sample period 01/2000-11/2020, split by maturity types of bonds and onshore-offshore issuance. Note that the volume at each point in time represents the cumulative face value of bonds but does not take into account early redemption or default. The bars are sorted according to the maximum notional volume from highest to lowest.

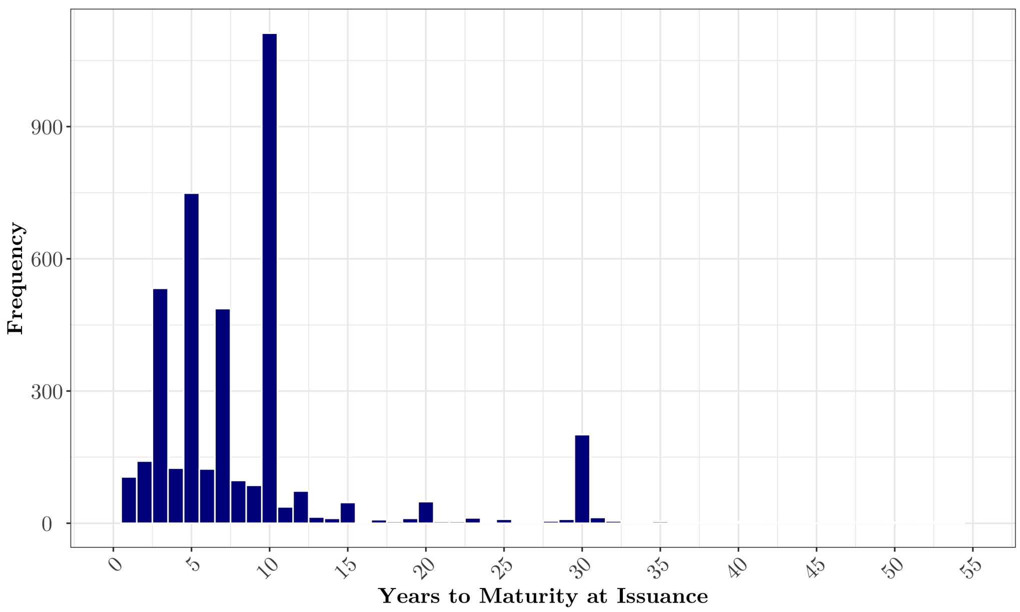


Figure 11: Maturities of corporate bonds

Note: This figure displays the number of corporate bonds in the sample according to the maturity length of the bond at issuance. The counts are based on the full, pre-trimmed sample.

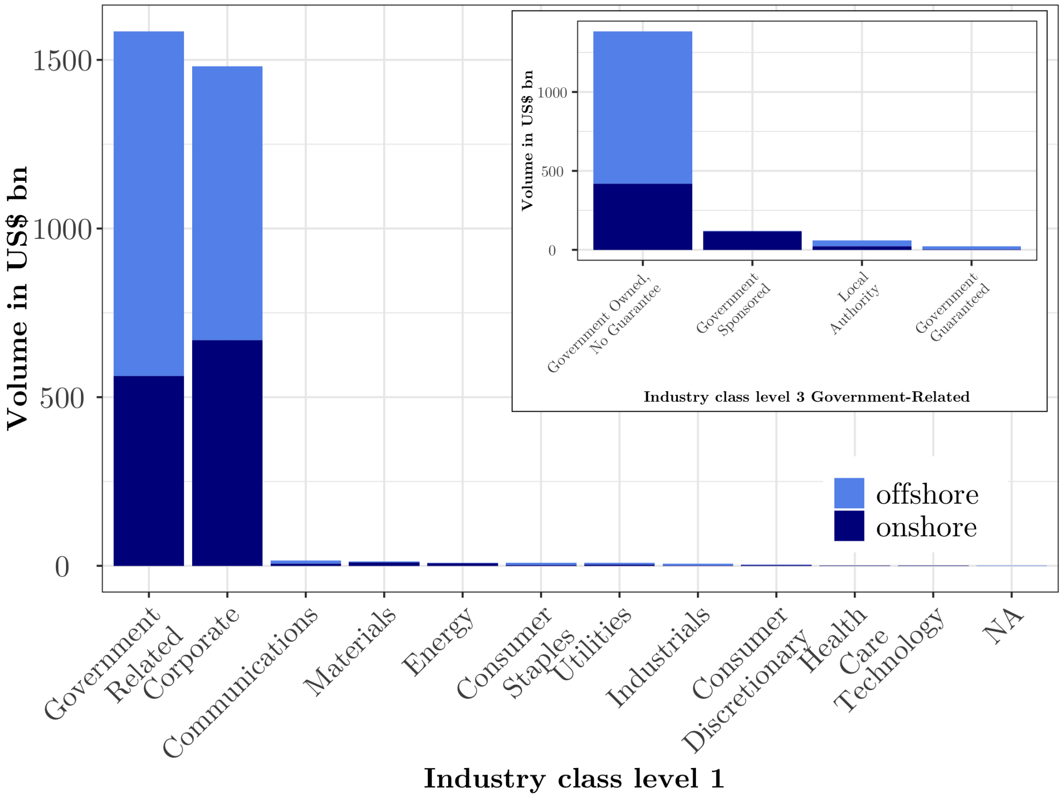


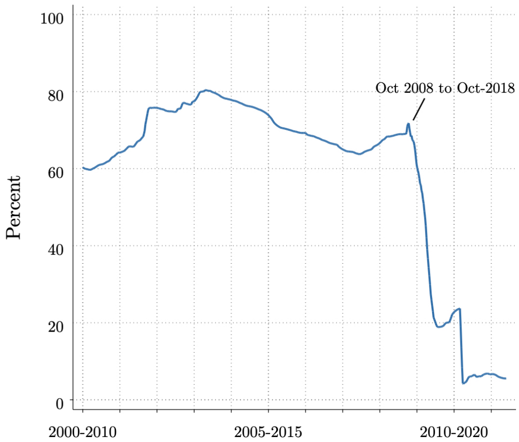
Figure 12: Volume of bonds of different industry classes split by onshore-offshore issuance.

Note: This figure displays the cumulative notional volume of corporate bonds outstanding over the sample period 01/2000-11/2020, split by industry class of the issuer and onshore-offshore issuance. Note that the volume at each point in time represents the cumulative face value of bonds but does not take into account early redemption or default. The bars are sorted according to the maximum notional volume from highest to lowest. The inset graph further breaks down government-related bonds into four sub-industry classes.

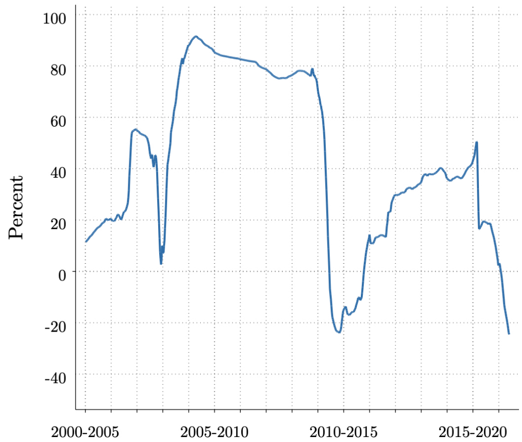
Figure 12 presents the breakdown of outstanding bond volume by Bloomberg's industry classification.[62] Approximately half of all bonds in the sample are issued by government-related firms. Of these bonds, about 80% are issued by firms where the ultimate owner is the government but without any explicit government guarantees for debt. Interestingly, Figure 12 also shows that government-related firms predominantly issue bonds offshore rather than onshore. This poses the question whether government relations as defined by the Bloomberg classification system truly map into ultimate ownership and implicit or explicit corporate control by the government – or whether these firms act in a stand-alone manner. Further research is warranted.

[62] The BCLASS classification system is the one most commonly used by users of Bloomberg commercial products. Alternative classification labels that are more prevalent in the academic literature include NAICs industry codes. These are available for firms in the Moody's database but not in the NUS-CRI database.

D Additional Results: Excess Bond Premium



(a) 10-year rolling window



(b) 5-year rolling window

Figure 13: Time-varying correlation between the EME-EBP and the US-EBP of Gilchrist and Zakrajšek (2012).

Note: This figure presents the 10-year and 5-year backward rolling window correlations, respectively, between the Excess Bond Premium of Emerging Market Economies (EME-EBP) and the US-EBP of Gilchrist and Zakrajšek (2012) estimated for the United States at a monthly frequency. The x-axes indicate the 10-year and 5-year time windows, respectively, over which the correlation is computed. The US-EBP series is publicly available via the Federal Reserve (see Favara et al. (2016)).

E Additional Results: Regressions

Table E.1: Z-spread decomposition: extracting idiosyncratic shocks to credit spreads

	(1) Est.	SE	(2) Est.	SE
$\text{EDF}_{j,t}$	107.398***	20.083	59.212	37.585
$\text{Duration}_{j,t}[k]$	-13.506***	4.329	-5.771	4.359
$\text{Coupon}_{j}[k]$	73.639***	15.922	77.865***	16.004
$\text{Age}_{j,t}[k]$	-0.144	0.099	-0.274***	0.090
$\text{Volume}_{j}[k]$	-42.210	34.882	15.080	24.596
$\text{CALL}_{j}[k]$	225.505***	35.798	266.894*	140.742
VIX_{t}	4.151***	1.300	2.538**	1.053
UST10Y_{t}	-111.915***	21.981	-73.355***	19.891
Gov-Related_{j}	-242.197*	121.156	-198.262	131.516
$\text{EDF}_{j,t}$ x $\text{CALL}_{j}[k]$			55.322*	31.866
$\text{Duration}_{j,t}[k]$ x $\text{CALL}_{j}[k]$			-24.416**	10.461
$\text{Coupon}_{j}[k]$ x $\text{CALL}_{j}[k]$			-3.197	21.994
$\text{Age}_{j,t}[k]$ x $\text{CALL}_{j}[k]$			0.831**	0.363
$\text{Volume}_{j}[k]$ x $\text{CALL}_{j}[k]$			-176.186***	36.608
VIX_{t} x $\text{CALL}_{j}[k]$			5.656*	2.862
UST10Y_{t} x $\text{CALL}_{j}[k]$			-100.104*	49.772
Country & Industry FE	YES		YES	
Observations	85,973		85,973	
Adjusted R^2	0.400		0.419	

Note: This table reports the results of a version of the corporate spread decomposition in equation (6) where the dependent variable is the Z-spread. The sample period covers 2000/01/07 – 2020/11/27. Standard errors are clustered in the country, industry, firm, and time dimension following Cameron et al. (2011). Daily expected default frequencies (EDFs) at the 1-year horizon are converted into weekly averages. The indicator variable $\text{CALL}_j[k]$ is one for bonds with any type of underlying call option. The VIX_t is the CBOE volatility index. The USD10Y_t is the 10-year US Treasury yield. Industry fixed effects are based on the BICS industry level 1 classification system. The country subscript c is suppressed to preserve space.

Table E.2: Spread decomposition with sovereign risk indicators interacted with government-related firms

	(1) Est.	SE	(2) Est.	SE	(3) Est.	SE	(4) Est.	SE
$EDF_{j,t}$	78.094***	10.390	78.039***	10.391	74.216***	4.551	74.264***	4.475
$Duration_{j,t}[k]$	-4.206	3.285	-4.115	3.228	1.802	2.356	1.564	2.214
$Coupon_{j}[k]$	60.221***	19.437	59.973***	19.305	45.336***	6.848	45.393***	6.878
$Age_{j,t}[k]$	-0.169*	0.087	-0.171*	0.087	-0.150***	0.038	-0.154***	0.040
$Volume_{j}[k]$	-26.455	18.989	-29.972*	16.135	-60.716***	12.043	-60.979***	12.353
$CALL_{j}[k]$	132.253***	33.655	131.794***	33.250	76.846**	28.152	76.417**	28.317
VIX_{t}	6.862***	1.228	6.872***	1.237	5.039***	0.660	5.041***	0.660
$UST10Y_{t}$	-117.904***	17.892	-118.105***	17.814	-81.903***	19.636	-82.076***	19.678
Gov-Related$_{j}$	-110.247	94.057	-138.147	105.949	-94.213	97.537	-62.901	119.653
$EMBI_{c,t}$	-0.211	0.200	-0.224	0.209				
$EMBI_{c,t}$ x Gov-Related$_{j}$			0.052	0.080				
$Gov10Y_{c,t}$					23.657*	11.350	24.455*	12.407
$Gov10Y_{c,t}$ x Gov-Related$_{j}$							-5.830	10.547
Country & Industry FE	YES		YES		YES		YES	
Observations	445,546		445,546		269,375		269,375	
Adjusted R^2	0.375		0.375		0.432		0.432	

Note: This table reports the results of an augmented version of the corporate spread decomposition in equation (6). The baseline model is augmented by the country-level JP Morgan Emerging Market Bond Index $EMBI_{c,t}$ (columns 1-2) and the country-level 10-year government yield $Gov10Y_{c,t}$ (columns 3-4). These two indicators of sovereign risk are also interacted with an indicator variable, Gov-Related$_{j}$, that takes a value of one for government-related firms following the BICS industry classification system. The sample period covers 2000/01/07 – 2020/11/27. The dependent variable is the option-adjusted spread (OAS). Standard errors are clustered in the country, industry, firm, and time dimension following Cameron et al. (2011). Daily expected default frequencies (EDFs) at the 1-year horizon are converted into weekly averages. The indicator variable $CALL_{j}[k]$ is one for bonds with any type of underlying call option. The VIX_{t} is the CBOE volatility index. The $USD10Y_{t}$ is the 10-year US Treasury yield. Industry fixed effects are based on the BICS industry level 1 classification system. The country subscript c is suppressed for most variables to preserve space.