Auto manufacturers: Climate performance and the cost of capital

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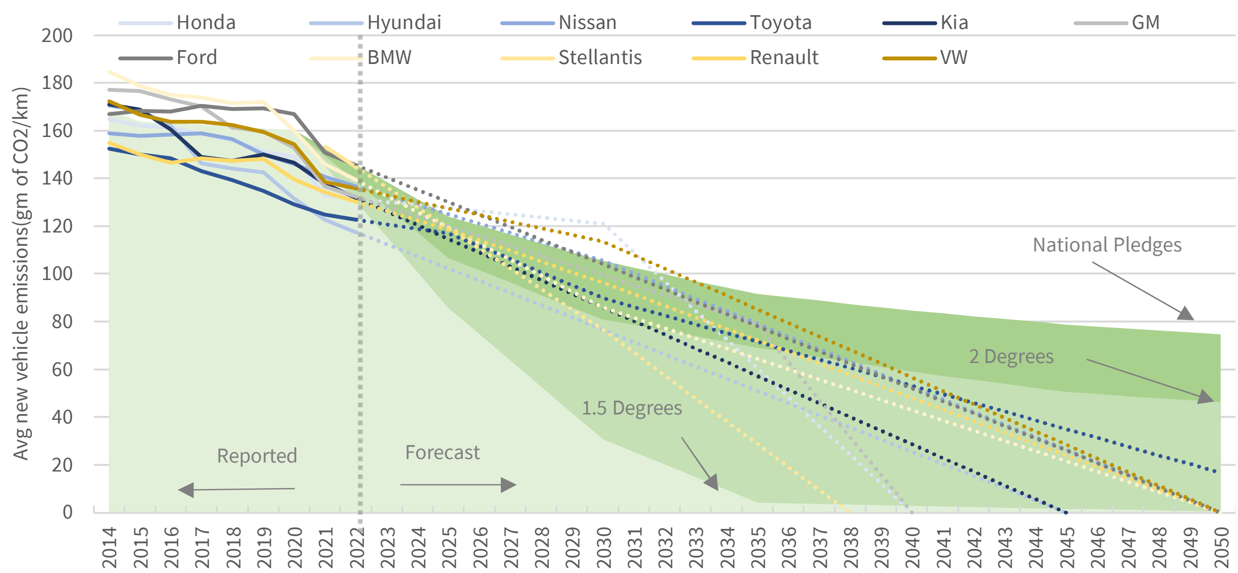
Road vehicles are a significant source of emissions; however, they are one for which there is a feasible transition due to ongoing developments in Electric Vehicle (EV) technology. 57 countries have committed to ending the sale of Internal Combustion Engines (ICE)[1] by 2050 at the latest. Business transition seems a clear strategy to maintain creditworthiness, and so tighter credit spreads, in this sector, will drive emissions reductions (see Figure 1).

In this note, we create a regression framework to understand the drivers of bond spreads in the automobile sector.[2] Specifically, we seek to analyse the impact of sustainability factors, such as implied temperature rise, emissions, or a general environmental score, on pricing.

- On a spot basis, lower aligned temperatures seem correlated with tighter spreads. This conclusion does not extend to other datasets, such as environmental scores or emissions.
- Historically, the relationship between environmental scores and spreads has become more significant with time, especially since 2019. Our comprehensive regression analysis confirms that sustainability is an important driver of spreads, albeit of low materiality.
- Hybrid manufacturer bond spreads have outperformed EV manufacturers in the past three years. Ongoing political support for EVs could drive spread tightening in that space.

Figure 1. Emissions intensity in the Auto manufacturing sector. Source, Transition Pathway Initiative, accessed 16 Oct 2023.



[1] "Phase-out of fossil fuel vehicles", Wikipedia, accessed 11 Dec 2023.
[2] For earlier work conducting a similar analysis in the oil & gas sector please see "Oil & Gas: climate performance and the cost of capital", AFII, 6 Mar 2023.

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Introduction

Road vehicles are a significant source of GHG emissions; private cars and vans used over 25% of global oil and created around 10% of energy-related CO_2 emissions in 2022.[3]

The transition of this industry is made possible by the initial success of hybrid vehicles, but now Electric Vehicle (EV) technologies. EVs have faced production difficulties, but volumes seem to have recently dramatically increased; more EVs were sold in the first half of 2022 than in any previous year,[4] and 2023 is projected to be 35% higher than 2022.[5]

COP26 saw a landmark agreement towards ending the sale of fossil fuel vehicles by 2040.[6] Although this agreement had some notable absences from both significant countries and manufacturers, the trend towards an accelerated electronification of road transport is clear.

The speed at which automotive manufacturers can transition their business towards the vehicles of the future will influence the sustainability of their ongoing business and, therefore, creditworthiness.

In this note, we consider the largest manufacturers and analyse funding spreads compared to sustainability performance to understand how it might impact the cost of capital.

Universe

To conduct this analysis, we first need to select a portfolio of securities from a universe of issuers.

Issuer selection

We identified the largest auto manufacturers by revenues with the most significant public debt outstanding. We first collected a list of 52 auto manufacturers from different sources and verified their outstanding debt with Bloomberg data.[7]

Though these are industrial companies, automakers often offer financing for the purchase of a vehicle, and so have corporate structures where the operating company is separate from a financing company, where both entities issue debt. The financial and credit risk inherent in their large financing arms is substantially different from the industrial part of the automakers, who face different kinds of risks which are not necessarily linked to the sustainability of the underlying manufacturing.

In debt markets, the bonds issued by financial subsidiaries carry different risk-reward structures and are also dependent on the macro and interest-rate conditions. The operating companies face traditional industry risk, and the bonds issued by such entities reflect that risk. As the credit risk metrics differ, we focus on the bonds issued by operating companies, which we identify by filtering for the 'Industrial' sector in Bloomberg. This still contains a few bonds from the financial arms of the automakers, and we apply further filtering using the reporting format, which is the 'Fundamentals Industry Code' in Bloomberg, to keep only companies that prepare accounts in

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[3] This is reported by the International Energy Agency in "Cars and Vans", IEA, accessed 4 Dec 2023.
[4] "This Was the Year That Electric Vehicles Took Off", wired, 27 Dec 2022.
[5] "Global EV Outlook 2023", IEA, accessed 4 Dec 2023.
[6] "Car firms agree at COP26 to end sale of fossil fuel vehicles by 2040", The Guardian, 10 Nov 2021.
[7] "Auto makers by market cap", companiesmarketcap.com, accessed 10 Oct 2023.

‘Industrial’ format rather than ‘Financial’ format. 31 operating companies issued bonds in the last eight years, which form the basis of our research. They are listed in Table 1.

Table 1: Automakers universe in this study. Source: Bloomberg, AFII, accessed 1 Nov 2023.

Ticker	Issuer	Region	Mkt Cap ($bn)	LTM Revenue ($mn)	Bonds outstanding ($bn)
VOW GR Equity	Volkswagen AG	Europe	62,027	332,562	107,675
7203 JP Equity	Toyota Motor Corp	Asia Pacific	308,098	298,758	107,636
F US Equity	Ford Motor Co	North America	42,351	174,228	67,665
GM US Equity	General Motors Co	North America	44,316	171,970	65,288
MBG GR Equity	Mercedes-Benz	Europe	68,783	164,417	60,540
005380 KS Equity	Hyundai Motor Co	Asia Pacific	29,440	121,384	51,318
BMW GR Equity	Bayerische Motoren	Europe	65,441	162,380	45,451
7267 JP Equity	Honda Motor Co	Asia Pacific	55,214	132,926	38,144
RNO FP Equity	Renault SA	Europe	11,608	54,555	24,371
STLA US Equity	Stellantis NV	Europe	69,564	198,957	19,766
7201 JP Equity	Nissan Motor Co	Asia Pacific	16,339	86,525	17,982
8TRA GR Equity	Traton SE	Europe	10,891	49,088	12,282
TTMT IN Equity	Tata Motors Ltd	Asia Pacific	31,033	42,701	7,568
GEELZ CH Equity	Zhejiang Geely	Asia Pacific		67,071	5,415
8291453Z LN Equity	Jaguar Land Rover	Europe		30,483	4,826
RIVN US Equity	Rivian Automotive I	North America	17,268	3,782	4,472
BMIHCZ CH Equity	Beijing Automotive	Asia Pacific		40,870	3,441
000270 KS Equity	Kia Corp	Asia Pacific	25,913	75,045	2,447
VOLCARB SS Equity	Volvo Car AB	Europe	9,898	37,209	2,430
P911 GR Equity	Porsche	Europe	82,322	43,807	1,393
AML LN Equity	Aston Martin	Europe	2,364	1,919	1,265
489 HK Equity	Dongfeng Motor Gro	Asia Pacific	4,282	13,527	1,210
175 HK Equity	Geely Automobile	Asia Pacific	10,508	23,444	710
7202 JP Equity	Isuzu Motors Ltd	Asia Pacific	10,040	24,089	544
RACE US Equity	Ferrari NV	Europe	64,502	6,210	491
2333 HK Equity	Great Wall Motor	Asia Pacific	25,926	22,305	490
TSLA US Equity	Tesla Inc	North America	759,222	95,924	364
NKLA US Equity	Nikola Corp	North America	1,045	31	330
1211 HK Equity	BYD Co Ltd	Asia Pacific	78,915	82,018	63
2238 HK Equity	Guangzhou Automobile	Asia Pacific	11,517	18,118	
7269 JP Equity	Suzuki Motor Corp	Asia Pacific	19,653	35,976	

Security selection

We next create the universe of bonds from these issuers. We filter for the most common types of bonds, which are the bullet, callable or make-whole bonds, the latter being a type of call provision where the borrower can pay off the remaining debt early. We considered bonds that were issued since 2015 and that have an issuance size of at least USD 200mn for each bond.[8] This leaves us with

[8] For issues smaller than USD 200mn the prices or spreads cannot be relied upon. Other kinds of bonds such as convertibles or perpetual bonds have different risk metrics. Their spread levels are not comparable so we exclude them from our analysis. Using a cut-off year of 2015, we expect most automakers to have tapped the markets in the last eight years which is also the limit for finding most climate-related data.

449 securities to comprise the bond universe. We sample the pricing of these bonds monthly over the last eight years.

As the bonds do not have the same maturity, and indeed, some mature during the period of study, our study is dynamic. We process the data further and remove bonds that have outlier spreads when doing monthly sampling. This brings the number of bonds to 429.[9] As we sample these bonds monthly, they generate 13,890 samples over the bond and time axis.

Table 2: Rating and currency composition of bonds, showing notional in USD bn and count. Source: Bloomberg, accessed 1 Nov 23.

Rating	USD	CNY	EUR	JPY	Others	Total
AA	52 (5)			87 (7)		139 (12)
A	856 (39)		1383 (33)	52 (3)	359 (35)	2650 (110)
BBB	2243 (66)		1284 (43)		203 (19)	3731 (128)
BB	856 (16)		523 (13)		99 (4)	1477 (33)
B	73 (3)		37 (3)			109 (6)
CCC	53 (2)					53 (2)
NR	26 (1)	600 (104)	123 (7)	315 (20)	88 (6)	1151 (138)
Total	4159 (132)	600 (104)	3349 (99)	454 (30)	748 (64)	9311 (429)

The rating and currency composition of these bonds are presented in Table 2. We provide the notional in USDbn for each currency and rating, along with the number of bonds that make up that sample in brackets. USD bonds are the biggest category in the currency dimension, and BBB-rated bonds dominate the ratings distribution. Most CNY denominated bonds do not have a rating from Bloomberg defined sources, but there is a meaningful amount of CNY issuance in the market, which warrants their inclusion.

Data selection

This analysis seeks to understand whether an issuer's sustainability performance drives its credit spread. We model this as a regression problem, so we have selected suitable datasets. Credit spreads will depend on financial data, e.g. an issuer's rating, maturity, and currency of the bonds, so we include these variables to isolate the potential impact of sustainability data.

Credit spread data

When analysing bond spreads, we use the Option Adjusted Spread (OAS), which is the spread needed to be added to a benchmark yield curve to discount the bond payments to match its market price when adjusting for any optionality. This is a model-implied spread, and our levels come from Bloomberg analytics.

As mentioned earlier, these are monthly spreads, balancing the granularity of change (removing short-term market moves) with the ability to analyse a significant overall period (eight years).

The market environment also drives the spreads, especially as markets trade in different regimes where different risks dominate at one time, such as high or low inflation regimes. To capture these differing risk perceptions, we include time-varying dummy variables, i.e. the year and month of the spread sample. The yearly dummy variable will capture any repricing specific to a year. There is

[9] Outliers are spreads that are sometimes negative due to short-term nature of the bonds or credits which are distressed. We removed credits with spreads less than 10bps or more than 1000bps.

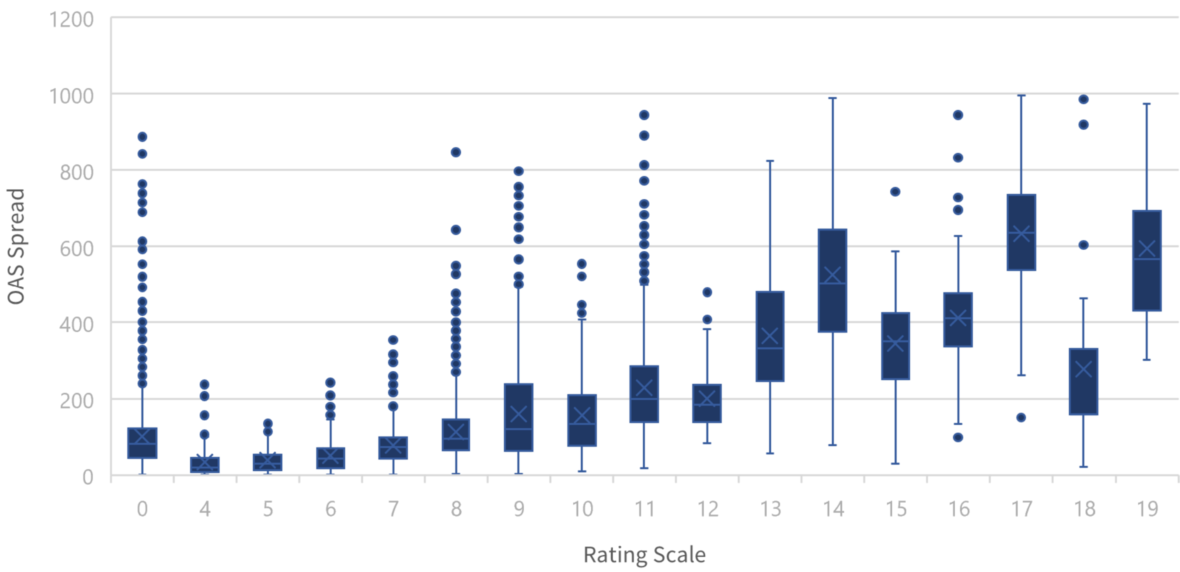
evidence of seasonality around bond spreads as trading is focused on a few months with high liquidity and some months where there could be large moves with sparse volumes which is captured by the monthly dummy variable.[10] The market microstructure for each bond is also important where large size bond issuers and better rated issuers have generally more liquidity, in our study we collect the issue size of the bond for this purpose and together with credit ratings the model should account for liquidity.

Financial data

There are many expected drivers of bond spreads, which we include in our analysis as independent variables.

We consider the credit rating and duration of all bonds to be the most significant drivers in explaining any bond spreads along with the sector.[11] The credit rating can move over time, so we capture these changes. The duration also reduces over time, and so we will be able to understand any non-linearity of the relationship between the ratings and duration. We map the credit rating from AAA to CCC to a numeric scale from one to 18 and lower and map the non-rated to 0. We take the steps within the rating as well into consideration where A+, A, A- will be 4, 5 and 6 respectively. A higher number is equivalent to a lower credit rating instead of categorical classification, as there is the relationship between the categories.

Figure 2: Box whiskers plot showing relationship between credit ratings and spreads of the bond, Source: Bloomberg, AFII, accessed 1 Nov 23.



The spread distribution for each rating scale in our data set, unadjusted for currency or duration, is given in the box-whiskers plot in Figure 2. The central bar for each rating represents the lower and upper quartile range with the median somewhere in the middle, shown with an 'X' mark. The lines show the minimum and maximum values in the range.[12] The outliers are marked as circles to show how outside they are of the min/max range. The non-rated category, 0, has the most outliers. Most

[10] "Seasonality in Daily Bond Returns", Susan and Bradford D. Jordan, Journal of Financial and Quantitative Analysis, April 2009.

[11] Given we are focusing on only one sector in this study, there is no need to include any sector-specific variables.

[12] The minimum is 1.5 times the range between the quartiles measured from lower or upper quartiles. Anything beyond that is considered an outlier.

outliers are in the upper extreme side, suggesting that they are wide to what their current credit rating would imply. We explain these spreads through various other features as well.

We also seek to capture time-invariant bond variables, i.e. those variables that do not change with time but do impact spreads. We consider currency, coupon, and the issuance size of each bond. The coupon of a bond impacts the cash price, which can be a driver of spreads, and the deal size is a proxy for liquidity, with large deal size bonds trading more. We capture the duration with time to maturity and the age of the bond since it was issued. Call options can also play an important role in spread movements, so we include a Boolean variable to address the callability of the bond.

A common observation in the markets is that the spreads of bonds from same issuer cluster around the issuer curve and are therefore quite correlated. To capture these similarities, we include issuer-specific categorical dummy variables. Any issuer level data, such as financial accounting data or emissions scores, will be in the issuer-specific variables as instrument level data is not feasible today.

Sustainability data

We use four variables related to sustainability in this study. Direct Greenhouse Gas (GHG) emissions (which is Scope 1 + 2 location based), GHG Scope 3, MSCI Implied Temperature Rise (ITR) and the Bloomberg Environment pillar score (E-score).

The GHG Scope 1 + 2 emissions are well tracked, and these are emissions generated by a company through resources it controls or uses indirectly in their business activities. The company's value chain creates the Scope 3 emissions. In the auto sector, it is mainly driven by the emissions of the cars or trucks driven by customers and the auto suppliers of the automotive company. The company directly reports the GHG variables or estimates them from similar peers.

The MSCI ITR is a well-known forward-looking variable. It calculates the undershoot or overshoot of the emissions targets that companies have promised over the long term, against the future carbon budget assuming a world temperature rise of under 2°C.[13]

The Bloomberg E-score is a sector-specific score derived from various climate-related issues, which considers aspects such as the number of EV or hybrid vehicles sold and the overall efficiency of the cars.[14]

The GHG variables and E-scores have historical availability, which helps evaluate the historical climate pricing evolution.

Table 3 (overleaf) shows the universe with sustainability data.[15]

[13] "Implied Temperature Rise Methodology", *MSCI ESG Research*, Jun 2023.
[14] "Environmental & Social Scores", Bloomberg, accessed 10 Nov 2023.
[15] Where data is unavailable, it is left blank, especially for privately held companies.

Table 3: Automakers with types of vehicles and sustainability data. Source: Bloomberg, Company sites, accessed 3 Dec 2023.

Ticker	Issuer	Region	Total vehicles(000s)	% Electric Vehicles	% Hybrid	GHG Intensity (tonnes of CO_2 /mn EUR sales)	MSCI ITR (°C)
VOW GR Equity	Volkswagen AG	Europe	8,263	7%		1,441	3.20
7203 JP Equity	Toyota Motor Corp	Asia Pacific	8,822	0%	31%	2,186	3.60
F US Equity	Ford Motor Co	North America	4,231	3%	4%	2,481	3.10
GM US Equity	General Motors Co	North America	5,939	9%		1,853	3.60
MBG GR Equity	Mercedes-Benz	Europe	2,456	7%	8%	825	2.50
005380 KS Equity	Hyundai Motor Co	Asia Pacific	3,943	6%	6%	1,030	1.70
BMW GR Equity	Bayerische Motoren	Europe	2,400	9%	7%	1,501	1.50
7267 JP Equity	Honda Motor Co	Asia Pacific	2,382	1%	7%	2,880	2.00
RNO FP Equity	Renault SA	Europe	2,051	8%	6%	1,232	4.10
STLA US Equity	Stellantis NV	Europe	5,782	5%	5%	2,509	1.60
7201 JP Equity	Nissan Motor Co	Asia Pacific	2,451	15%	9%	1,607	2.70
8TRA GR Equity	Traton SE	Europe	305			263	
TTMT IN Equity	Tata Motors Ltd	Asia Pacific	1,336			1,032	9.60
GEELZ CH Equity	Zhejiang Geely	Asia Pacific	2,300	29%		1,055	6.70
8291453Z LN Equity	Jaguar Land Rover	Europe	321			1,245	9.60
RIVN US Equity	Rivian Automotive I	North America	20	100%		804	1.40
BMIHCZ CH Equity	Beijing Automotive	Asia Pacific	1450			588	10.00
000270 KS Equity	Kia Corp	Asia Pacific	2,904	5%	9%	1,162	4.10
VOLCARB SS Equity	Volvo Car AB	Europe	615	11%		1,240	1.50
P911 GR Equity	Porsche	Europe	310	11%		2	2.50
AML LN Equity	Aston Martin	Europe	6			13	1.40
489 HK Equity	Dongfeng Motor Gro	Asia Pacific	2,465			3,468	10.00
175 HK Equity	Geely Automobile	Asia Pacific	1,433	18%	2%	2,411	5.00
7202 JP Equity	Isuzu Motors Ltd	Asia Pacific	671			4,541	3.10
RACE US Equity	Ferrari NV	Europe	13	0%	43%	162	2.30
2333 HK Equity	Great Wall Motor	Asia Pacific	1,068			1,265	6.00
TSLA US Equity	Tesla Inc	North America	1,314	100%		396	2.20
NKLA US Equity	Nikola Corp	North America				91	1.30
1211 HK Equity	BYD Co Ltd	Asia Pacific	1,869	49%		916	2.40
2238 HK Equity	Guangzhou Automobile	Asia Pacific	2,434			2,759	7.00
7269 JP Equity	Suzuki Motor Corp	Asia Pacific	3,225			1,146	

Spot analysis

Introduction

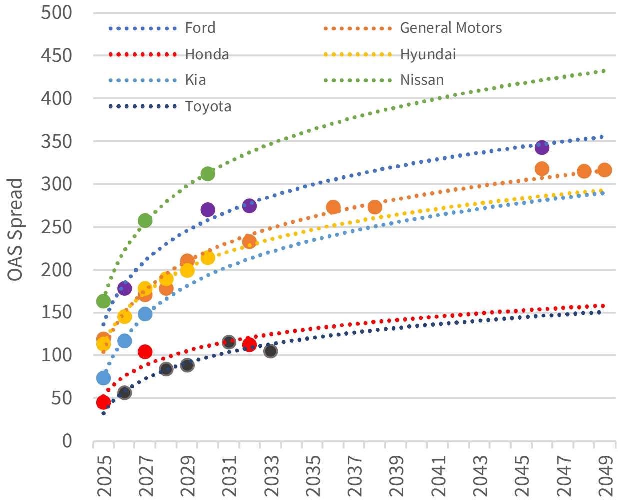
First, we look to understand whether, on a spot basis, sustainability performance is a driver of bond spreads. In this part of the analysis, we use data on 1 Nov 23.

Method

For the spot analysis, we use the current spread of similarly rated issuers in USD currency. We plot the curves of these issuers as shown in Figure 3. The credit curves are extrapolated through a log fit of the individual bond spreads. They are all rated investment-grade, ranging from A+ to BBB-. Nissan (BB+/BBB-) is the widest while Toyota (A+) has the tightest spreads.

For similarly rated issuers, we need to address whether there is any credit risk separation when observed through sustainability data. We use the E-score and ITR variables, and group them into high, medium, and low using 33% centile values. Low values of ITR and high values of E-score imply that a given company has stronger sustainability credentials.

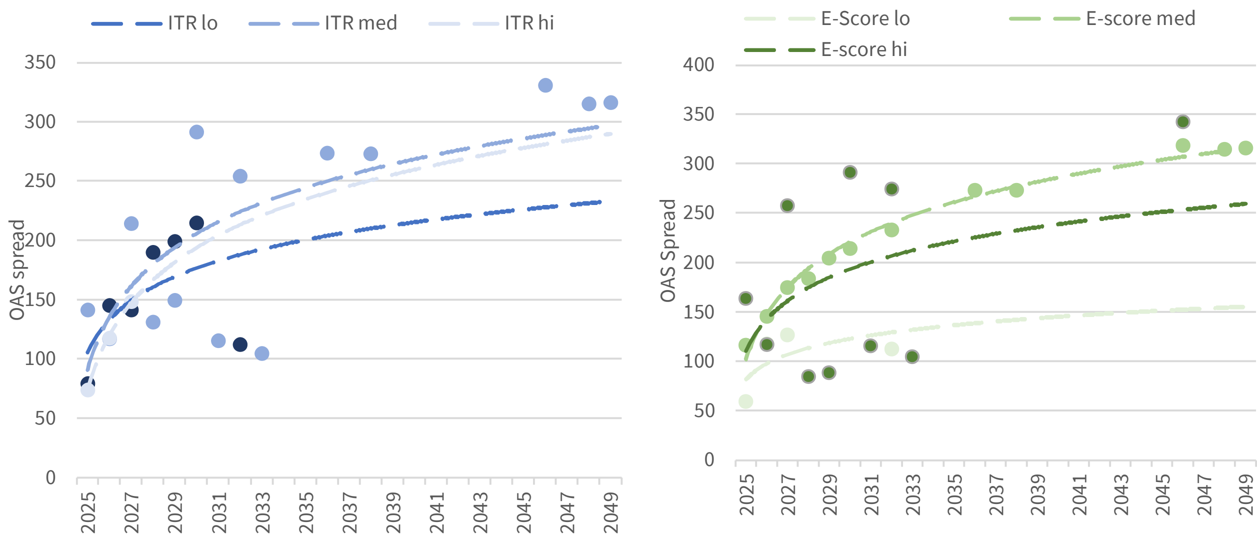
Figure 3. Automaker USD bond curves. Source: Bloomberg, accessed 1 Nov 2023.



Analysis 1a

In Figure 4, we plot the same data in Figure 3, but group the bonds based on the sustainability group. On the left-hand scale we show the spreads for ITR level, and on the right-hand scale the E-scores. We have bucketed the sustainability scores into categories, to see if we can observe a relationship. If there is a correlation with credit risk, we expect higher E-scores and for the lower ITRs to have a tighter spread.

Figure 4: Automakers USD Environment scores and Implied Temperature rise curves against credit rating. Source: Bloomberg accessed 1 Nov 2023.



Visual inspection of these graphs does not indicate a statistical relationship, but we see a few patterns worth highlighting. It is worth noting though, that these observations are dependent on the bucketing of sustainability data, and that is why we extend to a full statistical analysis in the next section.

There appears an intuitive relationship for the ITR at the longer-dated spreads, with the low category (with average temperature alignment of 1.25°C) having tighter spreads when we extrapolate the curves. There is less difference between the medium and high categories, which have average temperatures of 2.5°C and 3.7°C respectively.

The relationship between the E-score and the spread seems less intuitive. The tightest spreads are for the lowest scores, even at longer maturities. The highest score has the middle spreads, except at very short maturities.

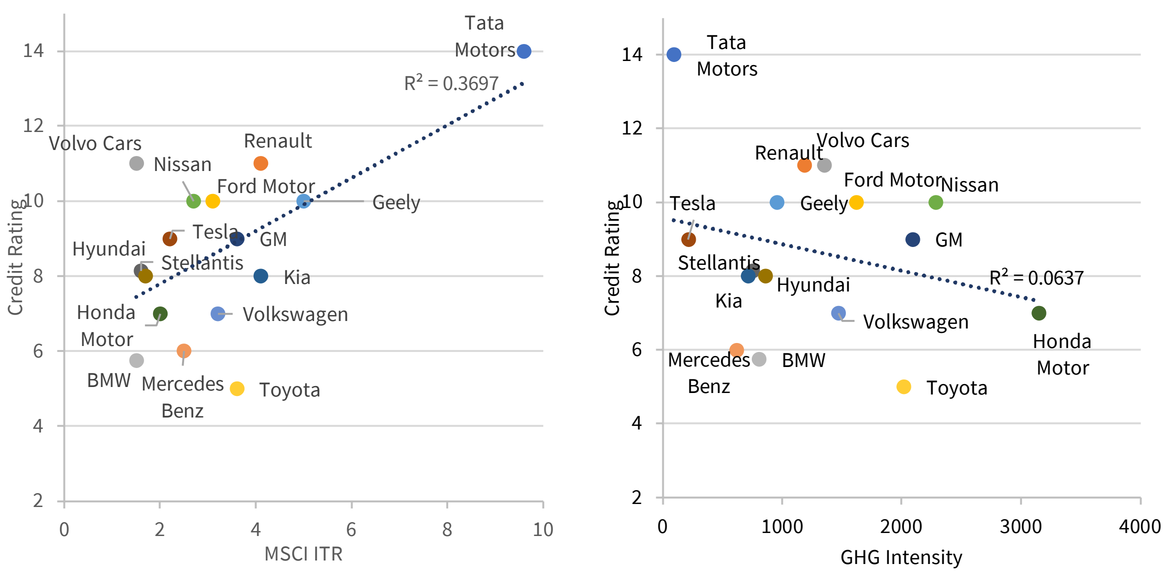
Studying the curves is essential, especially at the longer end of maturity, to see whether there is increased sensitivity for investors holding longer-term debt, due to material climate-related risk. With the caveat that the data is limited here, there is no evidence of long-term pricing differentials among different categories of sustainable data parameters.

Analysis 1b

We next expand the spot analysis to look at all the rated issuers by converting the alphabetic credit rating to a numeric scale (as described earlier in the Financial Data section). This allows us to control for the currency and duration and focus on credit risk metrics, which we cannot do under the curve study. We fit the credit scale to the GHG Intensity (Scope 1, 2 & 3 emissions scaled by the issuer's revenue) and the ITR data. This sample includes more issuers compared with the analysis in Analysis 1a, but only features rated issuers.

Figure 5 shows the results. We find higher that ITR values weakly correlate with higher or riskier credit rating categories. The GHG Intensity, however, is quite weakly downward sloping suggesting that the current credit ratings that are a proxy for term credit risk are not correlated with an issuer's historical emissions. Climate-risk pricing is too complex to be solely correlated with companies' emissions; instead, a company's forward-looking factors and strategies, alongside how it allocates future investments, could be stronger drivers of such ratings.

Figure 5: ITR and GHG Intensity fit over credit ratings. Source: Bloomberg, accessed 23 Nov 2023.



Conclusion

When looking at the current spreads of investment-grade USD bonds, we observe some confirmation that the ITR is correlated with both bond spreads and a company's rating, but no similar evidence for emissions or the environmental score.

However, these conclusions are based on observations of a single day data set, and so are not comprehensive. Next, we create a full regression model, both looking more completely at this data set, but also analysing how these relationships have changed over time. By including all relevant variables and taking a quantitative approach to determine the drivers of the spreads, we can place the climate-related data into context.

Trend analysis

Introduction

It is useful to understand not only how sustainability factors may influence credit spreads at one point in time, but also how those relationships have changed over time. In this section, we perform a historical regression analysis to understand any movement in the importance of sustainability factors in driving credit spreads.

Method

We use a quantitative regression to understand the drivers of bond spreads.

We use the 'least-squares dummy-variable' (LSDV) panel regression model to explain the spreads as given in the following equation (1). Where spd_{ijt} is the spread of the ith issuer's jth bond at time t. S_{ijt} are the bond-specific variables that vary over time, B_{ij} are time-invariant such as coupon, currency, the amount issued and callability. I_i, I_{it} are issuer specific variables that are time-invariant and time-varying, respectively. The T_t are categorical dummy variables representing the year and month of the sampling period of the companies. The coefficients $[\beta_1, \beta_2, \beta_3,\ \beta_4,\ \beta_5]$ are the appropriate dimensional coefficient vectors that are to be determined using the generalised linear regression. The ϵ_{ijt} is the residual term and α is a fixed intercept term.

$$spd_{ijt} = \alpha + \beta_1 S_{ijt} + \beta_2 B_{ij} + \beta_3 I_i + \beta_4 T_t + \beta_5 I_{it} + \epsilon_{ijt} \quad (1)$$

The p-values of the coefficients tell us how significant a given variable is to the bond spreads, and thus we can assess whether sustainability performance is a driver of an issuer's cost of capital.

We scale all the variables in the regression to minimum and maximum values to centre the variables, as the scale of each variable is different. The spreads vary from 50 to 1000 (bps) while the E-scores range from 1 to 10. We scale all the variables to be between 0 and 1.

The detailed results of the regression are shown in Appendix 1. The model has 0.71 R-squared, which shows a good fit for the spreads. More market-specific variables and other data sources could improve the fit by increasing the R squared value, but this study focuses on quantifying the climate risk element.

We filtered for only significant p-values at a 1% confidence interval and filtered out non-company-specific variables. The variable 'comp_val' is the credit rating and with highest positive coefficient, so any risky credit with a higher 'comp_val' score will have a wider spread, which shows the regression coefficients are in line with the expectations.

The next most explanatory variable is the time to maturity of the bond, suggesting that longer duration bonds will have wider spreads.

The tightest spreads are associated with Korean-denominated bonds and issuance in 2017. The 'e_score' variable has a small negative coefficient so more sustainable companies have tighter spreads, but the relationship is not material.

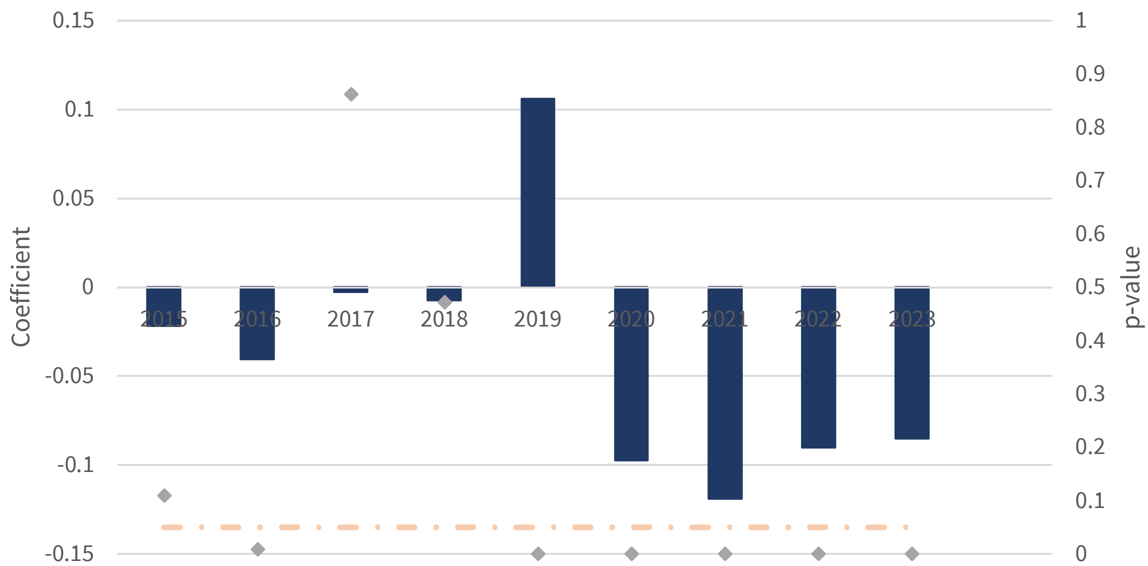
The coefficients can be used to calculate an importance analysis to figure out the exact contribution of the e_score. A preliminary analysis with SHAP values places that at 1.7% and the detailed plot and values are in Appendix 1. For a theoretical bond trading at 100bps, it implies 1.7bps is due to climate-related pricing, though the bid offer on such a bond could be higher than that. More importantly, we are interested in the evolution of the e_score contribution to the credit scores, to understand if its importance is changing with time.

Analysis 2

Figure 6 shows the e_score evolution where we plot against the p-values shown in grey dots and with a significance line of 0.05. Below a level of 0.05 p-value would be the starting point for us to consider the variable as being important in explaining the spreads.

The initial years from 2015 to 2018 show the values to be close to zero with insignificant p-values other than in 2016. However, since 2020, the coefficient is negative, which implies tighter spreads for better E-score bonds. Though the coefficients are quite low they are consistently below the significance line, which shows they are important in explaining the spreads.

Figure 6: Coefficient of E-score over time. Source: Bloomberg, accessed 1 Nov 2023.



We did a similar analysis with GHG Intensity and other GHG-related variables and found them to have small negative coefficients, which implies that higher-polluting companies have tighter spreads. As we saw in our earlier analysis, more complex variables that denote sustainability have a better correlation to credit ratings, and these results again confirm that. The E-scores unlike GHG intensity are sector-specific, which considers metrics such as vehicle production efficiency and electric vehicles sold, so they do play a small role in explaining the spreads.

This method allows us to utilise all the data so we can consider all issuers in different currencies, duration, and credit risk, thus isolating climate risk more effectively. These could easily be missed when filtering with other criteria. Over time, the sustainability metric E-score is on a correct trajectory, suggesting that markets reward the companies that invested in changing their fleet efficiency and EV strategy. With other simpler GHG metrics we found a slightly negative relationship between spreads and emissions.

Conclusion

We have constructed a model to explain bond spreads in our universe of auto manufacturers. This does confirm some relationship, especially in the recent years, between sustainability performance and bond pricing, with the environmental score explaining only 1.7% of the spreads. This is a quantification of our earlier conclusion, that sustainability factors do have a small impact on spread.

What is more interesting is that the relevance of ESG data has been increasing over time; these factors were not important prior to 2019 but have been a more significant input since. This trend suggests the relationship may continue to strengthen into the future.

Business analysis

Introduction

In this section, we look to understand the different strategies of automakers to transition their business profiles. A key question is whether there is a difference in market pricing between different kinds of auto manufacturing business strategies.

Toyota has invested in hybrid vehicles such that 31% of their sales come from this source. Nissan converted from a traditional automaker to invest in EVs along with hybrids, and there have been pure electric automakers since Tesla.

In the bond market, when issuers raise debt typically other than for general corporate purposes, they would be aiming to invest the proceeds in capex for future growth or for strategic M&A. If the market agrees with the strategy, it should be reflected in the spreads of these companies.

Method

Firstly, we classify the automakers into three categories: the 'dual strategy', EV strategy and Hybrid strategy. If an automaker has more than 5% of revenues in only EV, it is classified as an EV automaker. If there is a level of 5% of revenues in only a hybrid strategy it is classified as a hybrid automaker. Lastly, companies with more than 5% of revenues from EV and Hybrid separately are classified as 'dual strategy' automakers.

Table 4: Automakers by type of vehicles, Source: Bloomberg, AFII, accessed 3 Dec 2023.

Type	Name	E-score	ITR	Rating
Dual	HYUNDAI MOTOR	4.45	1.7	BBB+
Dual	KIA CORP	3.12	4.1	BBB+
Dual	NISSAN MOTOR CO	6.93	2.7	BBB-
Dual	RENAULT SA	5.43	4.1	BB+
EV	GEELY AUTOMOBILE	5.78	5	
EV	GENERAL MOTORS C	4.2	3.6	BBB
EV	RIVIAN AUTOMOT-A	2.65	1.4	
EV	VOLVO CAR AB-B	4.07	1.5	BB+
Hybrid	FERRARI NV	4.28	2.3	
Hybrid	HONDA MOTOR CO	2.66	2	A-
Hybrid	STELLANTIS NV	6.08	1.6	BBB+
Hybrid	TOYOTA MOTOR	6.14	3.6	A+

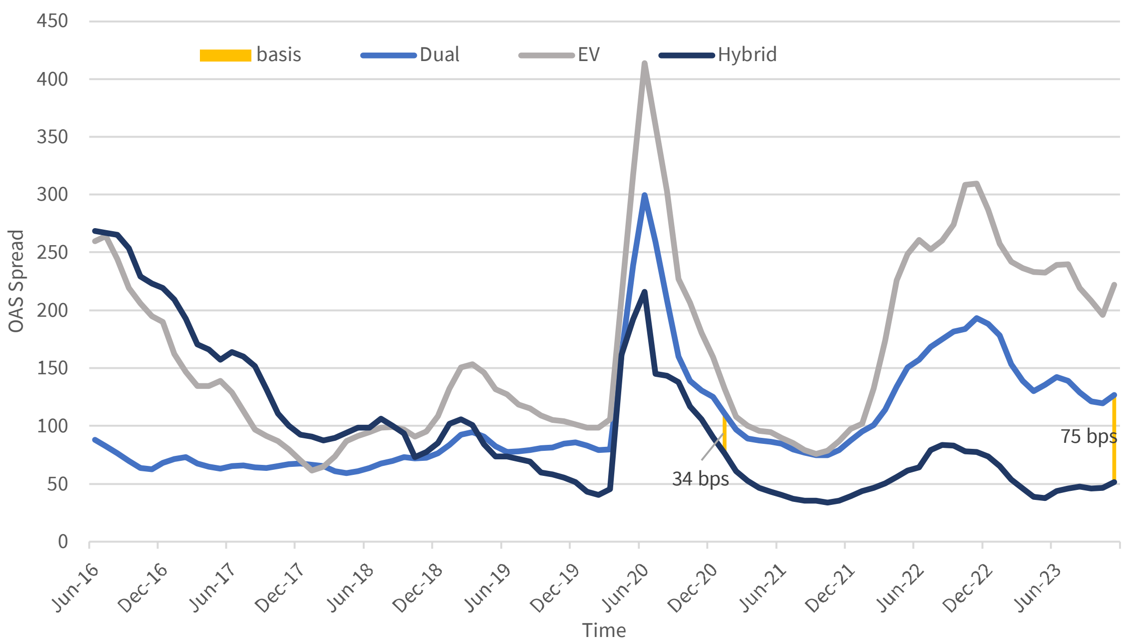
To find any trends, from our spread data we filter bonds by those with a similar duration of around five years and filter by currency. We used both EUR and USD to expand our data set. Both currencies have similar liquidity and on a cross-currency basis could be assumed constant. This filters issuers to a smaller subset given in Table 4.

The average ITRs for Dual, EV and Hybrid strategies are 3.15°C, 2.88°C, 2.38°C respectively. We also plot the historical spreads of these issuers in Figure 7 to understand the market pricing of these strategies.

Analysis 3

Figure 7 shows average historical spreads for automakers split by category. At the start in 2016, Dual strategy was best performing with tight spreads and EV makers were trading tighter to Hybrid automakers. Over time, the automakers following the dual strategy have underperformed, but hybrids have outperformed since the start and now trade significantly tighter relative to the ones with dual strategy.

Figure 7: historical spreads by Type of automakers. Source: Bloomberg, AFII, accessed 1 Nov 23.



Before the pandemic, the EV automakers traded tighter relative to the hybrid automaker bonds. Since 2022, The EV makers continued to underperform compared to the other two strategies. It is driven largely by Rivian which is the widest of all and was trading at a distressed level at the time of writing.[16]

The hybrid strategy containing the tightest credits probably reflects the fact that the business metrics are improving at a stronger rate than the dual strategy. The dual strategy results could be due to higher capital expenditures, which translate to lower cashflows because companies are still investing in electrification and continuing with traditional segments that do not have the same margins. However, the hybrid strategy might not need significant investment, which improves the cashflows and credit metrics of those companies.[17]

We note that despite ongoing political movement towards the phasing out of ICE vehicles, there have been some recent 'U-turns' on support for EVs, which may impact near-term market sentiment and widen some companies' spreads.[18]

The hybrid, dual basis level at the start of 2021 was 34bps, which has risen, and at the time of writing, it had reached 75bps. To understand this market pricing, in the following section we delve

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[16] Tesla did not have the same duration, so we removed it; however, including it did not change the electric car makers' spread performance significantly.
[17] "The inevitability of hybridization", Emissions Analytics, 15 Sep 2021.
[18] For example the US government has recently pushed its ICE ban further away as reported in "Britain Reverses New ICE Car Ban To 2035 Amid Protests And Praise", Forbes, 21 Sep 2023.

into two companies: Stellantis, representing a hybrid strategy and Renault, which has a dual strategy and is shifting towards electrification.

Conclusion

Our earlier analysis has concluded that ESG-factors are a driver of credit spreads. To further understand this, we have looked at the varying auto transition plans, to understand relative performance using more qualitative analysis.

Since the pandemic-related market shocks, Hybrid automakers have been the market winners, because they have outperformed compared with companies using other strategies. This is against a backdrop of an uncertain political environment for electric vehicles.

As markets evolve, individual credits might perform differently, but what strategies companies choose to take will influence the degree of their transition risk. To the extent that spreads represent capital flows into these strategies, the pricing levels could attract capital into EV investment, which could drive future outperformance.

Conclusions

When looking to understand whether sustainability performance is a driver of autos, there is reasonable evidence to suggest that it is.

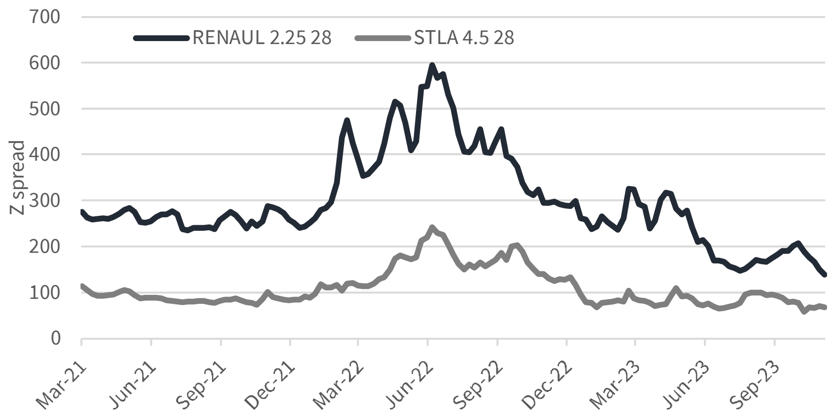
On a spot basis, the ITR can be visually determined as a driver of spreads, i.e. **automakers aligned with a lower temperature rise seem to have tighter bond spreads.** However, overall environmental score, and emissions, do not show the same relationship.

When calculating a full historical regression model, the result is confirmed: **that the environmental score (the data set with the best historical data) has an important - albeit weak - relationship with spreads.** What is more interesting here, **is that the strength of the relationship has been increasing with time**. This could be driven by investor sentiment, or a more fundamental relationship reflecting that better sustainability has driven stronger credit performance.

When analysing spread performance for different transition strategies, we see recent outperformance of hybrid manufacturers. This is against an uncertain political backdrop for EVs and as such **could present an opportunity for investors looking to support EV manufacturers.**

Case Study 1 – EV/Hybrid strategy- Renault vs Stellantis

Figure 8: Z spread comparison, source: Bloomberg, accessed 4 Dec 2023.



From the analysis of different strategies, it is clear there is differential market pricing. The hybrids continue to perform well, and the dual strategy includes the significant costs of EV investments. Stellantis, rated BBB+, has wide range of brands: Peugeot, Fiat, Chrysler, Jeep, Alfa Romeo, and luxury brands such as Maserati. It has revenues mostly from traditional cars and hybrids.[19] Renault, rated BB+, has an extensive alliance with Nissan and has fewer brands such as Renault, Alpine and Dacia. We chose these two automakers as both have EUR denominated bond curves and are comparable in our universe of dual and hybrid automakers.

Following from the results in our earlier section (

Business analysis), Stellantis spreads have been largely stable, while Renault had significant tailwinds, as can be seen in the high volatility of Renault spreads in Figure 8. We selected two similar bonds with the same benchmark and tracked the historical Z-spreads. The spreads to benchmark also follow a similar pattern as they have the same benchmark bond. The basis between them ranged from 57bps to 354bps at its widest point. The basis has compressed a lot in recent months as some of the strategy benefits have started to accrue.

Renault simplified its business by divesting stakes, especially in Nissan, and investing in an electric strategy.[20] These divestments provided a short-term boost to business metrics and translated to outperformance in the credit markets; however, the results of this are now more dependent on increased electric car adoption in the consumer market. Renault's management is committed to an investment-grade credit rating, which works favourably for spreads.[21] Stellantis, on the other hand, has the lowest capex as a percentage of sales compared with its peers and Renault; it also has a more complex portfolio of brands. Stellantis still targets earliest reduction than all the automakers as show in Figure 1. Significant investments ahead could depress the generative cashflows from the business, resulting in more volatility for its spreads.

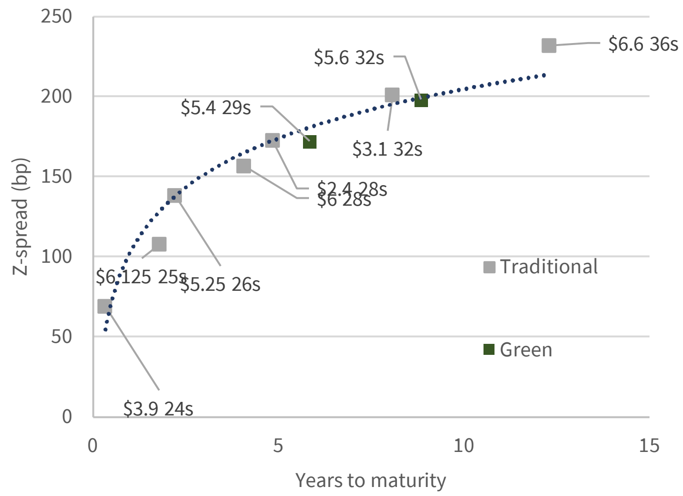
In recent years Renault has undergone significant change, which is reflected in their spread outperformance. However, Stellantis has a more complex business profile and is underinvesting relative to the degree of transition risk it faces.

[19] "Stellantis Rams Risk, May Dodge Outperformance", Bloomberg, 9 Oct 2023.
[20] "Renault cuts Nissan stake to 15% after transferring shares to trust", Reuters, 8 Nov 2023.
[21] "Renault's 2023 Margin boost may be short lived: Equity Outlook", Bloomberg, 10 Nov 2023.

Case Study 2 – Review of General Motors' green bonds

In previous research, we analysed green bonds from the auto sector and observed that they appear to trade at spreads wider than equivalent vanilla bonds.[22] In particular, the green bonds issued in Aug 2022 by General Motors (GM), an American multinational automotive manufacturer, were priced at a premium.[23]

Figure 9. GM USD bond z-spreads up to 15 years. Source: Bloomberg, accessed 5 Dec 2023.



We note that GM is reported to have taken 'the slow lane' when it comes to EV production.[24] Despite significant investment since 2017, it fell behind its key rivals in releasing new models, although it performed strongly in 2022 with four models at the higher end of the pricing scale.[25] Alongside its peers, in 2023, it has been reducing production, citing a slow-down in demand, posing the risk to its target to sell 1mn EVs by 2025.

From a pricing perspective, Figure 9 shows the most recent spreads of GM's USD bonds. The green bonds have compressed to the curve and now seem largely in line with vanilla securities. This represents an outperformance for green bondholders since issuance.

In conclusion, GM green bonds have performed strongly in the past year, which could provide evidence of increased interest from sustainable investors in the auto sector.

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[22] For full details please see "Auto bonds – Any colour so long as it is green", AFII, 17 Aug 2022.
[23] A basis trade was covered in more details in "Ace of Basis: Green cash-CDS basis to drive transition", AFII, 1 Aug 2022.
[24] "Why GM Is Taking the Slow Lane in the Great EV Race", Bloomberg, 20 Sep 22.
[25] "GM enters phase two of EV rollout after record 2022 earnings, massive new lithium stake", electrek, 31 Jan 2023.

Appendix 1

The coefficients of the regression with the most significant variables are shown in Table 5. The samples have 13,890 observations, and to explain the spreads, we have 72 variables, including the intercept. The Durbin-Watson statistic of 1.76 implies some positive autocorrelation, understood as momentum, where higher spreads lead to even higher spreads in the following months.[26] We removed the company-specific dummy variables as there are several of them. The same company bonds generally cluster around the same values once we adjust for maturity and seniority. For example, Rivian was the widest and strong predictor, but it is only important for Rivian bonds as they are more stressed than others, and to get those spreads, the Rivian dummy variable has the highest coefficient, like Aston Martin or Jaguar, all high-yield names. We can see some results of seasonality as well in any given calendar year; the model suggests that February is when the tightest spreads occur, while in April, spreads move wider.

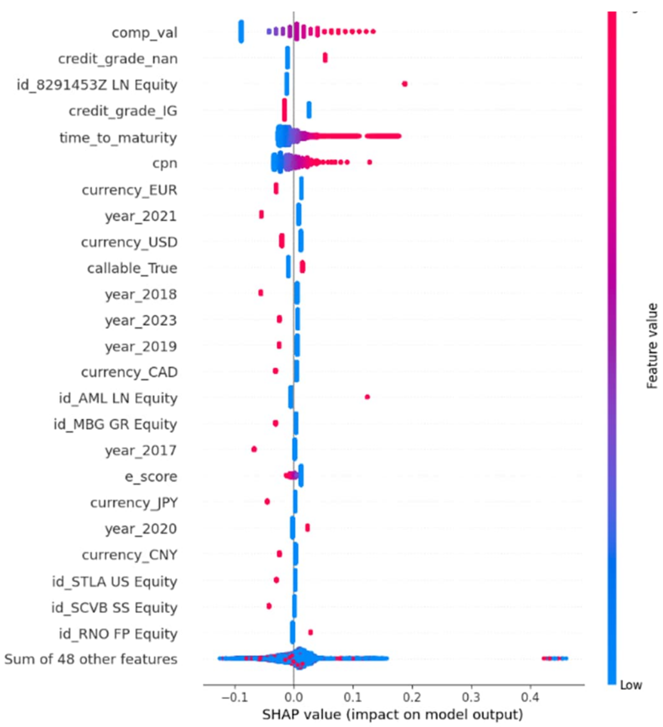
Dep. Variable:	spd	**R-squared:**	0.721	**Df Residuals:**	13817
Model:	GLS	**Adj. R-squared:**	0.72	**Df Model:**	72
Method:	Least Squares	**F-statistic:**	496.9	**Covariance Type:**	nonrobust
No. Observations:	13890	**Prob (F-statistic):**	0	**Omnibus:**	4798.216
Log-Likelihood:	16231.5	**AIC:**	-32320	**Durbin-Watson:**	1.759

var	coef	std err	t	P>|t|	[0.025	0.975]
comp_val	0.2231	0.018	12.67	0	0.189	0.258
time_to_maturity	0.2054	0.006	33.52	0	0.193	0.217
cpn	0.1625	0.009	18.743	0	0.146	0.18
const	0.0815	0.022	3.73	0	0.039	0.124
credit_grade_nan	0.0636	0.011	5.589	0	0.041	0.086
year_2020	0.0255	0.012	2.185	0.029	0.003	0.048
amt_iss_usd_bn	0.0303	0.008	3.755	0	0.014	0.046
callable_True	0.0236	0.002	9.676	0	0.019	0.028
month_4	0.0206	0.003	6.431	0	0.014	0.027
month_6	0.0153	0.003	4.782	0	0.009	0.022
month_7	0.015	0.003	4.749	0	0.009	0.021
month_5	0.0148	0.003	4.631	0	0.009	0.021
month_2	-0.01	0.003	-3.083	0.002	-0.016	-0.004
age	-0.0206	0.004	-4.987	0	-0.029	-0.013
e_score	-0.025	0.008	-3.266	0.001	-0.04	-0.01
year_2019	-0.031	0.012	-2.667	0.008	-0.054	-0.008
credit_grade_IG	-0.0414	0.004	-9.208	0	-0.05	-0.033
currency_EUR	-0.0429	0.016	-2.636	0.008	-0.075	-0.011
currency_JPY	-0.0474	0.016	-2.895	0.004	-0.079	-0.015
year_2018	-0.0615	0.012	-5.303	0	-0.084	-0.039
year_2016	-0.0302	0.012	-2.565	0.01	-0.053	-0.007
year_2023	-0.031	0.012	-2.589	0.01	-0.054	-0.008
currency_USD	-0.032	0.016	-1.992	0.046	-0.064	-0.001
currency_GBP	-0.0355	0.017	-2.101	0.036	-0.069	-0.002
currency_CAD	-0.0357	0.015	-2.37	0.018	-0.065	-0.006
year_2021	-0.0633	0.012	-5.39	0	-0.086	-0.04
year_2017	-0.0686	0.012	-5.897	0	-0.091	-0.046
currency_KRW	-0.0932	0.017	-5.39	0	-0.127	-0.058

Table 5: Results of LSDV Regression

[26] It is a small factor and does not change the results much. However, it complicates the results interpretation, so we avoid the auto regression and try to understand the important variables.

Figure 10: SHAP beeswarm plot showing variable importance.



The Shapley method is a game theoretic-based method to explain the models, and it allows us to calculate variable importance quantitively.[27] They are widely used in machine learning and other AI literature where models are often complex. These are also well suited to linear models where the features are standardised, which is the case here, and they are also more numerous. Instead of relying on coefficients, this method provides a more comprehensive picture of the importance of each variable. Figure 10 above is the beeswarm plot of each variable for all our data points. Each row is a variable, and it shows the distribution of SHAP values for all samples in our regression. Among them, the SHAP values in red have contributed highly towards the spread trajectory. The more red dots a certain variable has, the more explanatory power it has. The 'time to maturity' shows the variable has higher importance and increases as the value rises, but for a shorter duration, the picture is more mixed, and they have lower importance. The 'comp_val' has the highest importance, and it is not useful when the values are missing (the blue line on the left). The binary variables have a clear but small impact, while in 2020, there is a positive impact because this is when spreads were widest. Years 2017 and 2021 impacted spreads, but it was quite significant as they are still red in colour. These yearly dummy variables need to be understood in terms of what was driving the market in those years. The e_score has a very tiny power, just around 0, but is still red, which means it impacts the output spread.

Finally, we aggregate all these SHAP values by each variable and report their means in Table 6. From there, the percent contribution is calculated by scaling these mean values to 100, which gives 1.7% for the e_score variable.

variable	Mean SHAP value	% importance
comp_val	0.0391	11.44
credit_grade_nan	0.0205	6.01
id_8291453Z LN Equity	0.0202	5.92
credit_grade_IG	0.0197	5.78
time_to_maturity	0.0196	5.73
cpn	0.0178	5.21
currency_EUR	0.0176	5.16
year_2021	0.0162	4.74
currency_USD	0.0149	4.36
callable_True	0.0108	3.17
year_2018	0.0107	3.14
year_2023	0.0092	2.71
year_2019	0.0084	2.45
currency_CAD	0.0067	1.96
id_AML LN Equity	0.0066	1.94
id_MBG GR Equity	0.0065	1.92
year_2017	0.0061	1.79
e_score	**0.0058**	**1.70**
currency_JPY	0.0056	1.65
year_2020	0.0054	1.59

Table 6: mean SHAP values of each variable

[27] 'A Unified Approach to Interpreting Model Predictions', Scott M Lundberg and Su-In Lee, in *Advances in Neural Information Processing Systems*, vol. 30, 2017.

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