Globalization, ESG Investing and Emerging Market Cost of Capital*

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Abstract

We assess the impact of investors' ESG preferences on firms' cost of capital in an international context. By matching onshore and offshore bonds from the same issuer and using the opening of the Chinese bond market as a quasi-experiment, we control for time-varying issuer characteristics that potentially correlate with ESG scores. Our findings reveal that issuers in the top ESG quartile experience an 8.8% reduction in borrowing costs compared to those in the bottom quartile, despite modest overseas capital flows. These results highlight the role of heterogeneous investor preferences and demand elasticity when evaluating the impact of ESG investing.

JEL Classification Codes: C23, G12, G14, G20, Q56
Keywords: ESG-investing, Globalization, investor preferences, emerging markets, inelastic demand, Chinese bond markets

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1 Introduction

In recent decades, financial markets have been transformed by two significant trends: financial globalization, which lowers barriers to international investment, and the rise of ESG (Environmental, Social, and Governance) investing, which broadens investment criteria beyond traditional financial metrics. Together, these trends have the potential to significantly reshape capital markets in emerging markets (EMs), where foreign capital has become a crucial funding source increasingly influenced by ESG considerations.[1] Despite their potential significance, the combined impact of financial globalization and ESG investing on EM capital markets remains under-explored.[2]

Do global capital flows, facilitated by market liberalization, impact the pricing of ESG factors in local EM markets? A deeper understanding of it not only provides a fresh perspective on the current debate regarding the impact of ESG investing on asset prices (Pástor et al., 2022; Bolton and Kacperczyk, 2023; Zhang, 2023), but also sheds new light on the benefits and costs of globalization, especially as it faces potential retreat (James, 2018). Yet, existing literature has not specifically addressed this question.

This study addresses this question. We start by examining how global capital flows are empirically related to the pricing dynamics of high-ESG versus low-ESG firms, using a proprietary dataset on global investor portfolio positioning across EM corporate bond markets. We then assess the channel foreign capital flows impact ESG pricing locally through a triple-difference analysis building on the institutional features during the liberalization of China's onshore bond market – the largest in emerging markets.

Our findings reveal that the influx of global capital into local EM corporate bond markets are associated with a substantial reduction in financing costs for high-ESG firms compared to low-ESG firms across EM countries. Moreover, our triple-difference analysis demonstrates that this pricing reduction is unlikely due to inherent fundamental differences between high-ESG and low-ESG firms.

[1] According to IMF estimates, ESG-related investments in EMs have surged since 2016, with totals in 2021 quadrupling those of 2016, reaching 215 billion dollars and accounting for 18% of total foreign financing (Gautam et al., 2022). See Financial Stability Board (2022) for the role of global capital in financing EM firms.

[2] Research typically separates these two areas: one explores the role of global capital in shaping EM capital markets (Bekaert and Harvey, 1998; Karolyi and Stulz, 2003; Bekaert et al., 2005; Kacperczyk et al., 2021), and another examines the pricing of ESG factors globally (Bolton and Kacperczyk, 2023; Zhang, 2023), with ongoing debates on whether ESG factors are priced.

Instead, the evidence suggests that global investors are exporting their ESG preferences into EMs, influencing the local pricing of ESG factors.[3] Additionally, we hypothesize that the price impact of foreign capital is further amplified by local investors' low demand elasticity and find supporting evidence for this hypothesis.

We focus on the US-dollar denominated EM corporate bond market (EMCB), which accounts for over 70% of the hard-currency EM corporate bond market (Financial Stability Board, 2022). As of 2023, this market's total value stands at 2.5 trillion dollars, only slightly smaller than the U.S. High Yield bond market. By examining this extensive market, our study significantly expands the existing literature on green bonds (e.g. Flammer (2021)), which constitute about 1% of the market share in our sample (Masse, 2020). Our contribution lies in highlighting how global capital flows influence the cost of capital for high-ESG versus low-ESG firms, providing a broader perspective on ESG impacts in EM corporate bond markets beyond the scope of green financing (Liang and Renneboog, 2020).[4]

We have compiled a comprehensive dataset on EMCB, specifically including all bonds and their issuer information from the two major EM corporate indices widely used by institutional investors.[5] In summary, our dataset contains detailed information on more than 1,000 unique issuers and 3,000 issues across 69 countries, totaling a market capitalization of 2 trillion dollars. We use the ESG rating methodology from the JP Morgan ESG index (JESG), which was launched in April 2018, marking the start of our sample period.

We focus on the portfolio flows of non-bank financial institutions (NBFIs), now the primary investors in EMCB and significantly influenced by globalization trends (Chari, 2023).[6]

To measure their portfolio flows, we use two datasets. First, we obtain monthly aggregate portfolio flows from the Lipper Global Fund Flows Database, which tracks data from open-ended mutual

[3] The pricing effects from investors on ESG factors could stem from their non-monetary preference for supporting green firms (Pastor et al., 2021) or their awareness of risks associated with ESG-related issues Giglio et al. (2021); Bolton and Kacperczyk (2021). In this article, we use the term "ESG preference" to represent investor pricing as opposed to firm fundamental factors.

[4] Liang and Renneboog (2020) review the literature and also highlight the previous focus was on green financing or green bond markets.

[5] The JP Morgan CEMBI and EMBI indices.

[6] NBFIs include closed-end mutual funds, exchange-traded funds, hedge funds, pension funds, and insurance companies. Their importance as a financing source for EM firms has increased dramatically, replacing foreign banks as the main financiers.

funds and ETFs investing in EM corporate bonds. Second, we used a proprietary dataset detailing self-reported institutional investors' relative country allocations compared to benchmarks, such as the JP Morgan CEMBI index. The monthly changes in these institutions' "positioning" serve as proxies for country-level capital flows. Together, these data sets capture both aggregate time series and cross-country variations in global capital flows. This allows us to examine whether these flows are systematically related to changes in the EM "ESG premium" — defined as the difference between the average credit spreads of high-ESG and low-ESG firms in EMCB. More specifically, we refer to "ESG premium" as the price premium high-ESG firms receive in the market compared to low-ESG firms, all else being equal. Thus, a negative difference in credit spreads between high-ESG and low-ESG firms means a positive ESG price premium.

We find that increases in global capital flows are significantly positively related to changes in the ESG premium in EMCB locally. This conclusion holds across different measures of capital flow variables (aggregate versus country level) and different methodologies (time-series versus panel regressions). Furthermore, the economic magnitude of this relationship is substantial. For example, our estimates suggest that a one standard deviation change in country-level positioning from global capital leads to an average increase of 6.21 basis points (bps) in the EM ESG premium in that country, which is notable given that the average EM ESG premium is around 18 bps.

The significant relationship between global capital flows and the change in EM ESG premium motivates us to further understand the channels driving this relationship. Theoretically, this relationship could be driven by two channels if firms' ESG scores are partially correlated with firms' fundamental characteristics. First, foreign investors' capital flows may correlate with firms' changing fundamentals ("fundamental channel"); second, foreign investors' ESG-related considerations that are independent from firms' fundamental characteristics ("ESG preference"). Given that ESG scores are correlated with firm-level characteristics (as we confirm empirically), and foreign investors' ESG preferences are unobservable, we encounter an identification challenge in disentangling these two channels.

The Chinese corporate bond market, with its unique institutional characteristics, provides an ideal setting to tackle these challenges. Besides, its dominant size within the EMCB makes it inherently interesting for study.[7]

A key characteristic of the market is its dual structure: an offshore market, primarily trading hard-currency-denominated bonds in Hong Kong, and an onshore market, trading CNY-denominated bonds in mainland China. The investor bases differ significantly; the offshore market has a higher share of foreign investors outside mainland China, while the offshore market was largely inaccessible to foreign investors before 2017. Mainland firms looking to raise capital from a broader investor base may issue bonds in both markets, often leading to simultaneous trading with potentially different prices due to the differing investor bases.

We have developed a procedure to match bonds from these dual-market issuing firms and have compiled a panel of 56 issuers and 520 issues, totaling a market capitalization of 800 billion dollars ($132 billion offshore and $666 billion onshore). Despite the bonds having the same issuer and similar characteristics, we observe significant onshore-offshore spread differences, reflecting the distinct perspectives of the two different investor bases.

Starting in 2017, the Chinese regulator began to remove access restrictions for foreign investors to the onshore bond market. We use September 2019 as the primary "opening event" for our analysis, when multiple significant access schemes were introduced concurrently. This is also when J.P.Morgan announced the inclusion of Chinese government bonds in their flagship bond index from February 2020 onward. Data from the official clearing house confirm that foreign net holdings of Chinese corporate bonds increased almost fourfold around this event, reaching 200 billion CNY post-event. In contrast, our portfolio positioning data show that global investors' positioning in the offshore market remained stable.

Building on analysis from a simple theoretical model, we hypothesize that the significant shift in the investor base following the onshore market's opening leads to a shift in average tastes for ESG in the onshore market. If foreign investors are indeed more ESG-conscious than local investors, the opening could lead to a more ESG conscious investor base in the onshore market. This shift in average investor taste, combined with dual-trading bonds, allows us to design a triple-difference analysis to disentangle the two channels we outlined and assess the pricing impact of foreign capital flows through their ESG preferences.

[7] By the end of 2018, China accounts for 67.3% of the total EM bond markets (Masse, 2020).

Specifically, we implement the triple-difference analysis through a panel regression based on the matched sample of onshore and offshore bonds. In the regression, the monthly credit spreads of the bonds serve as the dependent variable, and as the main independent variable, a triple-interaction term that combines the bond issuer's ESG ratings, the trading location of the bond (onshore vs. offshore market), and a dummy variable indicating the time period before or after the market opening. In the regression, we include issuer-time, market-time, and bond fixed effects along with time-varying issue and issuer characteristics as controls.

Intuitively, the regression effectively involves comparing three sets of differences. First, using issuer-time fixed-effects, it compares credit spreads between onshore and offshore bonds of the same issuer ("on-off-shore spread") to control for time-varying unobservable firm-level fundamental factors. Second, the ESG rating variable groups firms based on their ESG scores to compare differences between high-ESG and low-ESG firms average on-off-shore spreads ("ESG-spreads"). Finally, the post-event dummy compares these average ESG-spreads before and after the market opening, identifying the effects of the shift in the investor base on bond prices.

We find that for firms in the top quartile of ESG scores (high-ESG), the influx of foreign capital during the bond market opening led to a credit spread reduction of 9.6 basis points compared to firms in the bottom quartile of ESG scores, amounting to 8.8% of the average spread observed in onshore bonds. Given our research design, this reduction therefore suggests that foreign investors' ESG preferences is the main driver behind the dynamics in ESG premium in the Chinese onshore markets.

Having established the channel of the price impact, we explore the mechanism behind the large economic magnitude of this effect. Net overseas capital inflow during the opening of the market accounted for only 1% of the total market capitalization of the onshore bond market, suggesting that cross-country capital flows are highly effective in impacting the cost of capital of emerging market firms. We hypothesize that the inelastic demand of local bond investors (Gabaix and Koijen, 2021), combined with the strong ESG preferences of foreign inflows, contributes to the large price impact. Indeed, stringent local-market regulations in China constrain bond mutual funds in their portfolio choices (Amstad and He, 2019). Applying the demand system framework of (Koijen and Yogo, 2019) to the data of the onshore Chinese mutual fund holdings, we find that the estimation results are consistent with our hypothesis.

In summary, our analysis provides a compelling set of evidence that the interplay between globalization and ESG investing yields compounding effects on global markets, which are obscured when these factors are considered individually. However, our study has limitations. First, our capital flow measures are imperfect, acknowledging the traditional challenges in measuring portfolio flows in the corporate bond market. Secondly, our analysis of the impact channels is confined to the Chinese market. Lastly, our demand-based analysis relies on limited data from local investor holdings, necessitating cautious interpretation. We see these limitations as promising avenues for future research.

Related literature

Our work is related to several strands of literature. First, it connects to research on how globalization, particularly through global capital flows, impacts capital market pricing (Stulz, 1999; Karolyi and Stulz, 2003; Bekaert and Harvey, 1998, 2000; Bekaert et al., 2005; Kacperczyk et al., 2021; Chari et al., 2024). This literature generally finds that financial globalization and the resulting capital flows lower the cost of capital in local EMs and improve price informativeness. We contribute by examining the joint effects of global capital flows and ESG investing on EM capital market pricing, showing that global capital flows significantly shape the distribution of capital cost along the ESG dimension. While Aggarwal et al. (2011) and Dyck et al. (2019) investigate the effects of international capital flows on corporate governance and social responsibility; Sun and Liang (2021) finds globalization improves the affordability of microfinance; they do not examine the impact on capital market pricing.

Second, our paper contributes to understanding whether and how ESG factors are priced (Gompers et al., 2003; Hong and Kacperczyk, 2009; Edmans, 2011; Hong et al., 2019; Zerbib, 2019; Bolton and Kacperczyk, 2021), especially on a global scale (Matos, 2020; Bolton and Kacperczyk, 2023; Karolyi et al., 2023; Stulz et al., 2023). Pástor et al. (2022) and Zhang (2023) find evidence suggesting that efficient ESG pricing globally is still underway. We extend this literature by demonstrating the critical role of global capital flows in pricing ESG factors in EMs, identifying global investors' ESG preferences ("the discount rate") as an important force driving this transition in EM. The latter results complement evidence in developed market (Krueger et al., 2020; Pástor et al., 2022; Zerbib, 2022).

Third, our paper relates to the growing literature on how investor demand elasticity affects asset pricing (Koijen and Yogo, 2019, 2020; Gabaix and Koijen, 2021). This literature finds that investors' demand inelasticity can lead to significant market pricing impacts; van der Beck (2021) finds that flows toward green funds investing in stocks with inelastic demand substantially reduce the cost of capital for those firms. We contribute by showing that global capital flows can generate large pricing impacts in EM markets due to the inelastic demand of local EM investors.

Finally, our paper relates to the literature on Chinese bond markets (Amstad and He, 2019; Ding et al., 2022). We contribute by showing how market liberalization can alter local Chinese bond market pricing according to foreign investors' ESG preferences. Related to our study, He et al. (2023) studies capital flows between Chinese onshore and offshore stock markets, while Deng et al. (2018) uses onshore versus offshore stock prices to examine the implications of Tobin taxes on financial price volatility.

2 Data

We use various data sets related to EM corporate bond markets, investor holdings, and capital flows. Here, we provide an overview of the data. For comprehensive details on the data sources, the methods employed in their integration, and the variables used in our analysis, refer to Appendix A.1.

In summary, we assemble two sets of data covering corporate bond markets, focusing on bond issues (e.g., credit spreads) and issuers (e.g., ESG scores). The first dataset spans the broad hard-currency EM corporate bond markets across different countries, while the second focuses on matched onshore and offshore Chinese corporate bond markets. More details are provided in Appendix A.1.1. Appendix A.1.1.2 describes the ESG scores used in detail.

We also compile two datasets on investor holdings and positioning in EMCB markets. Details of the data and the construction of aggregate holding and country-level positioning variables are provided in Appendix A.1.3. For our demand analysis, we collect onshore Chinese mutual fund holdings, detailed in Appendix A.1.3.3.

To give readers an understanding of the markets we study, we present summary statistics of the EM corporate bond markets and the matched sample of the Chinese corporate bond markets in the next subsection.

2.1 Summary Statistics Broader EM

Table 1 summarizes the statistics for the entire sample of emerging markets corporate bonds used in the analysis across emerging markets.

In panel (a), we show the distribution of bonds across rating categories, sectors, and regions, where the percentage refers to the number of bonds divided by the total number of bonds (as opposed to market capitalization).

Table 1: Summary statistics of offshore bonds across emerging markets

(a) Bond distribution

Sector	Percent	Region	Percent.1	Rating	Percent.2
Financials	40.4	Greater China	34.8	1: AAA-A	29.1
Energy	13.4	LATAM	24.8	2: BBB	37.9
Materials	10.4	CEEMEA	20.7	3: BB	20.4
Utilities	10	Asia (ex-China)	19.7	4: B	11.5
Communications	6.1			5: C and below	1.1
Industrials	5.5				
Consumer Discretionary	4.8				
Consumer Staples	4.2				
Government	3.3				
Technology	1.1				
Health Care	0.7				

(b) Number of bonds and issuers by regions

Region	# of issuers	# of bonds
All	1,074	3,460
Greater China	280	1,243
CEEMEA	279	768
LATAM	309	789
Asia (ex-China)	207	661

Statistic	N	Mean	St. Dev.	Min	Median	Max
ESG score (0-5)	111,902	2.2	1.0	0.04	2.2	4.9
Par Amt (USD Million)	111,902	695.8	421.7	300.0	500.0	2,750.2
Rating #	111,902	9.5	3.2	1	9	17
Ex-ante prob. of default (%)	111,902	3.9	5.0	0.2	2.4	34.8
Spread (bp)	111,902	293.8	301.6	32.0	195.0	2,054.0
Duration	111,902	4.8	3.6	0.1	3.8	17.2
Duration-times-spread (DTS)	111,902	12.9	13.7	0.3	7.9	69.1
Ex-ante annualized volatility (%)	111,902	7.2	9.4	0.4	4.0	58.9
Default next month (%)	110,202	0.04	1.9	0	0	100
Downgrade next month (%)	110,754	0.2	4.6	0	0	100

(c) Bond characteristics

Note: This table shows the summary statistics of our sample of offshore corporate bonds and quasi-sovereign bonds across all emerging markets.

Panel (b) shows the number of bonds and issuers we have per region. In summary, our sample comprises over 1,074 issuers and 3,460 bonds. Finally, panel (c) exhibits the mean, standard deviation, and main percentiles of the variables of interest, which include the amount issued, the Bloomberg ex-ante probability of default, spread, duration, duration-times-spread (DTS), ex-ante volatility, "default next month" dummy, and "downgrade next month" dummy. We compute the issuers' ex ante default probability from the Bloomberg DRSK model, which uses several financial ratios and the firms' estimated volatility to compute a distance-to-default, ultimately converted into a probability of default for the next five years at the issuer level.[8] We winsorize at 1% all bond-specific variables that can take extreme values, such as spread, ex ante probability of default, duration, and DTS.

The ESG scores in our sample ranges from 1 (worst) to 5 (best) and exhibit large variation both within and across sectors. The best sector is Technology with an excess score of 0.7 and low dispersion. The worst sector is Transport with an excess ESG score of -0.6, followed by Government with a -0.5 excess score. Despite these differences, the ESG scores are far from being fully explained by the sectors. We see large and similar dispersion within all sectors, and the medians are not much different after all. Appendix A.1.1.2 discuss the properties of the ESG scores in more detail.

[8]The Bloomberg Ticker is "BB_5Y_DEFAULT_PROB". For more details on the methodology, please refer to the Bloomberg Issuer Default Risk Model described in Bondioli et al. (2021).

Table 2: Summary statistics of filtered matched sample of onshore and offshore bonds

	N	Mean	St. Dev.	P5	P25	Median	P75	P95
Onshore								
# of issuers	56							
# of bonds	323							
# of bonds per issuer		5.77	7.44	1.00	2.00	4.00	7.00	13.25
ESG Score	4,522	1.93	0.77	0.53	1.56	1.85	2.58	3.10
Yield (%)	4,522	3.79	0.77	2.94	3.36	3.67	4.08	5.06
Spread (bp)	4,522	108.96	72.67	35.91	70.58	95.74	126.49	234.11
Duration	4,522	3.08	1.75	1.41	1.87	2.46	3.63	6.96
Credit Rating	2,896	5.91	1.42	5.00	5.00	5.00	7.00	9.00
Amt. issued ($ Million)	4,522	2,062.06	3,209.20	157.23	314.47	471.70	2,830.19	8,176.10
Coupon (%)	4,522	4.48	0.77	3.25	3.98	4.50	4.97	5.61
Offshore								
# of issuers	56							
# of bonds	197							
# of bonds per issuer		3.52	4.66	1.00	1.00	2.00	3.00	12.75
ESG Score	2,758	2.00	0.70	0.53	1.64	1.85	2.36	3.14
Yield (%)	2,758	3.21	1.12	1.99	2.54	3.00	3.57	5.27
Spread (bp)	2,758	141.03	99.43	64.00	91.00	118.00	151.00	351.30
Duration	2,758	3.03	2.13	0.07	1.75	2.76	4.15	6.85
Credit Rating	2,585	6.80	1.77	5.00	6.00	6.00	8.00	10.00
Amt. issued ($ Million)	2,758	669.00	377.02	300.00	500.00	500.00	750.00	1,400.00
Coupon (%)	2,758	3.85	1.04	2.45	3.15	3.62	4.38	6.00
Correlation								
Cor. btn. spreads	0.73							

Note: This table shows the summary statistics of our matched filtered sample of onshore and offshore bonds. The methodology to obtain this sample is explained in Section 2.

Table 2 shows the summary statistics of our matched sample of onshore and offshore bonds. In our sample, there are 56 issuers with 323 onshore bonds, totaling $666 billion in issued amount, and 197 offshore bonds, totaling $132 billion in issued amount, for which we measure spreads and yields from January 2019 to February 2020. The average ESG score is 1.9, and scores exhibit a wide distribution with standard deviation of 0.77. This heterogeneity in ESG scores provides ample variation for our analysis. The average yield is 3.8% for onshore bonds and 3.2% for offshore bonds, reflecting the higher interest rate in CNY than USD. Onshore bonds are, on average, larger, with approximately $2 billion amount issued compared to $670 million for onshore bonds. Average onshore ratings are 5.9 (corresponding to A) for onshore and 6.8 for offshore bonds (corresponding to A-).[9] In terms of bond characteristics, 78.5% of bonds have fixed coupons, 11.2% have variable coupons (a period of fixed coupon followed by floating), 9.7% have floating coupons, and 0.6% have step coupons (coupons that increase at threshold dates). In terms of sector distribution, 63.6% of issuers are Financials, 11.4% are Industrials, 9.1% are Utilities, 6.8% are Consumer Discretionary, 4.5% are Energy, 2.3% are Materials, and 2.3% are Government-linked. Additionally, 25% of the issuers are SOEs, and 75% are private. Finally, 97.8% of the bonds are traded in the interbank market, while 2.2% are traded in exchange markets.

2.2 Theoretical Background: An Ambiguous Relationship

The relationship between global capital flows and the EM ESG premium is ambiguous. Existing theories predict varying signs for the ESG premium. ESG-conscious investors may have non-pecuniary preferences that motivate them to offer cheaper financing to green firms compared to brown ones, resulting in a positive ESG price premium (Pastor et al., 2021; Pedersen et al., 2021). Conversely, if investors believe ESG-related damages, such as climate disasters, to be larger when the economy has stronger growth, we may expect to see a ESG price discount (Lemoine, 2021; Giglio et al., 2021). The complexity of the premium's sign is further compounded when investors implement different ESG investing practices (e.g., exclusion versus integration) as shown in Zerbib (2022), or when information imperfections exist (Goldstein et al., 2022). In Appendix A.2, we provide analysis to show the ESG premium directly.

3 Global Capital Flows and ESG Pricing in EM Corporate Bond Markets

Global investors consider factors beyond ESG when allocating to EM corporate bond markets, further complicating the relationship between their capital flows and the EM ESG premium. For instance, global investors also evaluate hedging opportunities for their home consumption when investing in EM dollar-denominated corporate bond markets (Stulz (1981)). These hedging mo-

[9]The rating scale is as follows: 1 (AAA), 2 (AA+), 3 (AA), 4 (AA-), 5 (A+), 6 (A), 7 (A-), . . . , 16 (B-). We use the median rating of all three rating agencies (S&P, Fitch, and Moody's) when all are available, and the minimum if less than three ratings are available.

tives lead them to assess the correlations between EM high-ESG and low-ESG assets and their home market portfolios. If high-ESG assets exhibit higher correlations with global investors' home portfolios compared to low-ESG assets, these investors might demand a higher premium for holding high-ESG assets.

Beyond the sign, the magnitude of the potential impact of global capital flows on the EM ESG premium is unclear. Theoretically, the magnitude of the impact depends on factors such as the wealth share of ESG-conscious investors (Pastor et al., 2021), their implementation policies (Berk and van Binsbergen, 2021), and the demand elasticity of different market participants (van der Beck, 2021). Existing empirical evidence has not provided clear insights on the sign and magnitude of this impact in an international context.

Next, we conduct empirical analysis on the empirical relationship between global capital flows and ESG premium in local EM corporate bond markets.

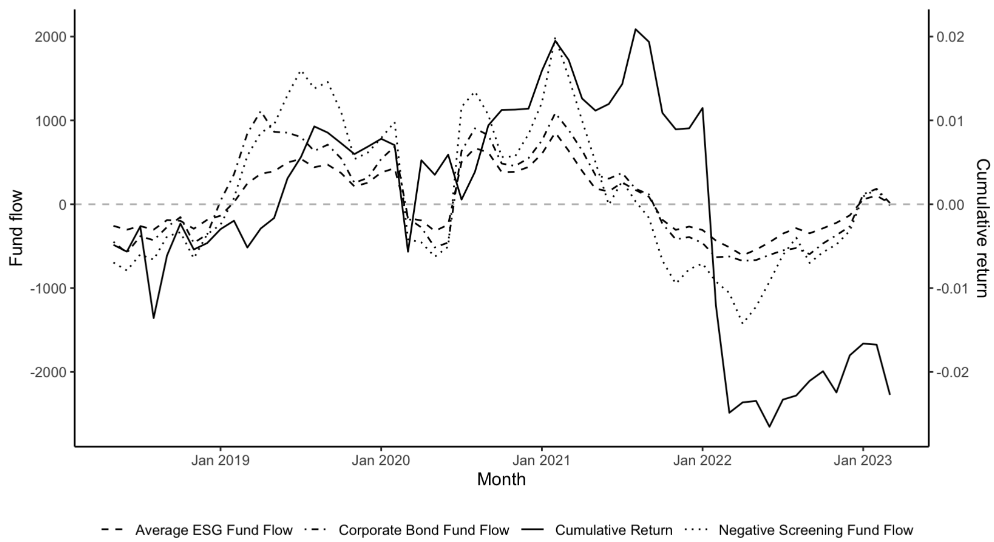
3.1 Capital Flows and ESG Premium

3.1.1 Aggregate Flows and ESG Premium

We present evidence that increases in the aggregate developed market fund flows (as defined in A.1.3.1) to EM corporate bond markets are associated with increases in the ESG premium in these markets.

Figure 1 illustrates the relationship between the fund flows originated from NBFIs in DM to EMCB and the changes in the ESG premium. The solid line represents the cumulative excess returns of a long-short portfolio of bonds based on firms' ESG scores. Specifically, the long (short) portfolio consists of the bonds issued by issuers ranked among the top (bottom) 50% based on ESG scores within each sector (defined by Bloomberg) and each month, weighted by the squared root bonds' market values (high-ESG-minus-low-ESG, or HML). This series captures the cumulative changes in the ESG premium in these markets.

Figure 1: DM Fund flows (left axis) and cumulative returns of high-ESG-minus-low-ESG portfolio



Note: Fund flows are in millions of U.S. dollars.

The other series show the 4-month moving average of the aggregate fund flows, whose magnitude is indicated on the left axis in millions of dollars. Specifically, dashed-, dot-dashed- and the dotted-lines represent the average ESG fund flow, corporate bond fund flow and the negative screening fund flows from DM to EM corporate bond markets.

As the figures suggests, fund flows co-move with the changes in ESG premium: periods of positive capital inflows (outflows) from DM also saw the cumulative returns of the high-ESG-minus-low-ESG portfolio in EM to increase (decrease).

We examine the statistical relationship by running the following regression:

$$ret_t^{HML} = a + bFundFlow_t + Control_t + e_t$$

where ret_t is the monthly excess returns of high-ESG-minus-low-ESG portfolio; $FundFlow_t$ is the negative screening fund flow at time t, and $Control_t$ includes benchmark (CEMBI index), size factor, value factor, VIX, SP500 index, Federal fund rate, and lagged monthly excess returns.

Table 3: DM fund flows and the excess returns of high-ESG-minus-low-ESG portfolio in EM

	Monthly excess returns (%)				
	(1)	(2)	(3)	(4)	(5)
Fund flow	0.216***	0.156***	0.156***	0.143***	0.146***
	(0.051)	(0.046)	(0.048)	(0.047)	(0.044)
Benchmark		0.047	0.048	0.071	0.069
		(0.038)	(0.038)	(0.049)	(0.049)
Size factor			X	X	X
Value factor			X	X	X
Other controls				X	X
Lagged dependent variable					X
Observations	59	59	59	59	58
Adjusted R^2	0.297	0.305	0.297	0.312	0.303
Note:				*p<0.1; **p<0.05; ***p<0.01	

Note: Sample period: May 2018 to Mar 2023. Fund flows in the regression are in billions of dollars.

Table 3 shows this relationship is statistically and economically significant. For every 1 billion dollar of increase in DM capital flow, the ESG premium would increase by 15 bps. Furthermore, the flow explain almost 30% of the return variation of the GMB portfolio. Finally, the estimate is statistically significant and robust to inclusion of the benchmark return as well as other controls.

3.1.2 Country-Level Positioning Changes and ESG Pricing Dynamics

We use the global investor positioning data (See Section 2) to examine whether the positive relationship between ESG premium in EM and global capital flow holds at the country level.

We run the following panel regression:

$$\Delta cs_{i,f,c,t} = a + bESG_{f,t} + c\Delta Positioning_{c,t} + \lambda \Delta Positioning_{c,t} \times ESG_{f,t} + Controls_{i,f,c,t} + e_{i,f,c,t} \tag{1}$$

where $\Delta cs_{i,f,c,t}$ is the monthly change in credit spread of bond i issued by firm f domiciled in country c at month t; $ESG_{f,t}$ is the ESG score of firm f at time t, and $\Delta Positioning_{c,t}$ is the monthly change of positioning of country c during month t.[10] Our key point of interest is the coefficient λ associated with the interaction between ESG score and aggregate change in positioning. A negative

[10] The timing of the survey has a one-month reporting time lag. Specifically, the positioning of the investor at the end of the month t is reported to the the survey and published by J.P. Morgan at time $t+1$.

(positive) coefficient estimate of λ implies that increases in positioning to a particular EM country are associated with a more negative (positive) relationship between ESG scores and credit spread changes, i.e. larger (smaller) ESG premium in a specific EM country.

Table 4: ESG-related effect of the cross-border fund flow on the change in spread

	$\Delta Spread$			
	(1)	(2)	(3)	(4)
ESG	0.48	0.84	1.51*	0.17
	(0.80)	(0.52)	(0.82)	(0.67)
$\Delta Positioning$	18.20**	16.26*	16.34*	−47.41
	(7.83)	(9.25)	(9.15)	(91.68)
ESG × $\Delta Positioning$	−7.55***	−7.21**	−7.57**	−6.80**
	(2.61)	(2.90)	(2.85)	(3.22)
Controls				X
Month FE	X	X	X	X
Region FE		X		
Country FE			X	X
Observations	64,591	64,591	64,591	64,591
Adjusted R^2	0.31	0.31	0.31	0.39

Note: *p<0.1; **p<0.05; ***p<0.01

Note: Panel regression as in Equation (2). Sample period: Apr 2018 to Nov 2021. Controls include spread duration, change in spread duration, bid-ask spread, change in bid-ask spread, rating, coupon types, callability, issuer type, payment rank, issued amount, and their interactions with the change in positioning. We report robust standard errors clustered two-way at the issuer and time levels.)

Table 4 shows the results of the regressions with four different specification. Across the four different specifications, we find the estimated coefficient associated with the interaction term between ESG scores and changes in positioning to be significantly negative. This implies country-level increases in global capital positioning are indeed associated with higher ESG premium.

Besides, the economic magnitude of the estimate is large. These estimates suggest, when global capital goes from underweight a particular country in their portfolio by 1 standard deviation (0.188) in positioning, the decrease in the spreads between high-ESG and low-ESG is -6.21 bps.[11] Given

[11] The sample mean of ESG scores is 2.113. So a one standard deviation change in positioning (0.188) leads to an average of $0.188*(-47.41-2.113*(-6.8)) = -6.2118$ decrease in delta spread, where the -47.41 is our point estimate for coefficient associated with flows in Column (4) of Table 4.

that the country-level standard deviation of the ESG premium is at 18 bps (see Appendix A.2.), our finding is a significant one.

4 Understanding the Relationship: Evidence from Chinese Bond Market Opening

4.1 The Theoretical Channels and Identification

The positive relationship between global capital flow and the change in the EM ESG premium documented in 3.1 could result from global investors pricing in ESG factors through two channels. First, investors' specific ESG preferences, such as non-pecuniary motives or hedging motives (as discussed in 2.2), could drive the premium. If ESG scores capture these preferences, the ESG premium would emerge. We term this the "preference channel."

Alternatively, the premium could be due to investors pricing in certain firm characteristics that happen to correlate with its ESG scores. In this case, ESG scores serve as a proxy for a set of firm fundamentals, independent of investors' ESG preferences. This is referred to as the "fundamental channel."

Understanding which channel predominates is crucial, as each has different implications. If the fundamental channel dominates, it suggests that high-ESG firms in EM receive cheaper financing because they exhibit fundamental characteristics (e.g. lower leverage ratios) that are more valued by global investors. This relationship would persist as long as global investors evaluate firms' fundamentals differently from local investors. Changes in their views on ESG investing would not significantly alter this relationship.

In contrast, if the preference channel drives the relationship, it implies that global investors are providing cheaper financing to EM firms with better ESG practices (higher ESG scores) due to externalities. This would also incentivize low-ESG firms to improve their ESG practices to lower their cost of capital. In this case, the globalization of ESG investing may contribute to overall improvements in ESG practices through capital markets.

In Appendix A.4, we use a model to analytically demonstrate how these two channels may endogenously impact bond pricing. In the model, two types of investors are considered: ESG-conscious investors, who prefer high-ESG-score assets and use ESG scores to guide their investment decisions, and ESG-indifferent investors, who base their decisions solely on firm fundamentals. Importantly, ESG scores are correlated with firm fundamentals. The model shows that equilibrium bond yields are influenced by both firms' fundamental factors and ESG scores (Prediction 1 in A.4.3). This makes it challenging to disentangle the channel empirically (Pastor et al., 2021), which we tackle next.

4.1.1 Identifying the Preference Channel

A potential method for identifying the preference-driven channel is through the (exogenous) variation in the wealth share of ESG-conscious investors in the market. As predicted by the model in A.4 (Prediction 2), an increase in demand from ESG-conscious investors would lead to a greater decrease in the yields of bonds from high-ESG-score firms compared to those from low-ESG-score firms if ESG preference indeed impacts prices.

The results of our capital-flow and ESG premium change analysis (3.1) are consistent with global investors' ESG preference channel impacting EM markets. However, this evidence cannot be used to directly identify the significance of the channel, as country-level capital flows may be endogenous to changes in the ESG premium in EM. Moreover, even though we control for granular observable firm and bond characteristics, we may have omitted unobservable firm-level fundamental characteristics that correlate with ESG scores. Indeed, as shown in Table A.4, a significant portion of the ESG score variation remains unexplained by the observable fundamental factors we use as controls.

Guided by our theoretical analysis, we use the opening of the Chinese onshore bond market, along with its dual-trading features, to identify the significance of the preference channel, which we discuss next.

4.2 Institutional background: the Chinese corporate bond market

We discuss two unique features of the Chinese bond markets. First, some Chinese bonds with the same issuer are traded in both the onshore and the offshore markets.[12] This allows us to better control for potentially unobservable firm-level fundamental factors that affect prices and correlate with ESG scores. Second, we take advantage of the opening of the Chinese onshore bond market, which we argue is a shock to the composition of the investor base, i.e. an increase in the proportion of ESG-conscious investors.

4.2.1 The Dual-Trading Market Structure

A Chinese mainland firm can issue bonds in both the onshore and the offshore market. On the other hand, overseas and mainland investors can only access their respective offshore or onshore markets. If an overseas (mainland) investor wants to access the onshore (offshore) market, they would need to go through special channels, which only became available in recent years.

Figure 2 provides an overview of how mainland firms issue bonds in the onshore and offshore market, as well as how investors access the onshore and offshore bond markets. Panel (a) illustrates how mainland firms issue bonds in both the onshore and offshore markets, highlighting that onshore and offshore bonds issued by the same parent mainland firm are exposed to similar fundamentals. Mainland firms can directly issue bonds in the onshore market. These onshore bonds are primarily traded in the *interbank* market, with a much smaller portion traded in the *exchange* market.

To issue bonds in the offshore market, mainland firms can either issue them directly or through special-purpose vehicles (SPVs) with guarantors. The most common guarantors include the mainland parent company, banks, and a keepwell deed with a deed of equity interest purchase undertaking (EIPU).[13] Amstad and He (2019) provide a more comprehensive account on how mainland firms issue bonds in different markets. It is important to note that even when the bond is issued by an offshore subsidiary, it is the parent mainland company that is ultimately responsible for the

[12] Throughout the paper, we use "onshore" to refer to China Mainland and "offshore" to jurisdictions outside of China Mainland, such as Hong Kong.

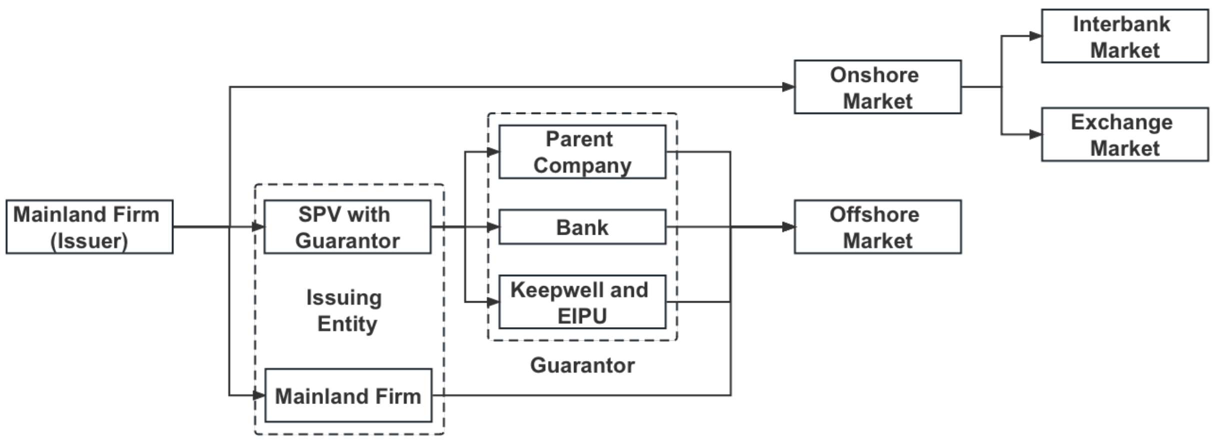
[13] Banks usually require a counter-guarantee from the mainland parent company. A keepwell deed is a contract between a parent company and its subsidiary to maintain solvency and financial backing. An EIPU is a supplement to the keepwell deed. In the event of a bond default, the parent company undertakes to purchase assets from the offshore subsidiary issuer, thereby fulfilling its debt obligations.

debt obligations. Therefore, onshore and offshore bonds issued by the same parent mainland firm are exposed to similar fundamentals.

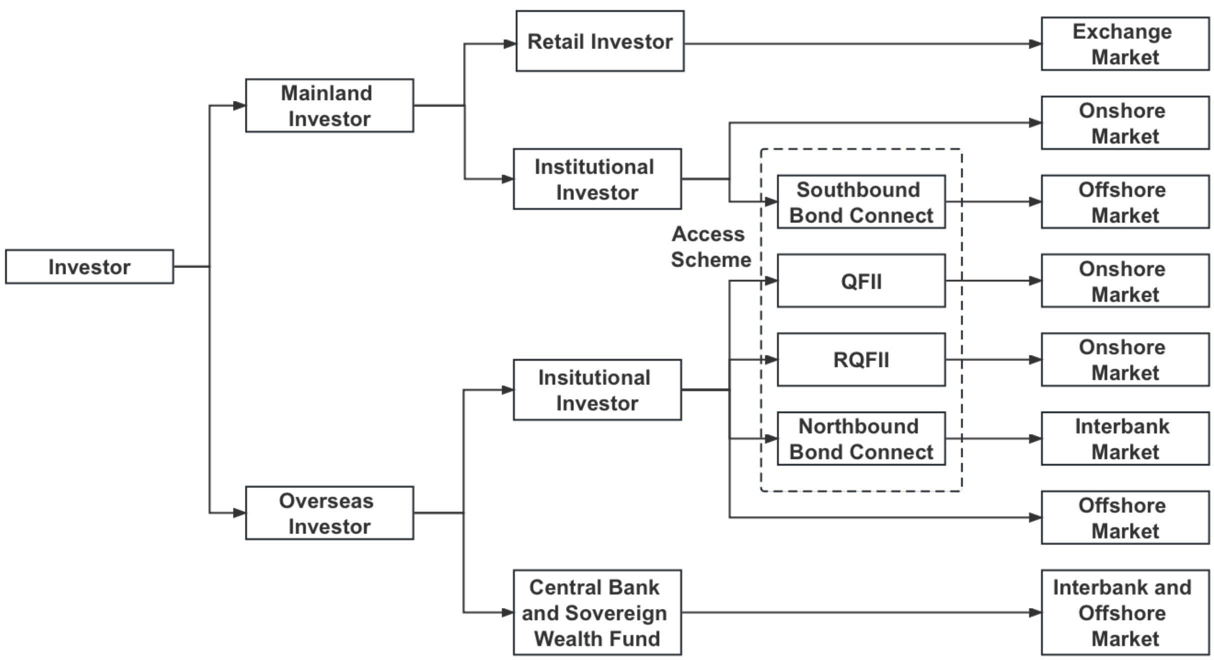
The key advantage for mainland firms to issue bonds in the offshore market is the access to a broader set of foreign capital. Moreover, offshore bonds could potentially boost the company's international reputation, which creates opportunities for expanding into international markets and pursuing an overseas customer base or stock listings.

Figure 2: Issuing and investing in bonds in China

(a) Issuing bonds in the onshore and offshore market



(b) Investing in bonds in the onshore and offshore market



Note: SPV stands for special-purpose vehicle. EIPU stands for equity interest purchase undertaking. (R)QFII stands for (Renminbi) Qualified Foreign Institutional Investor.

Regulations are more stringent on how different investors can access different markets. Figure 2 Panel (b) demonstrates how different types of investors can access different markets and the channel they need to go through. Specifically, mainland retail investors can only directly trade in the onshore exchange market, a very small market compared to the interbank market. These retail investors can access other markets by way of mainland institutional investors, such as through purchasing mutual funds issued by institutional investors. These institutional investors can access both the interbank and the exchange markets directly. Historically, they could not access the offshore market either until September 2021 when the Southbound Bond Connect was launched.[14]

Overseas investors have direct access to the offshore market; however, they need to go through special access schemes to access the onshore market. Figure 2 Panel (b) demonstrates the potential access schemes. For central banks and sovereign wealth funds, the access scheme is straightforward — they only need to register with the People's Bank of China (PBOC), who would grant their direct access. As of the time of writing, overseas institutional investors can access the onshore market through three schemes, which were introduced gradually over time. The first is the Qualified Foreign Institutional Investor (QFII) program, followed by the Renminbi Qualified Foreign Institutional Investor (RQFII) program, and finally, the Northbound Bond Connect, which gives the overseas investors access only to the interbank market. We discuss the introduction of these channels and the opening of the Chinese onshore bond market next.

4.2.2 The Opening of Onshore market

The opening of the market happened as the Chinese regulator rolled out access schemes for overseas investors to invest in the Chinese onshore bond market, which had largely remained closed despite its tremendous size. The regulation changes thus present a quasi-experiment to study the impact of ESG investing on asset prices, if a potential change in the composition of the investor base comes along with the opening of the onshore market.

The first step of the opening is the introduction of the Northbound Bond Connect in July 2017. This access scheme allowed overseas institutional investors to participate in the interbank market. They could trade enterprise and sovereign bonds in the interbank market through major dealers, such as Citi Group, while their assets were still in custody in Hong Kong. Nevertheless, several restrictions applied on how overseas investors could invest, including the lock-up periods and a

[14] Currently, the total annual quota for the Southbound Connect is 500 billion CNY, and the daily quota is 20 billion CNY.

maximum of $150 million investment quota.

We use September 2019 (2019 Q3) as the main "opening event" ("treatment date") for our analysis, as the opening of the onshore bond market experienced multiple tailwinds during this period. First, in September 2019, regulators removed lock-up periods for investors' invested assets, allowed QFIIs to hedge foreign exchange rates, and increased QFIIs' investment quota from $150 million to $300 million. The State Administration of Foreign Exchange (SAFE) also announced that it would repeal the QFII investment quotas in the near future. Furthermore, during that same month, the J.P. Morgan index announced that it would add Chinese government bonds to its index from February 2020.[15]

Figure 3 reports quarterly changes in holdings of onshore enterprise bonds, medium-term notes, and policy bonds held by overseas institutions.[16] The average net capital inflows increased nearly fourfold, from 50 billion CNY per quarter before the regulation change to 200 billion CNY per quarter after the regulation change. Confirming this pattern, Figure 4 shows an increase in U.S. holdings of Chinese bonds during our event window, based on data from the Treasury International Capital (TIC) system of the U.S. Treasury, which tracks U.S. holdings of foreign securities.[17] These two pieces of evidence confirm a positive flow into the onshore bond market.

We argue that the inflows from the overseas investors increased the proportion of the ESG-conscious investors in the onshore bond market due to the regulation changes. Our argument builds on the following evidence.

First, onshore investors did not pay much attention to ESG investing before the opening of the onshore market. For instance, the report from the Asset Management Association of China (AMAC, 2017) uncovered that only 6% of the sampled asset managers took ESG into account when making investment decisions in 2017. Additionally, a 2018 CFA survey of financial professionals in China revealed that only 9% of the respondents included ESG in their credit analysis (CFA Institute, 2019). Thus, we can reasonably state that the proportion of ESG-conscious investors could not have *decreased* following the market opening, given the extremely low starting point.

[15] See Reuters article of September 4th, 2019: https://www.reuters.com/article/china-markets-bonds/update-2-jpmorgan-adds-china-to-emerging-bond-index-from-february-2020-idUSL5N25V3F4

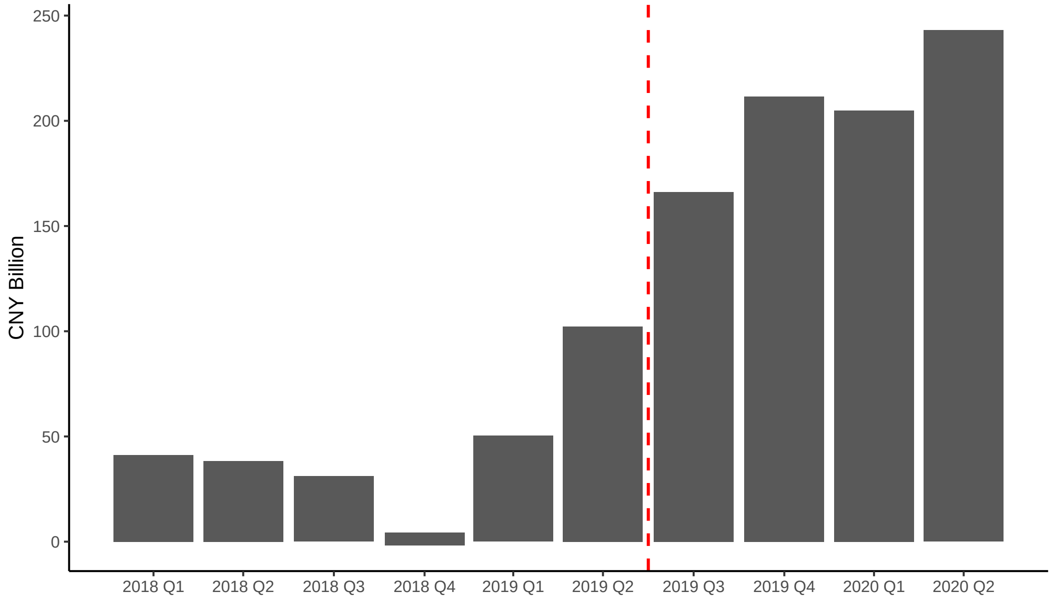
[16] The data is obtained from the China Central Depository & Clearing (CCDC) and the Shanghai Clearing House (SHCH).

[17] See https://home.treasury.gov/data/treasury-international-capital-tic-system for details of the data.

Second, the increase in the proportion of overseas investors has likely increased the proportion of ESG-conscious investors. There is considerable literature documenting the ESG-consciousness of U.S. and European investors (Martin and Moser, 2016; Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Ilhan et al., 2020; Bauer et al., 2021). This fact is also directly documented in local Chinese surveys. When asked about where the ESG demand comes from, all interviewees from the CFA survey indicated that the demand mainly comes from overseas investors, especially the United States and Europe (CFA Institute, 2019). Furthermore, this overseas-investor-driven ESG demand is well acknowledged in reports from mainland brokers (PingAn, 2020), overseas brokers (J.P. Morgan, 2021), and international organizations (PRI, 2020).

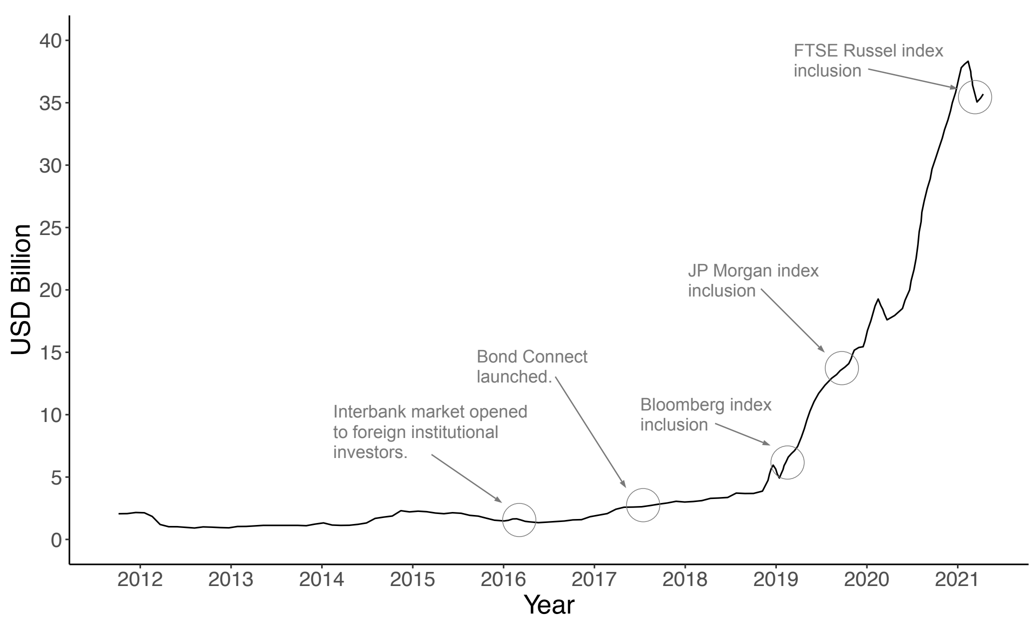
Third, mainland investors have also become more ESG-conscious following the onshore market opening. For example, the AMAC survey conducted in 2021 showed that approximately 50% of the respondent mainland mutual funds incorporated ESG criteria into their investment decisions.

Figure 3: Year-on-year change in net foreign holdings of enterprise bonds, medium-term notes, and policy bonds



Note: The red dashed line indicates the main event of Chinese onshore capital market opening used in this paper.

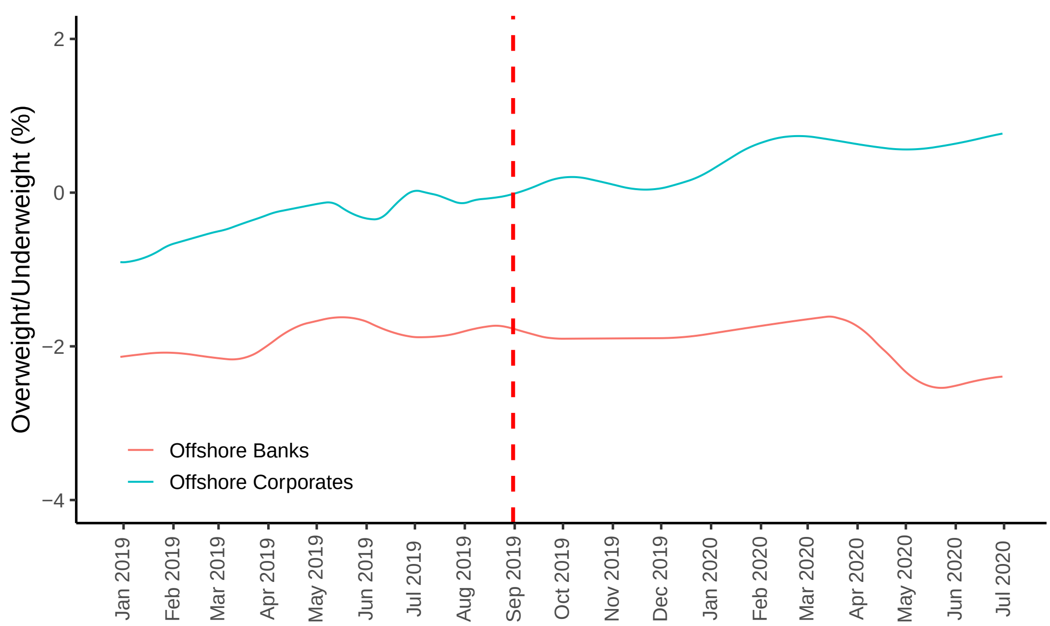
Figure 4: U.S. holdings of China bonds



Note: The figure shows the U.S. holdings of China Bonds in billion U.S. dollars from 2012 to 2021. The data is obtained the Treasury International Capital (TIC) from the U.S. Treasury.

Finally, we provide evidence that offshore bonds did not experience significant changes in their investor bases during this period. Offshore bonds are Euroclearable and can be traded by all investors worldwide without the need for local accounts, a condition that remained unchanged in 2019-2020. As evidence, we examine the positioning survey data for the offshore market during this period. Figure 5 shows a relatively stable trend with neutral positioning in corporate bonds and an underweight in banks. Corporate bond positioning started at approximately -1% (i.e., underweight) in January 2019, hovered around 0% during the months around September 2019, and reached approximately 0.5% in July 2020. For banks, it remained at approximately -2% throughout January 2019 to July 2020. Importantly, we did not observe any sharp increase around the date of the Chinese market opening, unlike the net inflows pattern shown in Figure 3. This evidence further supports that the regulatory changes endogenously changed the investor composition of the onshore market.

Figure 5: Chinese offshore positioning



Note: Data from J.P. Morgan EM Institutional Client Survey, more details on the data in A.1.3.2.

4.3 Methodology: triple difference with continuous treatment

We run the following triple-difference regression to estimate the impact of global investors' ESG-preference on EM ESG premium:

$$s_{i,s,m,t} = \alpha_i + \alpha_{s,t} + \alpha_{m,t} + \gamma ESG_s \times Onshore_m \times Post_t + \delta' X_{i,s,m,t} + \varepsilon_{i,s,m,t}, \tag{2}$$

where $s_{i,s,m,t}$ denotes the credit spread of bond i issued by issuer s in market m, where $m \in$ {offshore, onshore}, at the end of each month t. $Onshore_m$ is a dummy variable that takes the value of one if the bond is traded on the onshore market and zero otherwise; $Post_t$ is a dummy variable that takes one if $t \geq$ Sep 2019 — our treatment date when China eased the access to its onshore market for overseas investors; ESG_s is the ESG score of the company (bond issuer) at the time of capital markets opening in September 2019. We include a set of controls in $X_{i,s,m,t}$ to control for firm- and bond-level characteristics that are potentially related to pricing.[18] We include market-time fixed effects, $\alpha_{m,t}$, to control for common variations specific to the offshore and onshore markets, such as different policy rates set by the Fed and the PBOC, together with issuer-time fixed effect $\alpha_{s,t}$ and bond fixed-effect α_i .

Our main coefficient of interest, γ, is a triple-difference estimator based on the following three dimensions. First, the issuer-time fixed effect, or $\alpha_{s,t}$ in (2) constitutes the first dimension of difference. Effectively, this difference compares the onshore- and offshore- bonds' credit spreads from the same issuer, controlling for their bond-level characteristics (such as bond covenants and coupon type) through bond fixed effects α_i.[19] We term the resulting differences the "onshore-offshore spreads".

Second, through the $Post_t$ dummy in the specification, we are measuring the time-series differences of these onshore-offshore spreads ("difference-in-difference"). For a specific issuer, this difference-in-difference term should be driven by changes in the investor composition due to the opening of the market, as foreign capital flows in.

Finally, we group the firms with similar ESG ratings together and compare the difference in the

[18] We also include the $Duration_{i,t}$ of the bond and $Duration_{i,t} \times Onshore_m$ to allow for different duration effects on credit spreads in the onshore versus offshore markets. See Appendix A.5.1 for more details about the control variables we included.

[19] Coupon types include floating, fixed, step, or variable coupon.

difference-in-difference term between high-ESG and low-ESG firms. Our main coefficient of interest, γ, therefore measures how much the "difference-in-difference" in spreads would change for one unit change in firms' ESG ratings.

Compared to a simpler difference-in-difference (DiD) specification, the main advantage of our triple-difference specification is that it enables us to control for the issuer's unobservable time-varying fundamental factors. This is possible because we can observe both offshore and onshore bonds of the same issuer due to the institutional features of the Chinese corporate bond market.

To understand this advantage more clearly, consider a scenario where we only observe *onshore* bond prices and compute a DiD estimate before and after the bond market opening. Such a DiD estimate would be biased towards finding the existence of an preference-driven price premium, should high-ESG companies experience a disproportionate decrease in their probability of default compared to low-ESG companies. In other words, the coefficient associated with $ESG_s \times Post_t$ would be biased downwards, because the unobserved issuer-level fundamental changes are correlated with ESG ratings.

In contrast, our triple-difference specification is able to control for the time-varying probability of default of the issuer through $\alpha_{s,t}$. Continuing with our example above, if a company with high ESG rating experienced more decrease in probability of default post-opening, both its onshore and offshore spreads will decline, and the issuer fixed effect, $\alpha_{s,t}$ absorbs this common decline. Intuitively, through our triple-difference specification, we consider a specific company with either a high or a low ESG rating, compute their onshore-minus-offshore spread (the first difference), observe how this spread changes from pre- to post-opening (the second difference), and determine if this decrease was more significant than that observed for high- or low-ESG companies (the third difference).

4.4 Empirical Results: the Impact of Foreign Capital Flow on ESG Pricing

Table 5 shows the estimates of γ in Equation (2). Across different specifications, we find a statistically and economically significant increase in the ESG premium in the onshore Chinese market as it opened up to more overseas capital. Furthermore, the premium is driven by within-sector variation in ESG scores rather than cross-sector differences.

Our baseline estimate in Column (4) of Panel (a) shows an estimate of -9.6 bps (standard error = 3.79) for γ after accounting for all potential controls and fixed effects. This estimate indicates that firms with higher ESG scores (e.g., score 3 versus score 2) experience an average cost of capital reduction of 9.6 bps (standard error = 3.79) after an influx of foreign capital into the onshore bond market.

The baseline estimate also shows the price impact is economically meaningful. It is comparable to the average magnitude of the Chinese offshore ESG premium estimates (10.92 bps) shown in Panel (b) of Table A.3. Considering the size of the issuers in our sample, the estimate implies a substantial impact on the cost of capital for onshore Chinese firms. As shown in Table 2, the 75th percentile ESG score is 2.58 compared to 1.56 for the 25th percentile. This means firms in the top quartile of ESG scores would see a credit spread reduction of 9.6 bps compared to firms in the bottom quartile. This reduction represents approximately 8.8% of the average spread observed in onshore bonds (see Table 2). In dollar terms, this spread difference translates to a cost savings of 0.64 billion dollars for our matched onshore issuers with high ESG scores.

Table 5: Investors' preferences and ESG premium: Triple-difference regression

	Dependent variable:			
	Spread			
ESG Score × Onshore × Post	−6.87*	−10.11**	−10.09**	−9.58**
	(3.25)	(3.88)	(3.79)	(3.79)
Duration Controls		X	X	X
Rating Controls		X	X	X
SOE Controls		X	X	X
Size Controls			X	X
Coupon Type Controls				X
Bond FE	X	X	X	X
Issuer-Time FE	X	X	X	X
Market-Time FE	X	X	X	X
Observations	7,280	7,280	7,280	7,280
Adjusted R^2	0.96	0.96	0.96	0.96

(a) Main regressions

	Dependent variable:					
	Spread					
ESG Score × Onshore × Post	−9.58**	−11.44**				
	(3.88)	(3.88)				
Residual Sector ESG Score × Onshore × Post					−9.78**	−9.67**
					(3.46)	(3.68)
Sector ESG Score × Onshore × Post			−0.11	10.34		1.70
			(10.76)	(9.24)		(11.22)
Sector-Onshore-Post FE	X	X				
Controls		X		X	X	X
Bond FE	X	X	X	X	X	X
Issuer-Time FE	X	X	X	X	X	X
Market-Time FE	X	X	X	X	X	X
Observations	7,280	7,280	7,280	7,280	7,280	7,280
Adjusted R^2	0.96	0.96	0.96	0.96	0.96	0.96

*p<0.1; **p<0.05; ***p<0.01

(b) Regressions with sector effects

Note: This table shows the results from regression (2). The "Sector ESG Score" is the monthly sector-specific median across all emerging markets' ESG scores. The "Residual Sector ESG Score" is the company ESG score minus the sector median. We report robust standard errors clustered two-way at the issuer and time levels. The period spans from January 2019 to February 2020.

Panel (b) of Table 5 reveals that the ESG premium primarily comes from within-sector ESG score variation, not cross-sector differences. In Column (2), introducing sector fixed effects increases the ESG premium coefficient to -11.4 bps (standard error = 3.88) from -9.6 bps (standard error = 3.79) without sector fixed effects. Replacing firm-level ESG scores with sector median ESG scores in Column (4) results in a positive and statistically insignificant coefficient of 10.34 bps (standard error = 9.24), implying sector-level ESG scores do not drive our results.

We further validate that the ESG premium primarily stems from within-sector variation by including residual sector ESG scores in our regressions.[20] Column (5) shows that including residual sector ESG scores yields an estimate of -9.78 bps (standard error = 3.46). This result remains stable at -9.67 bps (standard error = 3.46) when including the sector median score as a control, as shown in Column (6). These results remain robust regardless of controls, as shown in Columns (1) and (3). Overall, these findings suggest that ESG-conscious capital focuses on firm-level ESG scores without discriminating against particular sectors. This is consistent with ESG rating agencies taking a sector-balanced approach when assigning ESG scores, as shown in Figure 9.

Overall, our results indicate that global investors significantly impact Chinese local firms through their ESG preferences as the market opens. Additionally, their main impact is within sectors. Next, we further examine the validity of the identification assumptions to evaluate the extent to which we can identify the preference channel.

4.4.1 Examining the validity of identification assumptions

We outline the identification assumptions and examine the validity of these assumptions empirically with a Granger test. As clarification, the following two are the key identification assumptions.

Parallel trends The key identifying assumption for the triple-difference estimator to be unbiased is *a parallel trend between the onshore-minus-offshore spread of high-ESG issuers and that of low-ESG issuers*. In other words, we assume that around 2019 Q3, the overseas net inflows induced by the opening of the local bond market is the only factor that would systematically make differential impacts on the onshore-minus-offshore credit spreads of high-ESG versus those of low-ESG issuers.

No anticipation of the shock Another identification assumption is that market participants had not anticipated the roll-out of the new regulation before September 2019. The validity of

[20] The residual sector ESG score is the difference between a firm's ESG score and the median ESG score within its sector.

this assumption determines the accuracy of our triple-difference estimate in capturing the ESG premium. Intuitively, it is possible that some market participants anticipated the further opening of the onshore market from Chinese regulators given the introduction of Bond Connect in July 2017, which signaled the government's willingness to further open the capital market to foreign investors. However, any anticipation would actually work against finding an ESG premium. This is because if domestic investors had anticipated increased demand from international investors before 2019 Q3, they would have started to rotate their portfolios towards high-ESG bonds. Consequently, this would have resulted in a tighter credit spread and thus decreased the estimate of γ in our framework.

The Granger Test We test the validity of both assumptions with a Granger causality test by estimating the following regression:

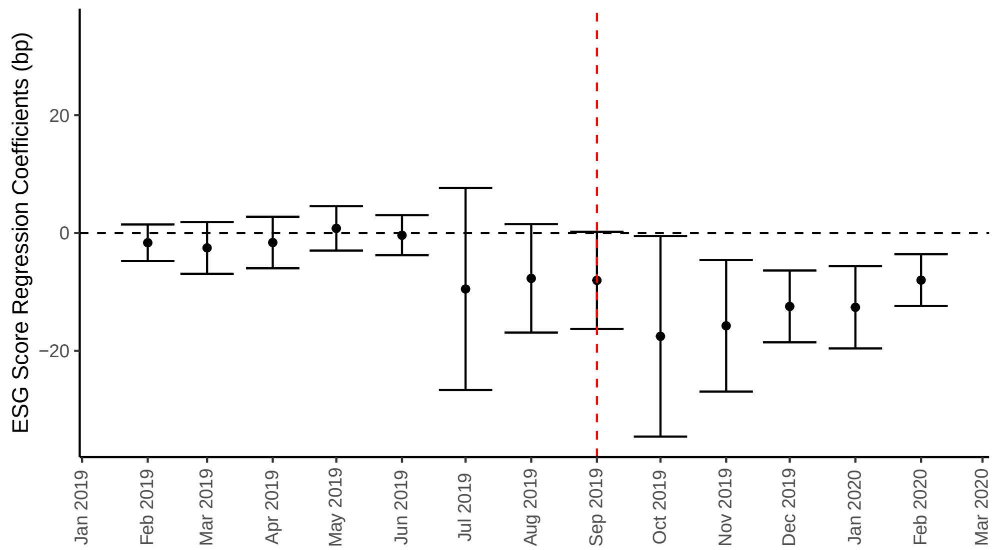
$$y_{i,s,m,t} = \alpha_i + \alpha_{s,t} + \alpha_{m,t} + \sum_{\tau} \gamma_\tau ESG_s \times Onshore_m \times D_t^\tau + \delta' X_{i,s,m,t} + \varepsilon_{i,s,m,t}, \tag{3}$$

where $\tau \in \{\text{February 2019}, \ldots, \text{ February 2020}\}$ and D_t^τ is a dummy variable taking the value one if $\tau = t$ and zero otherwise. The base month is January 2019, which is the first month of the year and sufficiently distant from the announcement date in September 2019.

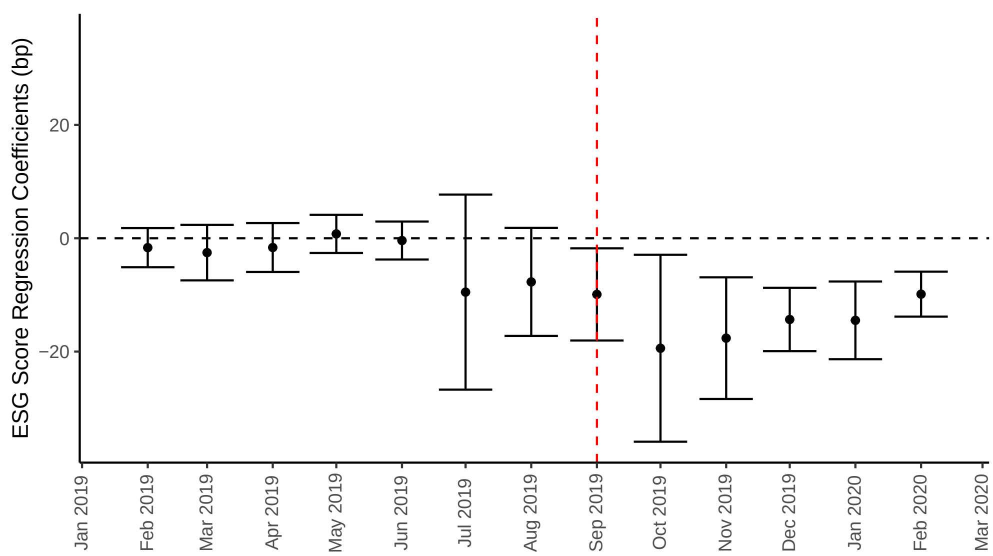
Support for the parallel trend assumption should come from failing to reject the null hypothesis, $H_0 : \gamma_\tau = 0, \forall\ \tau <$ September 2019. For the assumption of no anticipation of the shock to hold, we should observe that the onshore-minus-offshore credit spreads of high-ESG versus low-ESG issuers evolve similarly before the treatment date.

Figure 6: Bond yield and spread - dynamic coefficients associated with companies' ESG scores

(a) Without controlling for sectors



(b) With controls for sectors



Note: An illustration of the Granger tests based on Equation (3. The base month is January 2019.

Figure 6 shows the result of Granger test. There are no statistically significant differences between the onshore-minus-offshore spread of high-ESG and low-ESG issuers during any of the months' pre-treatment (from February 2019 to August 2019), both without controlling for sectors, as shown in Panel (a), and with controls for sectors, as shown in Panel (b). These results confirm the validity of our identification assumptions.

Differential preferences for bond characteristics between onshore and offshore investors

On- and off-shore investors could have distinctive preferences for certain bond characteristics due to institutional demand. If these bond characteristics are correlated with ESG scores, one could find the observed ESG premium, even though the driver of the ESG premium is the underlying differential preferences for certain bond/issuer characteristics.

The estimates in different columns of Panel (a) show that correlations between ESG scores and firm-level time-varying characteristics have limited price impact. Specifically, Column (1) shows an estimate of -6.87 bps (standard error = 3.25) for γ without any control variables but with bond-, issuer-, and time-fixed effects. Column (2) shows the estimate becomes more negative, at -10.11 bps (standard error = 3.88), when including issuer credit ratings, state-owned enterprise status, and bond duration, suggesting firms' ESG scores are positively correlated with these characteristics.[21] The estimate becomes slightly more positive when we include bond issuance amounts and coupon types in Columns (3) and (4), respectively, suggesting bond liquidity and coupon types do not drive our results.[22]

One characteristic that could correlate with ESG scores is a firm's long-run fundamental risk, which we cannot fully measure and control in our specification. Firms with strong ESG practices may be better equipped to withstand future climate-related events, potentially presenting lower long-run risk and bond yields. However, in our context, this concern is less relevant: the average maturity of bonds in our sample is relatively short, with 75% of bonds having a duration below 3.6 years and 95% below 7 years. Additionally, in untabulated results, we conduct our baseline regression excluding bonds with durations over 5 years and find similar results.

[21]When we include controls, we also include their two-way and three-way interactions with the post-opening and local-market indicators.

[22]These results remain robust when including bond seniority as controls (Table A.5) or using time-varying monthly ESG scores (Table A.6). Furthermore, when examining ESG scores discretely by including rounded ESG score (1 to 4) dummies, we find that the estimated effects increase monotonically in magnitude; the larger the score difference, the greater the impact (Table A.7).

4.5 Understanding the Magnitude of the Estimate

Our estimate finds that the inflow of foreign capital reduces the credit spreads of high-ESG firms (top quartile based on ESG ratings) by 9.6 bps, equivalent to 8.8% of the average borrowing costs in EM. To put this magnitude in context, the inflows during this period (around 250 billion CNY) amount to only about 1% of the market capitalization of our sample in the onshore market (close to 20 trillion CNY). Understanding how such a moderate quantity of inflows generates a large price impact is an intriguing question, one that a growing literature is beginning to address (Berk and van Binsbergen, 2021; van der Beck, 2021).

4.5.1 A Demand-System Based Explanation of the Large Impact: The Framework

Motivated by literature on how demand elasticity can generate excess price impact (Gabaix and Koijen, 2021), we assess whether the potentially inelastic demand from Chinese local investors could explain the large estimate we find. To that end, we apply the demand-system framework in Koijen and Yogo (2019) to local mutual fund holding data to evaluate the elasticity of mainland bond investors (See Appendix A.6 for more details on our implementation). Using this framework, we relate quantity data to price impact to assess whether our triple-difference estimate (based on prices) is plausible in a counter-factual analysis.

Estimating demand parameters of Chinese mutual funds We follow Koijen and Yogo (2019) and assume that returns have a factor structure and that expected returns are a function of the bonds' own characteristics. Under these assumptions, we can estimate the relationship between fund holdings and bond characteristics as follows:

$$ln\frac{w_{i,t}(n)}{w_{i,t}(0)} = \alpha_{i,t} + \beta_{0,i,t} mv_t(n) + \beta_{i,t}' \mathbf{x}_t(n) + u_{i,t}(n), \tag{4}$$

where $w_{i,t}(n)$ is the fraction of wealth invested in bond n by investor i at time t and $n = 0$ corresponds to outside assets; $u_{i,t}(n)$ is the log of latent investor i's demand that is not explained by market value and characteristics; $\alpha_{i,t}$ is the investor-quarter fixed effect; $mv_t(n)$ is the log of market value of bond n at time t; $\mathbf{x}_t(n)$ is a vector of characteristics of bond n at time t, which includes time to maturity, credit rating, and initial offering amount.[23] The parameters $\beta_{0,i,t}$ and $\beta_{i,t}$ are demand parameters to be estimated. In particular, $\beta_{0,i,t}$ measures the own-price elasticity of domestic investors' demand for bonds and serves as our main parameter of interest. The own-price elasticity can be computed as $elasticity_{i,t}(n) = 1 - \beta_{0,i,t}(1 - w_{i,t}(n))$.[24]

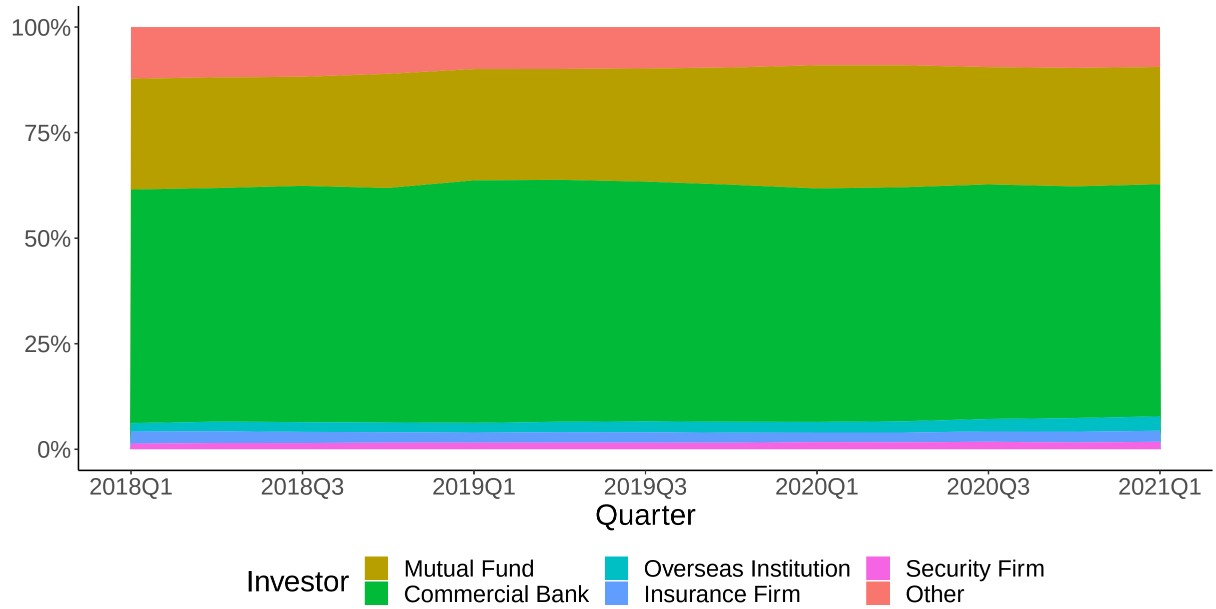
For the sake of completeness of the model as in Koijen and Yogo (2019), we define a residual sector that represents holdings of investors that are not currently captured by our sample. Formally, for each bond, the share held by the residual sector is defined as the difference between the bond's outstanding amount in CNY and the sum of the CNY holdings across all investors observed in the holding data.[25] In our sample, we only observe the mutual fund holdings. As shown in Figure 7, mutual funds and banks account for the majority of the holdings in the interbank market. Retail investors do not participate in the interbank market as explained in Section 4.2.1. Therefore, we denote the residual sector as banks, compared to Koijen and Yogo (2019) who denote it as household.

[23] The outside asset is the complement to the set of observed bonds which have complete characteristics.

[24] The own-price elasticity of demand is the percentage change in the quantity demanded of a good divided by the percentage change in the price.

[25] Assume each investor i in period t is endowed with an amount of wealth $A_{i,t}$. Following the market clearing condition for each bond, the market value of a bond must equal the wealth-weighted sum of the portfolio weights across all investors, $mv_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n)$.

Figure 7: Chinese interbank market investor structure



Note: The figure shows the investor structure of the Chinese interbank market between 2018Q1 and 2021Q1, based on data downloaded from monthly reports of China Central Depository & Clearing Company and Shanghai Clearing House. The category "Other" encompasses investors that do not consistently appear in both data sets over time, such as Policy Banks and trust companies.

Based on Equation (4), we run panel regressions using all investor holdings as well as using holdings of mutual funds and banks separately to obtain point estimates of the demand elasticity for the entire market as well as for each investor type. These estimates provide insights into the extent of inelasticity among domestic investors regarding onshore bonds. They also shed light on whether there is significant heterogeneity across different types of investors on average.

Next, we employ the generalized method of moments (GMM), with the moment condition

$$E[u_{i,t}(n)|mv_t(n), \mathbf{x}_t(n)] = 0,$$

to estimate the demand parameters for each quarter and investor type. We use these parameter estimates as inputs for our counterfactual analysis, which we discuss next.

Counterfactual analysis based on the demand system We use the demand parameter estimates to assess the plausibility of our triple-difference analysis estimates within the demand system. Specifically, we conduct a counterfactual analysis to determine the inflows required to observe the price impact estimated in our triple-difference analysis. The counterfactual analysis follows the intuition that if the model-implied inflows to high-ESG bonds align with the aggregate net inflows observed in the actual data, it validates the plausibility of our triple-difference estimate.

From the demand system, asset prices are fully determined by shares outstanding $\mathbf{s}_t$, characteristics $\mathbf{x}_t$, wealth distribution $\mathbf{A}_t$, coefficients on characteristics β_t, and latent demand ϵ_t, or

$$\mathbf{p}_t = \mathbf{g}(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t). \tag{5}$$

Building on Equation (5), we follow the literature to model the inflows of overseas investors as a negative residual supply shock to domestic bond investors (residual after the demand of overseas investors) particularly for high-ESG bonds.[26] This enables us to derive counterfactual prices and yields that mimic the prices and yields observed after the opening of the Chinese onshore markets following 2019 Q3.[27]

Specifically, denote $\Delta s(k)$ as the percent change in the shares outstanding for issuers of a particular ESG score k. $\Delta s(k)$ is the key variable whose magnitude we need to solve. To do so, we start by estimating the demand-system parameters using GMM as described the previous Section 4.5.1. With these parameter estimates, we can calculate the counterfactual price vector for all onshore bonds following this shock, denoted as $\mathbf{p}_t^{CF}(\Delta s(k))$, given by

$$\mathbf{p}_t^{CF}(\Delta s(k)) = \mathbf{g}(\mathbf{s}_t \times (1 + \Delta s(k)), \mathbf{x}_t, \mathbf{A}_t, \beta_t, \epsilon_t).$$

These counterfactual prices enable us to compute the counterfactual yields for bond n, $y_t^{CF}(\Delta s(k); n)$ through

$$y_t^{CF}(\Delta s(k); n) = -(\ln(p_n^{CF}(\Delta s(k); n)) - \ln(100))/\tau_t(n),$$

[26] The idea of using capital flows with inelastic demand as "residual supply shock" dates back to Harris and Gurel (1986) and Shleifer (1986), who use the index rebalancing as an instrument for supply shock to the other investors in the market. Recently, Koijen and Yogo (2020) and Koijen et al. (2021) use variations in central bank purchases as "residual supply shocks" to estimate demand elasticity.

[27] Here, we assume implicitly that the total supply of bonds (bond issuance) is slow moving, so additional demand from overseas investors does not lead to more bond issuance but instead reduces the supply left to local investors.

where $\tau_t(n)$ denotes the term to maturity of bond n at time t.[28]

Finally, we compute the model-implied difference-in-difference estimate, $\Delta\bar{y}_t^{\text{model}}(\Delta s(k))$, based on the average (equally weighted) counterfactual yields of a portfolio of bonds of ESG score k and score $k-1$, denoted as $\bar{y}_t^{CF,k}(\Delta s(k))$ and $\bar{y}_t^{CF,k-1}(\Delta s(k))$ respectively,

$$\Delta\bar{y}_t^{\text{model}}(\Delta s(k)) = \frac{1}{T}\sum_{t=0}^{T-1}\left\{\left[\bar{y}_{2019Q2-t}^{CF,k}(\Delta s(k)) - \bar{y}_{2019Q2-t}^{actual,k}\right] - \left[\bar{y}_{2019Q2-t}^{CF,k-1}(\Delta s(k)) - \bar{y}_{2019Q2-t}^{actual,k-1}\right]\right\},$$

where $\bar{y}_{2019Q2-t}^{actual,k}$ denotes the corresponding actual yields for bonds of ESG score k. We can solve for the optimal value of $\Delta s(k)$ by matching the model-implied yield differential with our triple-difference estimate.

Bias and data limitations We acknowledge that our demand-system analysis is subject to certain limitations due to data constraints and simplifications made in yield calculations. In order to address these limitations, we present an analysis in Appendix A.6.3.1 on the potential biases, including their direction and magnitude.

[28]We use pseudo-zero coupon yields following Bretscher et al. (2022) to convert between prices and yields.

4.5.2 Estimation Results

Table 6: Heterogeneity in the estimated demand parameters

	Whole Sample	Banks	Mutual Funds
	(1)	(2)	(3)
log Market Value	0.541***	0.989***	0.130***
	(0.039)	(0.009)	(0.039)
log Issuance Amount	−0.246***	0.011	−0.114***
	(0.039)	(0.010)	(0.039)
Time to Maturity	0.009***	0.001***	0.005***
	(0.003)	(0.0004)	(0.001)
Credit Rating	0.009	−0.006***	0.027***
	(0.006)	(0.001)	(0.006)
Average Own-price Elasticity	0.476	0.011	0.875
Fund × Quarter FE	X	X	X
Observations	14,711	5,025	9,686

*p<0.1; **p<0.05; ***p<0.01

Note: The table shows heterogeneity in the estimated demand parameters across investor types based on Equation (4). The sample period covers 2 quarters from 2019 Q1 to 2019 Q2.

The inelastic demand of the Chinese onshore bond market Firstly, Table 6 presents the estimated parameters of Equation 4 for the entire period of 2019 Q1 - 2019 Q2. Column (1) shows the coefficients estimated for both types of institutions, i.e., banks (the residual sector) and mutual funds. On average, investors exhibit an inelastic demand with an associated average own-price elasticity of 0.476, which aligns with the findings in existing studies using a demand system to estimate elasticity in the stock market.[29][30] However, when we differentiate between banks and mutual funds, we observe that mutual funds display a much more elastic demand, as evidenced by a substantially higher average own-price elasticity compared to banks.[31]

Additionally, we find that onshore bond investors have a preference for smaller bonds. Banks tilt their portfolios toward bonds with better credit ratings and longer maturities, while mutual funds

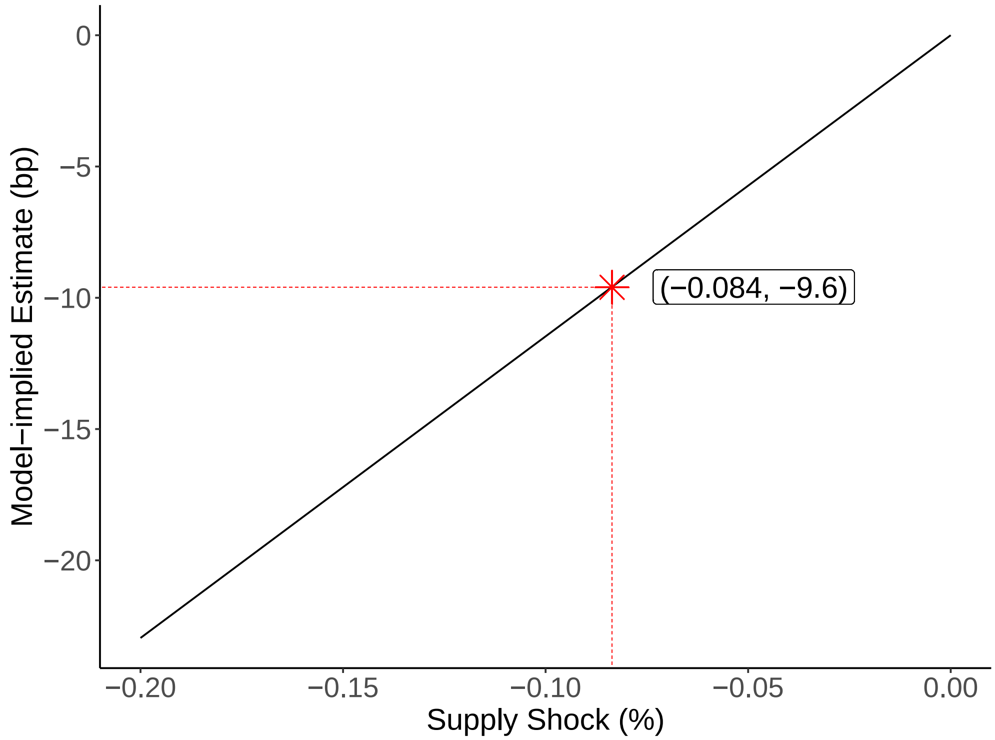
[29] If own-price elasticity is greater than 1, the demand is elastic; if less than 1, it is inelastic.

[30] Estimates for the U.S. stock market range from 0.3 (Koijen and Yogo, 2019; Haddad et al., 2021) to slightly over 1 (Chang et al., 2015)

[31] Bretscher et al. (2022) compute the market-wide elasticity for the U.S. corporate bond market as a whole by weighting the investor specific elasticities by their AUMs. The market-wide elasticity in the overall sample is 3.7.

tilt toward riskier bonds.

Figure 8: Effect of counterfactual supply shock on the model-implied estimate



Note: The figure plots the relationship between the counterfactual supply shock and the corresponding model-implied estimate for pricing impact described in Section 4.5.1. The sample period spans 2 quarters from 2019 Q1 to 2019 Q2. The asterisk denotes the point (-0.084, -9.6), where the resulting model-implied estimate of the counterfactual supply shock of -0.084% coincides with the reduced-form estimate of -9.6 bps.

Matching the Estimate with Quantity: A Counterfactual Analysis Next, we examine the results of the counterfactual analysis discussed in Section 4.5.1. The main objective is to see if our proposed economic mechanism can generate effects of similar magnitude than the triple-difference estimate.

Figure 8 illustrates the relationship between a hypothetical counterfactual supply shock to high-ESG bonds (with ESG score of 3) and the model-implied estimated change in spreads between high-ESG bonds and low-ESG bonds (with ESG score of 2). We highlight in red the estimate that corresponds to our reduced-form estimate of 9.6 bps. Given the estimated elasticities, we find that a supply shock as small as 0.084% in high-ESG bonds could result in such a spread differential.

This result shows that the economic mechanism we proposed is plausible. Firstly, Figure 3 indicates that year-on-year flows have ranged between CNY 150 billion and CNY 250 billion following the regulatory change (with an average of CNY 190 billion in 2019Q3-Q4). Additionally, we know from Table A.2 Panel (b), that the total market capitalization of our bond market sample was CNY 19,908 billion as of 2019Q3. Hence, the total net flows along with the opening represent approximately 1% of our total bond market capitalization. To put the result in perspective, it is as if foreign investors set aside 8.4% of the inflow of funds and used this fund to target high-ESG bonds. It therefore appears plausible that high-ESG bonds received an additional residual supply shock of 0.084% given the total inflows of 1%.

5 Conclusion

Our study demonstrates that global capital flows can significantly reshape the cost of capital among firms across their ESG ratings. We document a robust correlation between global capital inflows and the change in the ESG premium in the corporate bond markets across various emerging market (EM) countries. Our evidence suggests that this relationship is primarily driven by global investors' ESG preferences, whose price impact is further amplified by inelastic local investor demand.

These findings are particularly relevant in the current context of potential de-globalization and persistent global ESG-related issues. Globalization may offer additional benefits in addressing inherently global challenges such as ESG. Future research could explore other markets and investigate the implications of these dynamics on broader economic outcomes.

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Appendix

A.1 Data

A.1.1 Datasets on EM Corporate Bond Markets

A.1.1.1 EM corporate bond prices and issuer characteristics

First, we include all USD-dominated offshore bonds in the EM Global Diversified Bond Index (EMBI) and Corporate EM Broad Diversified Bond Index (CEMBI). Both are flagship indices maintained by J.P. Morgan.[32] Price-related characteristics of offshore bonds, such as spread, yield, and duration, are obtained from PricingDirect, a J.P. Morgan subsidiary. Other offshore bond characteristics, such as issuance amount and ex ante probability of default, are sourced from Bloomberg.

The bonds included in our indices have several features ensuring tradability for international investors. All bonds must be fixed-income instruments (fixed, floating, amortizing, or capitalizing) with at least six-month to maturity, not defaulted, internationally clearable, and with a minimum issue size of $300 million ($500 million for the EMBI index). We consider all corporate bonds, including bonds guaranteed by federal governments (quasi-sovereigns) but excluding those directly issued by national governments (sovereigns).

A.1.1.2 ESG scores

We use the company-level ESG scores computed by J.P. Morgan, which are also used in the construction of its two flagship emerging markets' ESG bond indices: the JESG CEMBI Broad Diversified index and the JESG EMBI Global Diversified index. These two ESG-related indices are among the first in its kind and broadly as benchmarks used by asset managers.[33]

The ESG scores computed by J.P. Morgan correspond to an equally weighted average of the ESG scores of RepRisk and Sustainalytics, two major providers of ESG scores globally. As opposed to

[32] J.P. Morgan consistently ranks among the top 3 investment banks in terms of underwriting activities for EM corporate bonds. See for example information from Cbonds (https://cbonds.com/rankings/727/).

[33] See for example https://www.jpmorgan.com/content/dam/jpm/cib/complex/content/markets/index-research/JPMorgan-Index-Perspectives-ESG-Investing-for-the-Future.pdf

using the single scores from other providers, such as MSCI or Refinitiv, there are several advantages in using this combined score. The first advantage is the high coverage of Sustainalytics and RepRisk. Overall, 99.7% of the market capitalization of the indices is covered by at least one ESG provider. The second advantage is the longer history of the indices. The JESG indices were launched in April 2018, whereas the only competing index for emerging markets was introduced by a Bloomberg-MSCI partnership in May 2021. Finally, the index ensures that the ESG scores used in this paper have not been restated or revised ex post, which may not always be the case with other data providers, as highlighted in Berg et al. (2020).

Sustainalytics Sustainalytics, which has recently been bought by Morningstar, is a leading ESG research provider for emerging markets, covering over 11,000 companies globally. The company's ESG Risk Ratings aim to identify financially material ESG risks at the firm level by measuring the magnitude of a company's unmanaged ESG risks. More specifically, a company's ESG Risk Rating comprises a numeric score and risk category. A higher score indicates more unmanaged risks. The firm scores are updated annually.

Sustainalytics follows a three-step process to find the ESG Risk Ratings. The first step is to find the company's exposure, which measures the company's vulnerability to ESG risks. The second step is to assess the unmanageable risks and management gap. The unmanageable risks are industry specific, while the management gap is company specific. The last step is to simply sum the unmanageable risks and management gap to obtain the unmanaged risks.

A company's exposure is computed as the industry exposure multiplied by the beta of the company. Industry exposure is determined by a set of ESG issues relevant to the industry in which the company operates. The estimate of the industry exposure considers external data (e.g., CO_2 emissions), company reporting, and third-party research. The beta of the company reflects the degree of the deviation of the company's exposure to ESG issues from the industry average. The betas enable the ESG ratings to be company specific. The computation of the betas has three stages: modeling of industry-specific beta indicators, analysis of firm-specific qualitative overlays, and application of technical correction factors.

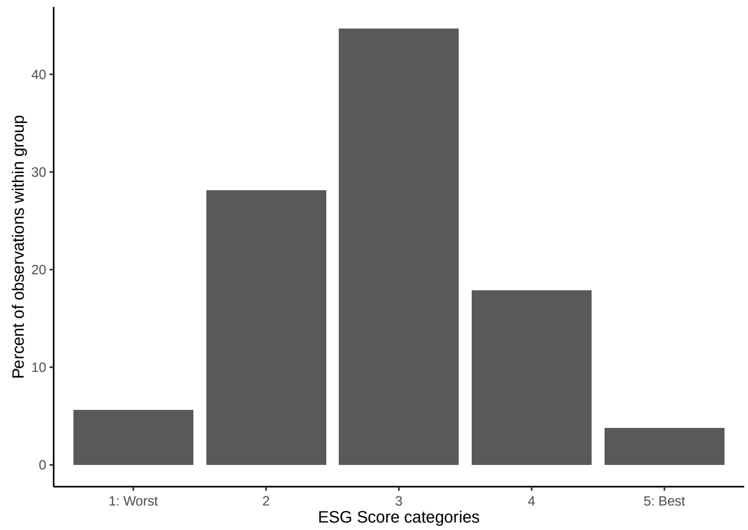
To quantify the unmanageable risks, Sustainalytics finds the industry-specific manageable risk factor (MRF). The determination of the MRF is based on four primary industry factors, hence ensuring the comparability of the ratings across companies and industries. Based on the MRF, Sustainalytics can calculate the unmanageable risks by multiplying the company exposure and (1 - MRF).

The other part of the unmanaged risks is the management gap, which is the failure of the company to sufficiently cope with manageable risks. This is computed as the product of the manageable risks and management score (in %). The management score stems from a set of management indicators and outcome-focused indicators. Management indicators assess a company's policies, management systems, and certifications, while outcome-focused indicators measure management performance, either directly in quantitative terms (e.g., CO_2 emissions) or by assessing a company's involvement in ESG-concerned controversial events.

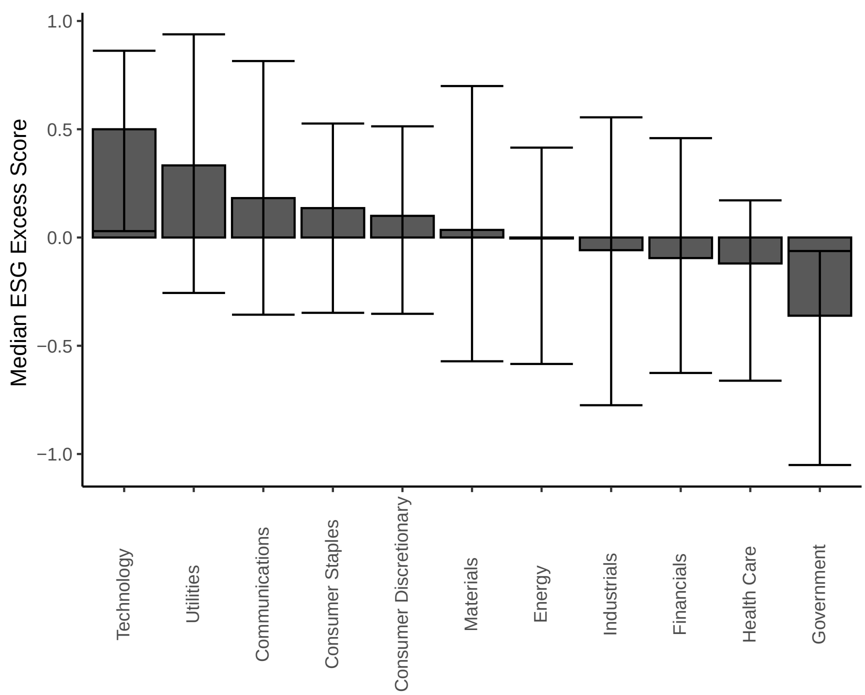
RepRisk The main score that RepRisk provides J.P. Morgan with is called the "RepRisk Index" (RRI). It is a score based on a RepRisk-developed algorithm, which dynamically captures a company's reputation risk exposure to ESG issues. The RRI depends on related risk incidents and reflects a company's actual risk management performance, as opposed to its ESG goals and policies. As a result, it is not influenced by potential greenwashing in companies' sustainable reports. It scrapes millions of sources, including, but not limited to, local regulators' reports, regional median outlets, press releases, NGO reports, think tank articles, law journals, blogs, and thought pieces. The RRI ranges from 0 to 100 and is updated daily. A higher value means higher risk exposure. There are three specified RRI indexes that provide dynamic measurements: (1) current RRI reflects the current level of attention that media and stakeholders pay toward ESG issues for a certain company, (2) peak RRI is equal to the highest level of the RRI over the last two years, acting as a proxy for the overall reputation risk exposure related to the ESG issues of a company, and (3) the RRI trend, which shows the increase or decrease of the RRI within the past 30 days. The RRI calculation combines two components: incident intensity and incident value. Incident intensity captures the frequency of risk incidents. It increases when the number of incidents associated with the company has risen in the past two months. Incident values are calculated as a time-weighted mean of the company's incidents from the last two years. RepRisk uses two years because it is their estimated time for a company to be able to mitigate any ESG conduct violation. The incident values are rated based on severity, reach of the information source, and novelty. Severity reflects the harshness of the risk incident or criticism. The reach of the information source is based on readership and circulation, as well as by the importance of the information in a specific country. Novelty reflects the newness of the issues addressed for the company: whether it is the first time a company has been exposed to a specific ESG issue in a certain location. The RepRisk dataset is incident based, which means each risk incident is automatically tagged in the different metrics mentioned above to all the related companies that have been identified in the risk incident.

Within- and Cross- Sector Distribution of the ESG Scores Figure 9 shows that ESG scores are approximately normally distributed, with 40% scores in the $[2, 3)$ category and less than 5% in the tail categories $[0, 1)$ and $[4, 5]$. Panel (b) shows the median deviation of ESG scores from the overall median for each sector, and the error bars indicate the 25th and 75th percentiles.

Figure 9: Distribution of ESG scores



(a) Distribution of ESG scores



(b) Median ESG scores by sector

Note: This figure shows the distribution of companies' ESG scores as of September 2019 for the entire JPM CEMBI and EMBI indices (excluding sovereign issuers). Panel (a) provides the percentage of ESG scores in each category, where category "1" contains all scores from 0 to 1, "2" contains scores from 1 to 2, ... until category "5", which contains all ESG scores between 4 and 5. In Panel (b), we plot the median ESG score by sector as well as its 25th and 75th percentiles with error bars.

A.1.1.3 Chinese corporate bond prices and issuer characteristics

The offshore Chinese corporate bond market information is included in our USD-dominated offshore bonds dataset. For the onshore market, we collect onshore bond prices, yield to maturity, duration, amount outstanding, and volume traded from THS-iFind (THS), a major commercial data vendor for market practitioners in China. To ensure quality and consistency, we complement and compare the THS data with WIND, another popular data provider, used in Ding et al. (2022).[34] Furthermore, following the market structure of Chinese onshore bond markets, we include enterprise bonds, corporate bonds, financial bonds, medium-terms notes, and commercial papers.[35] Our original sample goes from January 2015 until September 2021, but we focus on a short window around the regulation change in September 2019.

Chinese onshore bonds are traded on exchanges in Shanghai or Shenzhen or on the interbank market (IB). Investors active in the IB are mostly institutional investors, while retail investors have only access to exchange markets. Foreign investors who gain access to the Chinese onshore bond market through BondConnect can only access IB. In contrast, foreign investors who obtain a QFII license can access both the IB and exchange markets. Therefore, we collect bond information on both IB and exchange markets (Shanghai and Shenzhen) when applicable, to maximize the matching of onshore and offshore bonds. Bonds that trade both on IB and in exchanges have different identifiers in our database. We provide additional institutional background about the types of onshore bonds included in this study in the next paragraph. The price and returns of bonds traded on IB are based on actual transactions, reported by dealers to the National Association of Financial Market Institutional Investors (NAFMII).[36] Based on these reported transactions, THS collects the dirty prices of the last transaction each day as daily prices. Furthermore, THS also reports the low, high, last, average clean price, accrued interest, corresponding yield to maturity, and volume traded for each bond each day, and computes price-related measures, such as bond yields and duration. If no transaction occurs for a particular bond, THS uses the price of the previous transaction. We compute the bond spread as the difference between the corporate bond's yield and the duration-

[34] The reason we chose THS over WIND as our main data source is the better coverage of THS. For example, THS reports 6,647 enterprise bonds and the corresponding number for WIND is 5,152. Furthermore, THS reports 10,567 financial bond tickers, with 4,672 tickers being additional issuance and subsequent offering. Meanwhile, WIND classification reports 2,718 financial bonds.

[35] We exclude municipal bonds, asset-backed securities, and private placement notes.

[36] This association is similar in its nature to FINRA in the United States.

equal yield of the Chinese local sovereign bond yield curve. We estimate the Chinese government curve at the end of each month by using the Nelson and Siegel (1987) model.

Bond types in the Chinese onshore market A special feature of the Chinese bond market is the distinction between enterprise bonds and corporate bonds. Both of these types of bonds are issued by corporations, so they would be interpreted as "corporate bonds" in the U.S. However, they differ in China because of the ownership of their issuers and regulatory supervisor of their issuing activity. Specifically, enterprise bonds are issued by state-owned enterprises (SOEs) that are not listed on stock markets. On average, enterprise bonds have longer maturities than corporate bonds. Moreover, most enterprise bonds are debenture bonds. Since August 2021, enterprise bonds and financial bonds have been exempted from mandatory credit ratings, which means corporate bonds are the only bonds that require credit ratings.[37]

Enterprise and corporate bonds exclude bonds issued by financial institutions. Financial bond issuers include commercial banks, investment banks (securities companies), and insurance companies. Medium-term notes (MTN) and commercial papers (CP) trade on IB only. One interesting fact is that although most MTNs have maturities between three to five years, as in the U.S. market, there are 183 bonds with maturities longer than 10 years. This could be because of the issuance of listed SOEs, who cannot be listed on IB because of the regulation. To access the IB, these publicly listed SOEs use MTNs as long-term instruments to access the IB.

A.1.2 Matching Chinese onshore and offshore bonds

For our triple-difference design to understand how foreign capital flows impact bond prices in the Chinese corporate bond markets, we match the onshore and offshore bonds issued by the same company. As explained in Section 4.2.1, mainland firms often issue offshore bonds through special-purpose vehicles. To overcome this issue, we utilize the "CAST PARENT ID" provided by Bloomberg, which identifies the ultimate parent company. This allows us to match bonds issued by different entities. For example, we match bonds issued by China Evergrande Group and Evergrande Real Estate Group Ltd as the former is ultimately liable for all cash flow payments.

[37] Enterprise bonds and corporate bonds have equal requirements on minimum assets. However, these constraints are never binding for giant SOEs.

We match onshore and offshore bonds into one issuer by using the Bloomberg issuer identifier from each bond ISIN. We use the concept called "CAST_PARENT_ID", which identifies the ultimate parent of the company, and thus allows us to match bonds that are issued by the same company but through different special vehicle subsidiaries. For instance, the China Evergrande Group directly issues USD-denominated bonds. There are other bonds issued by Evergrande Real Estate Group Ltd, a subsidiary. Using the company ticker would not match the bonds issued by these two entities, despite being the same company ultimately liable for all cash flow payments.

Once all bonds are sorted into issuers, we further require that offshore and onshore have at least $150 million amount issued, that the bonds within an issuer have amounts issued that are not more than 10 times apart between onshore and offshore bonds, that the difference in spread is at most 1% as of the treatment date in September 2019, that the time to maturity is at least 1.5 years, and the difference between onshore and offshore bonds' time to maturity is not more than four years.[38] We additionally require that as of the treatment date, onshore bonds have been traded at least twice during the past six months and their bond yield correlations with offshore bonds had been at least 50% in the past 12 months. The results are robust to slightly different filtering parameters. Having too stringent restrictions reduces the number of issuers and, thus, the number of tests we can conduct, such as looking at within-sector ESG effect. After the merging process, we have a sample of 56 issuers with 323 onshore bonds and 197 offshore bonds for which we measure spread and yields from January 2019 to February 2020. We exclude the COVID-crisis because of the large spike in spreads across both onshore and offshore markets, with the lack of liquidity being a major driver for these movements.

The credit rating scale is as follows: 1 (AAA), 2 (AA+), 3 (AA), 4 (AA-), 5 (A+), 6 (A), 7 (A-), ..., 16 (B-). We use the median rating of all three rating agencies (S&P, Fitch, and Moody's) when all are available, and the minimum if less than three ratings are available. We download the

[38] We use $150M as our threshold for the amount issued because it corresponds to the minimum amount required for bonds to be included in a flagship J.P. Morgan Asian index. We also require a maximum of 1% spread difference to avoid selecting bonds that could have large differences in their covenants. This concerns less than 10% of the sample of matched bonds. The median spread difference between matched onshore and offshore bonds is approximately 0.25%. This difference is not necessarily equal to zero, given the absence of credit repo specials markets and single name default swap markets (Hill and Jia, 2021). Additionally, it can be difficult to perfectly hedge the exchange rate risk and duration risks between USD- and CNY-denominated bonds, as their cash flow schedule and duration can vary; liquidity on interest rate swap markets is low (Hill and Jia, 2021).

end-of-month time series of onshore and offshore ratings for each issuer from Bloomberg.[39] We also include a category "not rated" for issuers for which no ratings are available.

A.1.3 Investor holdings and portfolio positioning

A.1.3.1 Aggregate capital flows to EM Corporate bond markets

We source aggregate fund flows from the Lipper Global Fund Flows database. Our selection includes fund flows from developed market NBFIs (closed-end funds, open-end funds, exchange-traded funds, insurance funds, mutual funds, and pension funds) to emerging markets corporate bond markets. These flows are classified under "Bond Emerging Markets" in the "Lipper Global Macro Sectors" and span from May 2018 to March 2023, aligning with the timeframe of our EM corporate bond database.[40] All fund flows are denominated in US dollars and recorded at a monthly frequency.

In our analysis, we consider aggregate fund flows alongside specific ESG fund flows and negative screening fund flows. The ESG fund flows are identified based on funds flagged by Lipper as ESG-related, according to their prospectus or fund description. Negative screening fund flows represent the total fund flows from EM corporate bond funds that explicitly exclude sectors such as alcohol, drugs, fossil energy, genetically modified organisms (GMO), nuclear energy, tobacco, and weapons, as specified in their fund descriptions.

A.1.3.2 Investor portfolio positioning to EM corporate bond markets

We use a proprietary dataset, the J.P. Morgan Emerging Markets Client Survey to measure portfolio allocation to EM corporate bond markets at the country-level from global investors.

Each month, institutional investors are surveyed by J.P. Morgan to provide their portfolio positioning to a specific EM fixed-income assets (sovereign, corporate and currency) among 200+ options,

[39]The Bloomberg tickers for onshore rating are RTG_MDY_LC_CURR_ISSUER_RATING (Moody's), RTG_FITCH_LT_LC_ISSUER_DEFAULT (Fitch), and RTG_SP_LT_LC_ISSUER_CREDIT (Standard & Poor's). For the offshore ratings, the tickers are RTG_MDY_FC_CURR_ISSUER_RATING (Moody's), RTG_SP_LT_LC_ISSUER_CREDIT (Standard & Poor's), and RTG_FITCH_LT_ISSUER_DEFAULT (Fitch).

[40]Included funds are domiciled in Australia, Austria, Denmark, Finland, France, Germany, Italy, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the UK, and the USA.

including for example, Brazilian corporate bonds or Chinese sovereign bonds. The survey distinguishes between three types of investors: dedicated investors, who have dedicated or pure emerging market portfolios; crossover investors, who have a benchmark containing small or no allocations to emerging markets; trading investors, who have a total return benchmark, which are usually hedge funds or proprietary traders.

Specifically, each month t, J.P. Morgan asks each of the participant j among N to rank their positioning in each asset i as "Very Overweight," "Overweight," "Neutral," "Underweight," "Very Underweight" relative to their perspective benchmarks, and assigns a numerical score, $score_{i,j,t}$ as 10, 5, 0, -5, -10, respectively. Next, at the country-asset level, i, J.P. Morgan computes an aggregate $ExposureScore_{i,t}$, as a weighted average of all the participants' scores or

$$ExposureScore_{i,t} = \sum_{j=1}^{N} \frac{AUM_{i,j,t}}{\sum_{i=1}^{N} AUM_{i,j,t}} \times score_{i,j,t}$$

The weights $\frac{AUM_{i,j,t}}{\sum_{i=1}^{N} AUM_{i,j,t}}$ correspond to the share of assets under management of the respondent compared with the total assets under management of the participants. We use the monthly change in the $ExposureScore$, or

$$\Delta ExposureScore_{i,t} = ExposureScore_{i,t} - ExposureScore_{i,t-1}$$

for a particular asset as the measure for the capital flows to that country.

Table A.1 presents the summary statistics for the aggregate capital flows together with the portfolio positioning changes we use for our analysis.

Table A.1: Summary statistics of data used in the cross border regression

Statistic	N	Mean	St. Dev.	Min	Max
Change in positioning	69,746	0.027	0.188	−0.812	1.292
Long-short portfolio return	59	−0.038	0.533	−2.331	1.097
Corporate bond fund flow	59	92.974	860.983	−3,645.980	1,562.040

Note: This table shows the summary statistics of our data used in the cross border regression.

A.1.3.3 Chinese mutual fund holding data

Mutual fund bond-holding data is acquired from the China Stock Market & Accounting Research Database (CSMAR), a leading provider of financial market data in China. In compliance with regulatory requirements, mutual funds in China must report their top five bond holdings, and CSMAR collects the holding data from the funds' quarterly reports. In our demand estimation, we merge the onshore bond data with the mutual fund bond-holding data.

Table A.2: Summary of Bond Holdings by Funds

	Obs	Mean	SD	P5	P25	Median	P75	P95
Yield (%)	5,456	4.20	6.68	2.77	3.50	3.95	4.49	5.99
Price	5,456	101.73	10.55	98.09	101.66	103.40	105.24	107.77
Issuance Amount (Billion CNY)	5,456	7.37	23.46	0.50	1	2	3	32
Market Value (Billion CNY)	5,456	7.03	21.79	0.45	1.03	2.00	3.13	31.56
Time to Maturity	5,456	2.67	1.95	0.24	1.39	2.31	3.67	6.25
Credit Rating	5,025	1.47	0.96	1	1	1	2	3
ESG Score	1,191	2.19	0.83	1	2	2	3	4

(a) Summary of bonds held by funds

Year	Number of Funds	Total Market Cap (Billion CNY)	Observed Market Cap Held (Billion CNY)	% Market Held	Fund AUM (Billion CNY)	
					Median	90th Pct
2019Q1	2,979	18,955	1,139	6.01	0.61	6.69
2019Q2	2,922	19,428	1,161	5.98	0.64	6.42

(b) Summary of Fund Holdings

Note: Panel (a) reports the summary statistics of bonds held by funds in the sample. Bond credit ratings are converted into numeric values ranging from AAA (1) to D (22). Raw ESG scores range from 0 to 100 and are transformed into a discrete scale from 0 to 5 by dividing the raw scores by 20 and rounding to the nearest integer. Panel (b) reports the summary statistics of the fund holdings in the sample. Due to data restrictions, the following columns, "Total Market Cap (Billion CNY)", "Observed Market Cap Held (Billion CNY)", and "% Market Held" are based on the observed top 5 holdings and we consider only the bonds that are observed at least once in the holdings of the funds in each quarter. The sample period of both tables spans 2 quarters from 2019 Q1 to 2019 Q2.

Table A.2 shows the summary statistics of our final sample used for the demand estimation. In Panel (a), we present the summary statistics of the bonds. The average ESG score is 2.19, which is comparable to the onshore bonds in the matched sample. The average yield stands at 4.20%, which is also close to the average yield of onshore bonds in the matched sample. This is not surprising, as companies that can also issue in international markets tend to be safer and thus command a lower yield. Moving to Panel (b), we present the summary statistics of the holdings by mutual funds. The number of mutual funds in our sample increases over time, ranging from around 2,500 at the start of the sample to around 2,900 at the end of the sample period. On average, the funds in our sample are observed to collectively hold approximately 6% of the total outstanding amount of corporate bonds.

A.2 ESG Premium in EM Corporate Bond Markets

We regress secondary market bonds' credit spreads onto companies' ESG scores with control variables proxying for systematic, liquidity, and default risks. Specifically, we run the following regression for bond i, company s, at time t:[41]

$$s_{i,s,t} = \gamma ESG_{s,t} + \delta' X_{i,s,t} + \alpha_t' D_{i,s} + \varepsilon_{i,s,t}, \tag{A1}$$

where $s_{i,s,t}$ indicates the yield spread of bond i issued by firm s on top of duration-matched U.S. treasury yields. γ indicates the coefficient of interest — how bonds' yield spreads change with ESG scores. $ESG_{s,t}$ corresponds to the company's ESG score, a continuous variable ranging from 0 (worst score) to 5 (best score) we described in Section 2.

[41] Crifo et al., 2017, Baker et al., 2018, Ghouma et al., 2018, and Ben Slimane et al., 2019 do similar analysis for other markets.

Table A.3: Cross-sectional regression of spreads on ESG company score

	Spread					
	Whole sample		Pre-Covid		Post-Covid	
ESG Score	-18.86^{***}	-18.42^{***}	-12.27^{***}	-11.81^{***}	-20.05^{***}	-19.59^{***}
	(3.71)	(3.67)	(3.38)	(3.32)	(4.44)	(4.44)
Sector-time FE		X		X		X
Controls	X	X	X	X	X	X
Observations	87,888	87,888	38,551	38,551	49,337	49,337
Adjusted R^2	0.70	0.71	0.74	0.74	0.71	0.72

*p<0.1; **p<0.05; ***p<0.01

(a) Across all emerging markets

	Spread					
	Whole sample		Pre-Covid		Post-Covid	
ESG Score	-8.94^{**}	-10.92^{***}	-6.86^{**}	-7.58^{**}	-9.16^{*}	-11.53^{**}
	(3.49)	(3.87)	(2.95)	(3.25)	(4.68)	(5.15)
Sector-time FE		X		X		X
Controls	X	X	X	X	X	X
Observations	30,260	30,260	12,547	12,547	17,713	17,713
Adjusted R^2	0.84	0.84	0.84	0.84	0.85	0.85

*p<0.1; **p<0.05; ***p<0.01

(b) China

Note: This table presents the ESG premium in basis points, which corresponds to the coefficient γ of Equation (A1) Sample period: April 2018 to March 2022. The pre-COVID period stops in March 2020, and the post-COVID period starts in April 2020. We report robust standard errors clustered two-way at the issuer and time levels.

We include bid-ask spread (liquidity risk), bonds' beta to the EM corporate index (systematic risk), duration (interest rate risk) and Bloomberg's measure of bonds' ex ante default probability (default risk) as control variables ($X_{i,s,t}$) . Besides, we control for time fixed effects, α_t', specific to issuers' and bonds' characteristics contained in the vector of dummy variables, $D_{i,s}$. These dummies include rating (from AAA to CCC), coupon type (fixed, floating, step, variable, zero), callability (callable and non-callable) and ownership status (corporate or quasi-sovereign), and whether the bond's amount outstanding is above \$500M, and sector dummy variables.[42]

[42] We choose \$500M as the threshold for the bond's amount outstanding dummy variable because J.P. Morgan has another index, the CEMBI, which includes "large" bonds with minimum \$500M in amount outstanding. The CEMBI Broad contains all bonds with at least \$300M in amount outstanding. The sectors are Communications, Consumer

We run in total six alternative specifications and present the results in Table A.3 . In the first two columns, we estimate the ESG premium for the entire period from April 2018 to March 2022, with and without sector-time fixed effects. Across all emerging markets (Panel (a)), the estimated coefficients are between -18 bps and -19 bps independently of the sector fixed effects. These estimates are statistically significant with two-way clustered standard error at the time and issuer level. The estimates are of similar magnitude with and without sector fixed effects, which suggests that the premium comes mainly from within-sector variation.

The estimates are also economically significant. Given that the ESG score scale goes from zero to five, all else being equal, our estimate suggests that a bond issued by the best ESG company has an average credit spread of approximately 90 bps (=18 bps $\times$ 5) lower than the worst ESG-rated issuer within the same sector. For a specific firm, given their ESG scores are highly persistent, the top 25% firms with the most improvement in their ESG scores increase their ESG scores by 0.20 on average, which would translate into a decrease of 3.6 bps in their credit spreads.

We also find that the premium has increased in magnitude post-COVID, from 11-12 bps to 20 bps. This suggests potentially an increase in the ESG consciousness of the average investor in our sample. This is consistent with the sharp increase in flows toward sustainable funds starting in 2020 and continuing in 2021, as well as the interest from funds themselves to become more ESG-aware following the introduction of the Sustainable Finance Disclosure Regulation (SFDR). Additionally, given the ESG index was launched in April 2018, it is likely that investors only started paying serious attention to these scores in 2019.

To focus on China, we also estimate the ESG premium within China in Panel (b). We find a smaller, but statistically significant, magnitude of the ESG premium of approximately 10 bps for the whole period, 7 bps pre-COVID and 11 bps post-COVID. Again, the effect originates from the within-sector variation, given the similar coefficients with and without sector fixed effects. Finally, for the CHinese market, we find a larger magnitude of estimate post-Covid.

Discretionary, Consumer Staples, Energy, Financials, Government, Health Care, Industrials, Materials, Technology, and Utilities.

A.3 ESG Scores and Firm Fundamentals

Table A.4 reports the coefficients from a regression of ESG scores on issuer characteristics.[43] We find that the ESG scores negatively correlate with firms' credit ratings (high-ESG companies tend to be of better credit quality), positively correlate with bonds' beta, and negatively correlate with bond size and bonds' past volatility. Overall, issuer characteristics traditionally linked to systematic, default, and liquidity risks explain approximately 13.3% of the variation in ESG scores. For the investment-grade segment, the R-squared increases slightly to 20.2%. As a result, the ESG scores contain considerable orthogonal information.

[43]We aggregate all bond characteristics at the issuer level by taking the market value weighted average of each bond characteristic each month for each issuer. All the data for Table A.4 comes from the J.P. Morgan EMBI and CEMBI indices as explained later in the data section.

Table A.4: ESG scores and ex ante risks

	ESG Score		
	All	High Yield	Investment Grade
Ex ante default prob.	-0.329	0.245	-0.931
	(0.693)	(0.684)	(1.412)
Rating	-0.016^{*}	-0.036^{**}	-0.017
	(0.009)	(0.017)	(0.022)
Duration	0.012	0.0004	0.006
	(0.009)	(0.014)	(0.011)
Beta	0.107^{***}	-0.009	0.181^{***}
	(0.040)	(0.040)	(0.067)
Vol	-0.053^{***}	-0.020	-0.013
	(0.015)	(0.017)	(0.022)
log(Par)	-0.119^{***}	-0.019	-0.173^{***}
	(0.030)	(0.042)	(0.039)
Sector FE	X	X	X
Cluster S.E.	Issuer+Time	Issuer+Time	Issuer+Time
Observations	35,587	16,619	18,968
Adjusted R^2	0.133	0.123	0.202

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the coefficients from a linear regression of company ESG score on company's fundamental variables, over the entire sample, the high-yield segment, and the investment-grade segment in columns 1, 2, and 3, respectively. We report robust standard errors clustered two-way at the issuer and time levels.

A.4 Model

A.4.1 Model environment

We decompose the yield of corporate bonds as the sum of the bond's expected return and the expected loss, similar to Nozawa (2017). Let y be the vector of bond yields, μ the vector of expected returns, and l the vector of expected losses for all bonds in the economy. We have

$$y = \mu + l. \tag{A2}$$

For the sake of simplicity, we assume the risk-free rate to be zero, i.e., $r_f = 0$. The expected loss component is mostly driven by firms' fundamental (default) risk, while the expected returns are the equilibrium outcome resulting from investors' pricing of the fundamental risks and preference for potentially more ESG-friendly assets.

Similar to Baker et al. (2018), we consider two groups of investors who jointly decide the equilibrium expected returns of assets: a group of ESG-indifferent investors with a total capital of I and the other group of ESG-conscious investors with a total capital of C. Both groups have identical risk aversion and the same understanding of the fundamental risks of the bonds, captured by Σ. The key difference is that ESG-conscious investors require their portfolio to have a minimum average ESG score. In addition, we follow the literature to allow ESG-indifferent and ESG-conscious investors to have institutional preferences for particular bond characteristics, g and h, respectively.[44] In sum, both groups face a mean-variance optimization problem:

$$\begin{aligned}
&\text{ESG-indifferent Investors (I):} \max_{w_I} w_I'\mu + w_I'g - \frac{\gamma}{2} w_I'\Sigma w_I \\
&\text{ESG-conscious Investors (C):} \max_{w_E} w_C'\mu + w_C'h - \frac{\gamma}{2} w_C'\Sigma w_C \\
&\qquad\qquad\qquad\qquad \text{s.t.} \quad w_C'z \geq \bar{z},
\end{aligned} \tag{A3}$$

where Equation (A3) is the minimum ESG score constraint that ESG-conscious investors face. Specifically, z is a vector of ESG scores and $\bar{z}$ is the minimum weighted-average ESG score required by ESG-conscious investors. The additional constraint imposed on ESG-conscious investors is supported by empirical observations in the asset management industry, where such constraints are common.[45]

[44] This feature of the model is motivated by the literature on demand-driven asset pricing, where investors have specific demand for certain characteristics (Koijen and Yogo, 2019, Bretscher et al., 2022). For instance, pension funds and insurance companies tend to prefer investment-grade bonds due to regulatory constraints (Ellul et al., 2011), while mutual bond funds prefer more liquid bonds (Choi et al., 2020).

[45] For instance, the Carmignac Portfolio Prospectus writes "Average exposure weighted score is above 3 making a positive contribution to society and the environment."

A.4.2 Equilibrium bond pricing with ESG investors

Denoting the Lagrangian multiplier for ESG-conscious investors by λ, and the vector of deviation of ESG score versus the minimum threshold $\bar{z}$ by $\tilde{z} = z - \bar{z}$, we have the optimal portfolio weights for the ESG-indifferent and the ESG-conscious investors, respectively:

$$w_I = \frac{1}{\gamma}\Sigma^{-1}(\mu + g) \tag{A4}$$

$$w_C = \frac{1}{\gamma}\Sigma^{-1}(\mu + h + \lambda\tilde{z}). \tag{A5}$$

Let c be the proportion of ESG-conscious investors in the market, i.e., $c = C/(C+I)$. The market-clearing condition implies that the vector of weights of the market portfolio, w_m, is

$$w_m = (1-c)\,w_I + c w_C, \tag{A6}$$

Finally, substituting Equations (A4) and (A5) in the market-clearing condition Equation (A6), we obtain the equilibrium expected return as

$$\mu = \beta\mu_m - c\lambda\tilde{z} - (1-c)\,g - ch, \tag{A7}$$

where $\beta = \frac{\Sigma w_m}{\sigma_m^2}$.[46] Substituting μ in the original yield Equation (A2), we can express the yield of any bond i as

$$y_i = \beta_i\mu_m - (1-c)\,g_i - ch_i - \lambda c\tilde{z}_i + l_i. \tag{A8}$$

As Equation (A7) shows, a bond's expected returns does not only depend on the conventional CAPM term, $\beta\mu_m$, but also on the ESG scores, $\tilde{z}$, as well as other bond characteristics, g and h, that are valued by both group of investors. The impact of these characteristics depend on the proportion of ESG-conscious (ESG-indifferent) investors in the market.

[46]For simplicity, we assume that the market portfolio is ESG- and characteristic-neutral, such that the weighted-average ESG score exactly equals the threshold level $\bar{z}$, and $w_m' g = w_m' h = 0$.

A.4.3 Testable predictions

Equation (A8) implies two testable predictions for bond yields and related characteristics, particularly the ESG scores of bond issuers.

Prediction 1: *Given the same default risk l_i, systematic risk β_i, and characteristics g_i and h_i, bonds with higher ESG scores have lower yields than those with lower ESG scores. The difference in yields increases with the demand of ESG-conscious investors, or λc.*

The prediction shows that in the presence of the ESG-conscious investors, who also make investment decisions based on their ESG preferences, bonds are partially priced based on non-fundamental factors. Issuers with higher ESG scores receive more capital from ESG-conscious investors and experience lower cost of capital relative to their own fundamental risks. However, disentangling the influence of the fundamental channel from the preference channel poses a challenge for empirical work, as ESG scores are correlated with both factors.

On the other hand, the model explicitly illustrates that the benefits (lower cost of capital) obtained by issuers with high ESG scores depend on two key factors: how much capital ESG-conscious investors have in the market (c) and the strength of preference the ESG-conscious investors have to forgo expected returns (λ). By exploring these relationships further, we derive Prediction 2, which forms the foundation of our empirical research design.

Prediction 2: *Given the same default risk l_i, systematic risk β_i, and characteristics g_i and h_i, when the proportion of ESG-conscious investors increases, the equilibrium yield of high-ESG bonds decreases more than that of low-ESG bonds, with a difference proportional to $\lambda \tilde{z}_i$.*

Prediction 2 offers clear insights into how changes to the investor composition can impact the equilibrium pricing of bonds with different ESG scores. Since ESG-conscious investors have a particular preference for high-ESG bonds, as their share of capital increases high-ESG firms receive relatively more capital from ESG-conscious investors, which results in lower cost of capital compared to low-ESG firms.[47]

In sum, our model predicts that the presence of ESG-conscious capital *lowers* the cost of capital for issuers with higher ESG scores, *given the same level of fundamental risks.* Furthermore, as

[47] We can see this relationship analytically by taking the partial derivatives of the bond yield with respect to the change in the share of ESG-conscious investors and obtain *assuming constant risk premium μ_m, the partial derivative*

ESG-conscious capital increases, it becomes more concentrated in assets with higher ESG scores, resulting in a greater reduction in their cost of capital. Next, we discuss alternative hypotheses based on other existing theories.

A.5 Robustness checks

Table A.5 shows our results for estimating Equation 2 are robust to adding controls for bonds' seniority. The seniority types include senior secured, senior unsecured, subordinated and convertible. Table A.6 shows our results are robust when using monthly ESG scores instead of static ESG scores.

of bond yield y_i with respect to the proportion of ESG-conscious investors is:

$$\frac{dy_i}{dc} = -\lambda\tilde{z}_i + \mu_m\frac{d\beta_i}{dc} - (1-c)\frac{dg_i}{dc} + g_i - c\frac{dh_i}{dc} - h_i + \frac{dl_i}{dc}.$$

Table A.5: Preferences and ESG premium: DDD regression with seniority and maturity controls

	Dependent variable:			
	Spread			
ESG Score × Onshore × Post	-6.87^{*}	-9.08^{*}	-9.32^{*}	-8.92^{**}
	(3.25)	(4.60)	(4.49)	(4.11)
Duration Controls		*X*	*X*	*X*
Rating Controls		*X*	*X*	*X*
SOE Controls		*X*	*X*	*X*
Seniority Controls		*X*	*X*	*X*
Maturity Controls		*X*	*X*	*X*
Size Controls			*X*	*X*
Coupon Type Controls				*X*
Bond FE	*X*	*X*	*X*	*X*
Issuer-Time FE	*X*	*X*	*X*	*X*
Market-Time FE	*X*	*X*	*X*	*X*
Observations	7,280	7,280	7,280	7,280
Adjusted R^2	0.96	0.96	0.96	0.96

(a) Main regressions

	Dependent variable:					
	Spread					
ESG Score X Onshore X Post	-9.58^{**}	-10.32^{**}				
	(3.88)	(4.22)				
Residual Secctor ESG Score X Onshore X Post					-8.39^{**}	-8.92^{**}
					(3.76)	(4.02)
Sector ESG Score X Onshore X Post			-0.11	-0.58		-8.34
			(10.76)	(8.57)		(10.50)
Sector-Onshore-Post FE	*X*	*X*				
Controls		*X*		*X*	*X*	*X*
Bond FE	*X*	*X*	*X*	*X*	*X*	*X*
Issuer-Time FE	*X*	*X*	*X*	*X*	*X*	*X*
Market-Time FE	*X*	*X*	*X*	*X*	*X*	*X*
Observations	7,280	7,280	7,280	7,280	7,280	7,280
Adjusted R^2	0.96	0.96	0.96	0.96	0.96	0.96

*p<0.1; **p<0.05; ***p<0.01

(b) Regressions with sector effects

Note: This table shows the results from regression (2):

$$s_{i,s,m,t} = \alpha_i + \alpha_{s,t} + \alpha_{m,t} + \gamma ESG_s \times Onshore_i \times Post_t + \delta' X_{i,s,m,t} + \varepsilon_{i,s,m,t}$$

where $Onshore_i$ is a dummy that takes value one if the bond is onshore, $Post_t$ is a dummy that takes one if month $t \geq$ Sep 2019, and ESG_s is the ESG score of the company at the time of opening in September 2019. The "Sector ESG Score" is the monthly sector-specific median across all emerging markets' ESG scores. The "Residual Sector ESG Score" is the company ESG score minus the sector median. We report robust standard errors clustered two-way at the issuer and time levels. The period spans from January 2019 to February 2020.

Table A.6: Preferences and ESG premium: DDD regression with seniority and monthly ESG

	Dependent variable:			
	Spread			
ESG Score × Onshore × Post	−6.92**	−8.49*	−8.79*	−8.29*
	(2.99)	(4.49)	(4.32)	(3.94)
Duration Controls		X	X	X
Rating Controls		X	X	X
SOE Controls		X	X	X
Seniority Controls		X	X	X
Size Controls			X	X
Coupon Type Controls				X
Bond FE	X	X	X	X
Issuer-Time FE	X	X	X	X
Market-Time FE	X	X	X	X
Observations	7,256	7,256	7,256	7,256
Adjusted R^2	0.96	0.96	0.96	0.96

(a) Main regressions

	Dependent variable:					
	Spread					
ESG Score × Onshore × Post	−8.94**	−9.76**				
	(3.70)	(4.16)				
Residual Sector ESG Score × Onshore × Post					−8.09**	−8.35**
					(3.60)	(3.83)
Sector ESG Score × Onshore × Post			0.82	−0.32		−5.82
			(11.29)	(8.37)		(10.96)
Sector-Onshore-Post FE	X	X				
Controls		X		X	X	X
Bond FE	X	X	X	X	X	X
Issuer-Time FE	X	X	X	X	X	X
Market-Time FE	X	X	X	X	X	X
Observations	7,256	7,256	7,256	7,256	7,256	7,256
Adjusted R^2	0.96	0.96	0.96	0.96	0.96	0.96

*p<0.1; **p<0.05; ***p<0.01

(b) Regressions with sector effects

Note: This table shows the results from regression (2):

$$s_{i,s,m,t} = \alpha_i + \alpha_{s,t} + \alpha_{m,t} + \gamma ESG_{s,t} \times Onshore_i \times Post_t + \delta' X_{i,s,m,t} + \varepsilon_{i,s,m,t}$$

where $Onshore_i$ is a dummy that takes value one if the bond is onshore, $Post_t$ is a dummy that takes one if month $t \geq$ Sep 2019, and $ESG_{s,t}$ is the monthly ESG score of the company. The "Sector ESG Score" is the monthly sector-specific median across all emerging markets' ESG scores. The "Residual Sector ESG Score" is the company ESG score minus the sector median. We report robust standard errors clustered two-way at the issuer and time levels. The period spans from January 2019 to February 2020.

Table A.7: Preferences and ESG premium: DDD regression with rounded ESG score

	Dependent variable:			
	Spread			
ESG Score × Onshore × Post, Score 1	−4.59	−6.49	−7.31	−7.58
	(7.39)	(5.91)	(5.26)	(5.30)
ESG Score × Onshore × Post, Score 2	−3.79	-8.81^{***}	-9.82^{**}	-9.88^{**}
	(2.83)	(2.60)	(4.00)	(3.98)
ESG Score × Onshore × Post, Score 3	-22.31^{***}	-29.92^{***}	-30.83^{***}	-30.09^{***}
	(4.98)	(6.60)	(6.97)	(6.94)
ESG Score × Onshore × Post, Score 4	-10.44^{***}	-36.76^{**}	-36.12^{**}	-34.41^{**}
	(2.03)	(14.59)	(14.97)	(14.80)
Duration Controls		*X*	*X*	*X*
Rating Controls		*X*	*X*	*X*
SOE Controls		*X*	*X*	*X*
Size Controls			*X*	*X*
Coupon Type Controls				*X*
Bond FE	*X*	*X*	*X*	*X*
Issuer-Time FE	*X*	*X*	*X*	*X*
Market-Time FE	*X*	*X*	*X*	*X*
Observations	7,280	7,280	7,280	7,280
Adjusted R^2	0.96	0.96	0.96	0.96

*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results from regression (2):

$$s_{i,s,m,t} = \alpha_i + \alpha_{s,t} + \alpha_{m,t} + \gamma ESG_s \times Onshore_i \times Post_t + \delta' X_{i,s,m,t} + \varepsilon_{i,s,m,t}$$

where $Onshore_i$ is a dummy that takes value one if the bond is onshore, $Post_t$ is a dummy that takes one if month $t \geq$ Sep 2019, and ESG_s is the rounded ESG score of the company at the time of opening in September 2019. We report robust standard errors clustered two-way at the issuer and time levels. The period spans from January 2019 to February 2020.

Table A.8: Fund flow and return of long-short portfolio based on ESG - issuer level

	Change in spread		
	(1)	(2)	(3)
Fund flow	0.0780***	0.0968***	0.0964***
	(0.0110)	(0.0232)	(0.0254)
Benchmark		−0.0147	−0.0105
		(0.0185)	(0.0194)
Controls			X
Observations	59	59	59
Adjusted R^2	0.1337	0.1257	0.1044
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results from regression:

$$ret_t = a + bFundFlow_t + Control_t + e_t$$

where ret_t is the long-short portfolio return based on ESG, $FundFlow_t$ is the negative screening fund flow at time t, and $Control_t$ includes benchmark (CEMBI index), VIX, SP500 index, and Federal fund rate. The portfolio comprises long positions in bonds with top 50% ESG scores and short positions in bonds with bottom 50% ESG scores, sorted monthly and by sector. We report Newey-West standard errors with lag of 6 months. The period spans from May 2018 to Mar 2023.

A.5.1 Controlling for differential preferences between onshore and offshore investors

Our motivating model in Appendix A.4 demonstrates the possibility that ESG-indifferent and ESG-conscious investors may exhibit distinct institutional preferences for specific bond characteristics (denoted as g and h, respectively). Empirically, if these characteristics have different correlations with the ESG scores, the observed ESG premium may be attributed to these institutional preferences for other characteristics, instead of their preference for ESG.

To address this possibility, in our empirical specification, we include controls in $X_{i,s,m,t}$ that could influence the investment decisions of overseas investors through their institutional demand, such as measures of liquidity (Choi et al., 2020) and credit risk classifications (Ellul et al., 2011).

Specifically, we include the following control variables standalone, together with their double- and triple-interactions with the post-opening dummy and onshore dummy to ensure the completeness of our model:

- SOE_s: the dummy variable SOE_s equals one if the issuer is a state-owned enterprise (SOE), which has been shown to be an important variable that drives the borrowing costs of Chinese firms;
- $\log(Amount\ Issued_i)$: the size of the issuance captures the liquidity constraints faced by institutional investors;
- $CPN\ Type_i$: the coupon type (fixed, floating, etc.) is related to the bonds' liquidity;
- *Rating*: an issuers' rating belongs to one of the following categories: $\{AAA{-}A, BBB,$ and $HY\}$.

A.6 Demand system

A.6.1 Processing of holding data

In accordance with regulatory requirements, mutual funds in China are obligated to report the top five bonds ranked by market value as a percentage of the funds' net asset value. Our mutual fund holding data comes from China Stock Market & Accounting Research Database (CSMAR) and includes key variables such as the mutual fund code, bond code, bond-holding in shares, bond-holding in CNY, and quarterly dates.

To address missing data in the bond-holding in shares variable, we merge the holding data with bond data and impute missing shares by calculating the bond-holding in CNY divided by the bond price.

In addition, we merge the main holding data with fund-specific information from CSMAR. This enables us to obtain the quarterly asset under management, mutual fund type, and investment company details.

To account for the rest of the outstanding bond balance in the market, we create an investor that absorbs the remaining bonds that have been observed at least once to be held by any mutual fund in a given quarter. Given the substantial presence of banks as the largest investors in the interbank market, we denote this investor as the banks.

A.6.2 Merging bond and holding data

For our demand-based estimation, we calculate pseudo-zero coupon yields and prices based on Bretscher et al. (2022). Both pseudo-zero variables are winsorized at the 1% and 99% levels to mitigate potential outliers. As an additional variable, we introduce "shrout" which represents the amount outstanding divided by 100 CNY. Finally, we filter the observations, retaining only those with non-missing and non-zero shrout and prices.

We merge the bond data with the holding data using the quarterly date and bond code as identifiers. In addition, we define inside assets as bonds that possess complete pricing and characteristics information. For mutual funds, asset under management data is obtained from fund-specific information available on CSMAR. For banks, we calculate their asset under management by summing their quarterly bond-holdings in CNY. Finally, we create portfolio-related variables, including the portfolio weight, outside portfolio weight of bonds, and the ratio of portfolio weight of bonds to outside portfolio weight.

A.6.3 Counterfactual experiment

A.6.3.1 Bias and data limitations

The limited mutual fund holding data, for which we only observe the top 5 holdings of each fund in each quarter, and yield simplification constrain our analysis in four aspects.

First, we implicitly assume that our identification condition is

$$E[u_{i,t}(n)|mv_t(n), \mathbf{x}_t(n)] = 0.$$

That is, we assume that the prices (or market values) of bonds are exogenous. Koijen and Yogo (2019) examine the direction of such bias in the setting of U.S. stock market, and they find that without using the instrument for price, the estimation is biased towards inelasticity. We do not use the instrument for price proposed by Koijen and Yogo (2019) because that instrument is not strong enough given our data.

Second, we fail to incorporate the zero holdings of mutual funds into our estimation. By taking the log of the left-hand side of Equation 4, we implicitly omit zero holdings of mutual funds. Koijen and Yogo (2019) find that including zero holdings leads to estimations that are more elastic for smaller institutions, while the difference is not significant for larger institutions. However, since we only observe the top 5 holdings, we cannot reliably impute the zero holdings of mutual funds.

Third, our observed market share held by mutual funds is lower than actual interbank market share held by mutual funds. As shown in Table A.2, the observed market share held is around 6% while the actual market share is approximately 30% as shown in Figure 7. As a result, we have to attribute bonds that are actually held by mutual funds to the residual sector. This may lead to the residual sector appearing more inelastic in our estimation than it actually is.

Lastly, we follow Bretscher et al. (2022) and use pseudo-zero-coupon yield in our analysis to facilitate easier conversion between bond prices and bond yields. This oversimplification may distort the true dynamics of the bond market.