Second Quarter 2022

Supply Chain Climate Exposure

Executive Summary

To manage climate risks, investors need reliable climate exposure metrics. This need is particularly acute for climate risks along the supply chain, where such risks are recognized as important, but difficult to measure. We propose an intuitive metric that quantifies the exposure a company has to customers, or suppliers, who may in turn be exposed to climate risks. We show that such risks are not captured by traditional climate data. For example, a company may seem green on a standalone basis, but may still have meaningful, and potentially material, climate risk exposure if it has customers, or suppliers, whose activities could be impaired by transition or physical climate risks. Our metric is related to scope 3 emissions and may help capture economic activities such as emissions offshoring. However, while scope 3 focuses on products sold to customers and supplies sourced from suppliers, our metric captures the strength of economic linkages and the overall climate exposure of a firm's customers and suppliers. Importantly, the data necessary to compute our measure is broadly accessible and is arguably of a higher quality than the currently available scope 3 data. As such, our metric's intuitive definition and transparency may be particularly appealing for investors.

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Introduction

Climate-related risks and opportunities have become one of the most pressing priorities for investors. For most, climate-aware investing means managing a portfolio's carbon emissions, or its exposure to carbon reserves or green revenues. This is a natural starting point but unlikely to offer a complete, holistic view of a portfolio's climate risk. Importantly, most traditional metrics will not capture climate risks along the supply chain; those few metrics that do (e.g., scope 3 emissions) are generally thought to be extremely noisily estimated.[1] We aim to fill this gap by proposing a simple and intuitive measure of supply chain climate exposure that is related to but distinct from scope 3 emissions, and that can be readily computed by investors using data that is verifiable and of arguably higher quality.

To motivate our approach, we consider an example company, FleetCor Technologies (FLT).[2] FLT is a payments services company, and as such resides in a sector (IT) and industry (IT Services) that are rarely associated with climate risks. In fact, based on the standard climate data such as carbon intensity or carbon footprint, FLT seems green even compared to its sector or industry peers. For example, its scope 1 and 2 emissions are lower than the industry and sector median, and its scope 3 emissions are actually in the greenest quartile within its industry. Based on this information alone we may conclude that the company has little climate risk exposure. However, our assessment may change once we look at FLT's customers. For example, in the company's 2012 10Ks, FleetCor reported that their *"top three strategic relationships with major oil companies represented in the aggregate approximately 21%, 22% and 18% of [their] consolidated revenue for the years ended December 31, 2011, 2010 and 2009, respectively."* The large exposure to oil majors may indicate that the company might be indirectly, but possibly materially, exposed to disruptions, and potential loss of revenue, caused by climate-related risks.

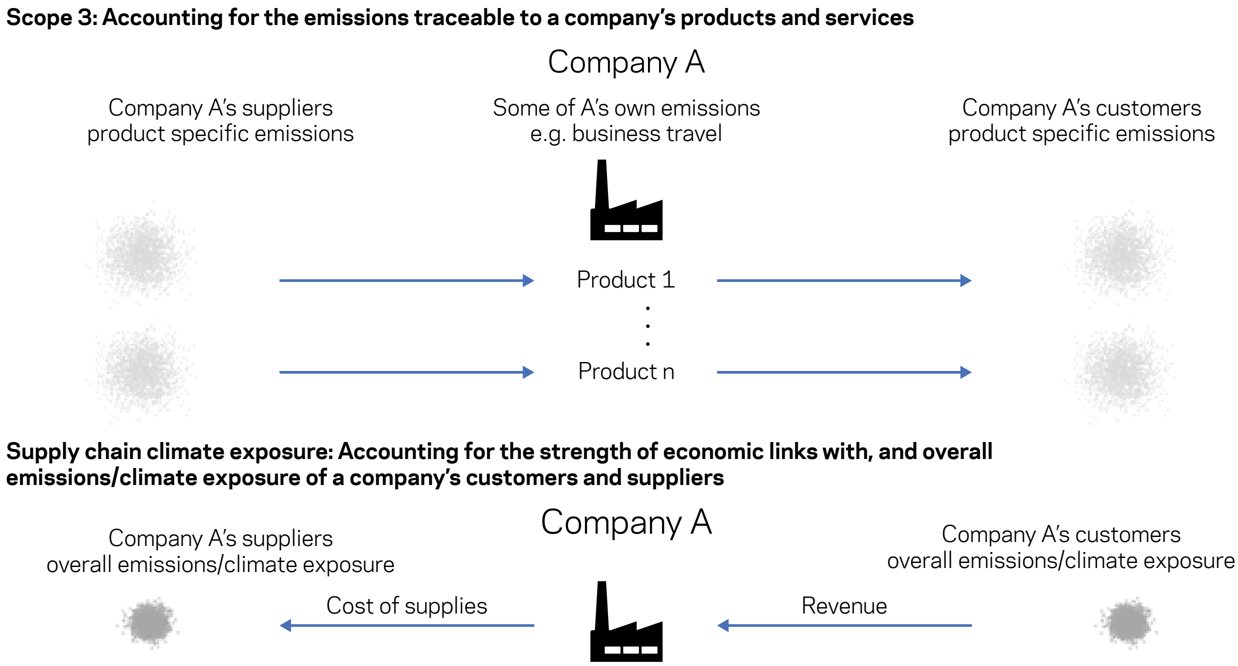
This motivating example underlies the measure we propose. In essence, our measure is a revenue-weighted average of climate exposures of a company's customers (or a cost-weighted average of suppliers' exposures). There are of course various ways to measure the climate exposure of each customer or supplier. In our analyses, we use customers' and suppliers' own scope 1+2 carbon intensity, but the approach easily generalizes to other climate risk measures. This definition highlights the key difference between our measure and scope 3 emissions. Scope 3 isolates those emissions of suppliers and customers that are attributable to a given company's products. This is a daunting challenge, even in those situations where we know the customers' and suppliers' overall emissions. In contrast, our approach is to focus on economic linkages instead, assessing commercial ties with firms with large climate exposures, regardless of whether such exposures are attributable to a specific firm's product or not. We summarize this simple

1 For example, Busch et al. (2020) report scope 3 estimates are very rarely reported by portfolio companies and third-party estimates are essentially uncorrelated across data providers; Callan (2020) survey found no respondents who use scope 3 data in investment practice.

2 To identify a company suitable for an illustrative example, we sorted firms on their supply chain exposure and on their own emissions, focusing on those that are at the top of the distribution of the former and at the bottom of the latter. We then analyzed the public statements the companies made to identify the ones that disclosed the importance of customers who may have large climate exposure (e.g., oil majors).

but - powerful insight in **Figure 1** below. The exhibit showcases the key data ingredients necessary to compute scope 3 emissions, as compared to our supply chain climate exposure measure.

Figure 1: A Simplified Comparison Between Scope 3 Emissions and Supply Chain Climate Exposure



The schematic shows which data inputs are relevant for each climate measure, highlighting the product-centric nature of Scope 3 emissions and the economic linkage-centric nature of the supply chain climate exposure measure proposed in this paper. Source: AQR. For illustrative purposes only.

The economic intuition above suggests our measure may be differentiated compared to traditional approaches, which focus predominantly on firms' direct climate exposure. We test this conjecture empirically and show that our supply chain measure is indeed only partially explained by a range of traditional climate data. More importantly, our measure correlates with market price reactions to climate-related news sentiment. In fact, as we show below, our measure subsumes climate-related information that third-party measures (e.g., scope 1, 2, or 3 emissions) have. We also demonstrate that supply chain climate exposure exhibits intuitive patterns around those few climate-related events that have already materialized in our sample. These empirical findings indicate that our measure may be a powerful addition to investors' climate toolbox.

The usefulness of our indicator goes beyond the climate risk application we outlined above. Our measure can also capture potential emissions offshoring. Emission offshoring occurs when a company switches from making the most carbon-intensive components inhouse to buying them from suppliers instead.[3] When such components are produced using company-owned assets, they increase the company's scope 1 emissions; when they are bought from suppliers instead, they only affect

3 See e.g., Ben-David et al. (2021) and Dai et al. (2022). Offshoring may also be an issue for sovereign emissions.

scope 3 emissions. Because most investors today focus on scope 1 and 2, emissions offshoring may artificially increase investors' assessment of how green the company is and consequently increase their investment in the portfolio company. This behavior would of course be readily apparent in scope 3 emissions data, but as we mention above, scope 3 data at investors' disposal is deemed to be very noisy (e.g., Callan, 2020). Our measure can help to at least partially fill this gap. While it is not a replacement for high quality scope 3 data, it may nonetheless help identify potential "emissions offshorers" among those companies that dramatically reduce their scope 1 emissions but at the same time look increasingly brown on our measure.

An important advantage of our approach is that it can be adjusted to address at least some of the data weaknesses that are a perennial problem in climate and in ESG investing more broadly. For example, while we use customers' scope 1+2 emissions in our demonstration below, investors who have a higher conviction in another measure of (direct) climate exposure can easily use our methodology with their favored metric. Moreover, when customers' carbon emission data is not available, in our application below we assume that customers' own climate exposure is in line with that of their sector peers. Such approximations may greatly extend the resulting data coverage. We believe that such features will be attractive to investors interested in using our measure in investment practice.

Finally, our study has a methodological contribution in that we present a detailed analysis of how a climate risk measure may be cross-validated using the relatively little climate data investors today have at their disposal. Such cross-validation is a clear challenge, which may explain why it is attempted relatively infrequently. Nonetheless, we believe investors should insist on such analyses before they use a novel dataset in practice. We propose a series of such data tests, with the goal of not only increasing conviction in our supply chain climate exposure measure, but also giving investors a blueprint for testing other climate indicators.

Data

For our empirical analysis below, we focus on large cap developed stocks, roughly equivalent to the holdings of the MSCI World index. Importantly, we do not restrict the universe of customers or suppliers of such stocks: for example, if a global developed firm in our sample has emerging markets customers, we will utilize data on such customers to assess the firm's supply chain climate exposure.

To measure supply chain climate exposure, we need two core pieces of data. First, we need data on the commercial linkages between a company and its customers. This data has been popularized by academic papers going back to Cohen and Frazzini (2008) and Menzly and Ozbas (2010). Ideally, this data would not only reflect a commercial link between two companies, but also give a measure of the strength of this link, for example by quantifying what fraction of a firm's revenue comes from a particular customer. Cohen and Frazzini (2008) collect such revenue data, leveraging disclosure regulations in the U.S. market. The supply chain data we utilize here is from two 3rd party vendors: Bloomberg and Revere; these vendors collect data on suppliers and customers links globally and exploit a number of company and industry publications, as well as news sources to comprehensively track supply chains and the strengths of linkages. We merge the two datasets to maximize our coverage and precision.

The second piece of data we need is a measure of a customer's (or a supplier's) own climate exposure. In the analyses below, we opted for a simple measure that we believe will resonate with investors: scope 1+2 carbon intensity of customers and suppliers, as reported in the Trucost database. We use this as an intuitive indicator of which customers and suppliers are relatively greener or browner. We do not claim that this simple indicator is necessarily the "best" measure of climate risk exposure. We expect that investors interested in our approach will instead substitute their favored instruments, be they climate emissions from another vendor such as MSCI, climate VaRs, Implied Temperature Rise scores, etc. Our methodology easily accommodates such measures.

While our supply chain measure can be used to gauge the brownness of both the customers and the suppliers of a given company, for simplicity, we focus on the customer side in our discussion below.

Finally, we use a variety of standard returns and financials data from XpressFeed, and a variety of ESG-related metrics from MSCI and Trucost, as indicated below. Overall, our sample spans the period of January 2009 through December 2021.

Missing Data

Missing data are an inevitable part of research, and how missing data is dealt with may meaningfully influence the analysis. We assume that a company with missing carbon intensity data has similar carbon intensity as its same-sector peers. This is preferable to ignoring customers or suppliers with missing data, and effectively giving them a free pass even when they are in sectors that are very pollutive. As we discuss below, when dealing with missing data on the fraction of revenue companies have from a given customer, we impute the strength of the relationship using both the number of customers with missing revenue data and their market cap, so that same-sized customers account for the same fraction of revenue.

The missing data that is the most difficult for us to manage is not observing a customer-supplier linkage in the first place. To partially address this, we normalize the data we do have to 100%. For example, if the data at our disposal captures only 70% of a firms' revenue, we rescale it so that it sums up to 100%. This implicitly assumes that the missing firms are as green as a typical customer that we do have coverage on. This is not ideal because in some circumstances the missing data may be statistically biased. For instance, our data does not include companies' retail customers. One might expect that retail customers have a different, perhaps "greener" profile than that a typical corporate customer does. Unfortunately, we do not know how much of the missing data covers retail versus corporate customers, making it challenging to adjust the measure. Similarly, companies that may be offshoring emissions, as we discuss in the introduction, may strategically seek suppliers less likely to be covered by data providers (e.g., private firms, or companies in emerging or frontier markets).[4]

4 These biases could perhaps be alleviated by leveraging data on revenues from geographic segments, and assessing the climate exposure in each region a company does business in. We believe this approach is coarser than what we propose; in addition, it would require data on climate exposures of specific regions or countries, which itself may pose challenges.

In our assessment, data quality is sufficient for practical applications, in spite of the concerns above. Customer-supplier linkages have featured prominently in academic and practitioner research, so it seems fair to assume that much of the industry is familiar and perhaps even comfortable with such data.[5] Moreover, we expect that while the data coverage is not perfect, it is likely to be more reliable for larger and hence more material customers of a given firm, which could make our measure informative even if we miss information on smaller customers. As for climate exposure data necessary to build our measure, we use scope 1+2 emissions data that are in widespread use in the investment industry. Of course, it is only one of the many climate metrics investors may consider, and our approach easily extends to such other metrics. To the extent an investor is comfortable using a different variable to gauge climate exposure of a portfolio company, it stands to reason that the investor should be comfortable using the same variable to gauge supply chain climate exposure.

Constructing the Supply Chain Climate Exposure Measure

To make our measure more tangible, we start with a hypothetical example, showing how our measure is computed. Consider a firm with four customers, who we label with subscript *j* below (so, *j* = A, B, C, or D for the four customers). As mentioned above, we do not restrict the customers to be in the same investment universe: for example, the firm we study may be a large cap developed stock, while its customers may be small cap and emerging markets companies. To compute our measure, we need to know each customer's climate exposure, C_j. As explained in our introduction, in our applications below C_j is customer *j*'s scope 1+2 carbon emissions intensity. In our example, we assume we have this data for each of our hypothetical customers; in practice, missing data could be replaced for example by industry or sector averages. We also need data on the fraction of revenue each customer *j* represents. To make our example realistic, we assume that we have that data for two customers, A and B, and that the data is missing for customers C and D. **Table 1** below summarizes the data for our example.

Table 1. Computing supply Chain Climate Exposure for a Hypothetical Company *i*, with Four Customers *j* = A, B, C, and D.

	Customer's carbon intensity (C_j)	% Revenue from each customer	Imputed % revenue ($w_{i,j}$)
Customer A	200	40%	40%
Customer B	100	30%	30%
Customer C	100	NA	15%
Customer D	50	NA	15%

Source: AQR. For illustrative purposes only.

5 For example, a sampling of papers utilizing such data include Cohen and Frazzini (2008), Menzly and Ozbas (2010), Agarwal et al. (2017), or Lee et al. (2019).

We first impute the missing revenue data for customers C and D by normalizing the total revenue to 100%. This implicitly imposes the assumption that the company only has four customers, that is, that we are not missing any customer linkage. For most firms in our sample, this is likely to be an approximation only, but we would expect that our data would include at least the most important commercial relationships of each firm. For example, for U.S. companies, we would know all relationships that account for more than 10% of revenue, given the regulatory requirement to report them. In **Table 1**, we assume that customers C and D are equally important; in our empirical tests below, we impute the fraction of revenue using both the number of customers and their size, arriving at higher imputed revenue for customers with a higher market cap.

Once we have the data on both customers' own climate exposure, C_j, and their relative revenue, w_{ij} to company i, our supply chain climate exposure measure for company i is simply the revenue-weighted climate exposure, as per equation (1):

$$\textit{Supply Chain Climate Exposure}_i = \Sigma_j w_{ij} * C_j \qquad (1)$$

where in our empirical tests below C_j is customer j's scope 1+2 carbon intensity, defined as scope 1+2 emissions divided by sales. We normalize by sales rather than use overall emissions in tons: using the latter variable would skew the metric towards large companies (a large company will generally have higher carbon emissions).

We focus on the customer version of the supply chain measure in our subsequent discussion. The supplier version can be computed analogously, with the difference that w_{ij} would then be the fraction of business that company i does with supplier j (so, the resulting metric would be a cost-weighted climate exposure of a company's suppliers). Data on the fraction of business each supplier represents may be more difficult to obtain, but we note that it can be inferred from the usual customer revenue data, at least partially.

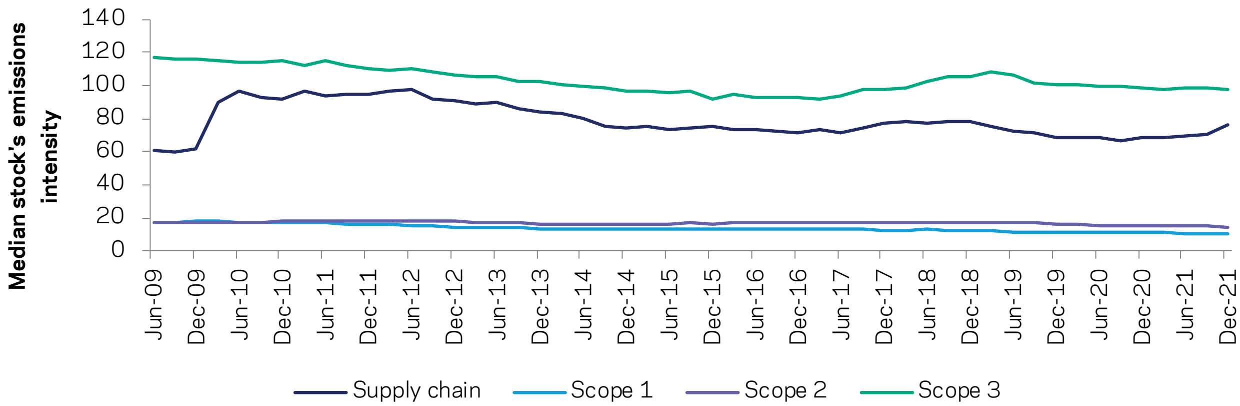
Summary Statistics of Supply Chain Climate Exposure

We begin by comparing our supply chain measure to the typical carbon emissions metrics: scope 1, 2, and 3 carbon intensity. Our analysis deals with large cap developed equities, so not surprisingly the resulting data coverage is excellent. Our supply chain measure can be computed for 93% of the index weight in the average sample quarter and covers 96% of the index toward the end of our sample; standard intensity measures, as reported in the Trucost data, cover 87% of the index weight on average and 95% toward the end of our sample. While the resulting coverage happens to be similar for our measure and for standard carbon intensity data, we note that this is not guaranteed. We can compute our metric even for those stocks that are not covered by Trucost, as long as we can identify at least some of their customers. In fact, we can compute our measure even if we do not have such customers' own carbon intensity data, because we can use sector or industry membership of these companies and use say sector averages instead. For example, an IT services company that received 10% of its revenue from an Oil&Gas customer is likely exposed to supply chain climate risks, whether we explicitly have the company's and its customer's emissions data or not. These features of our approach may be particularly important in those investment universes where the coverage of standard emissions data is poor, for example for small cap equities or for private issuers in credit.

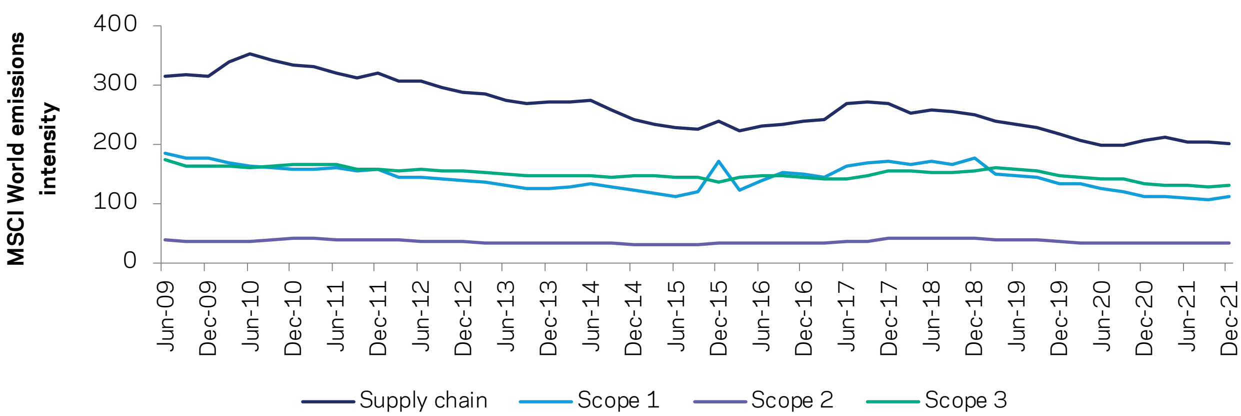
Figure 2 presents supply chain and standard emissions statistics for both a typical MSCI World constituent and for the MSCI World index overall. As explained in the earlier sections, our supply chain climate exposure measure is a portfolio-level average of the carbon intensities of each firm's customers.

Figure 2: Carbon Emissions Statistics Over Time

Panel A: Median Stock Carbon Emissions Exposures



Panel B: MSCI World Index-Weighted Carbon Emissions Exposures



The figure shows the supply chain climate exposure, as well as scope 1, scope 2, and scope 3 emissions intensity. These metrics are shows for the median MSCI World constituent in Panel A, and for the overall MSCI World index in Panel B, for the period of June 2009 through December 2021. Source: MSCI, Trucost, AQR.

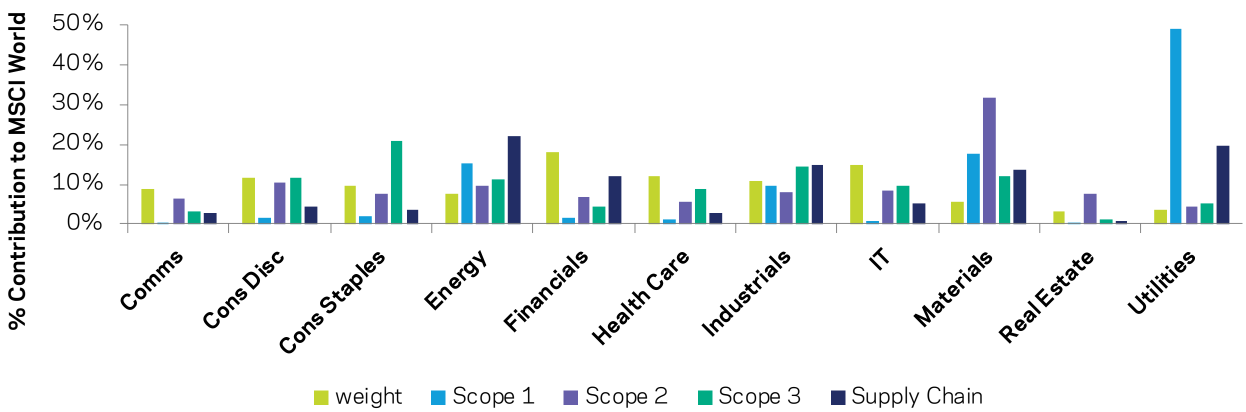
The median stock's supply chain exposure is smaller than, but relatively closer to scope 3 emissions than to either of scope 1 or scope 2. In contrast, at the index level, estimated supply chain climate exposure is meaningfully higher than that implied by traditional emissions data. This is driven by larger firms having higher supply chain exposure (indeed, we see a strong correlation between supply chain exposure and market cap).

The time series patterns indicate that our measure is correlated with the standard carbon emissions metrics. This may not be too surprising for scope 3, given that both measures focus on the supply chain. However, we observe correlations of only 0.1-0.15 between the two. More surprisingly perhaps, as **Figure 2** suggests and as we confirm below, our measure correlates more strongly with scope 1 emissions, meaning that firms that produce more emissions from company-controlled sources on average have customers who emit a lot as well. In this case, the correlations increase to more meaningful but still relatively low level of 0.3-0.4.

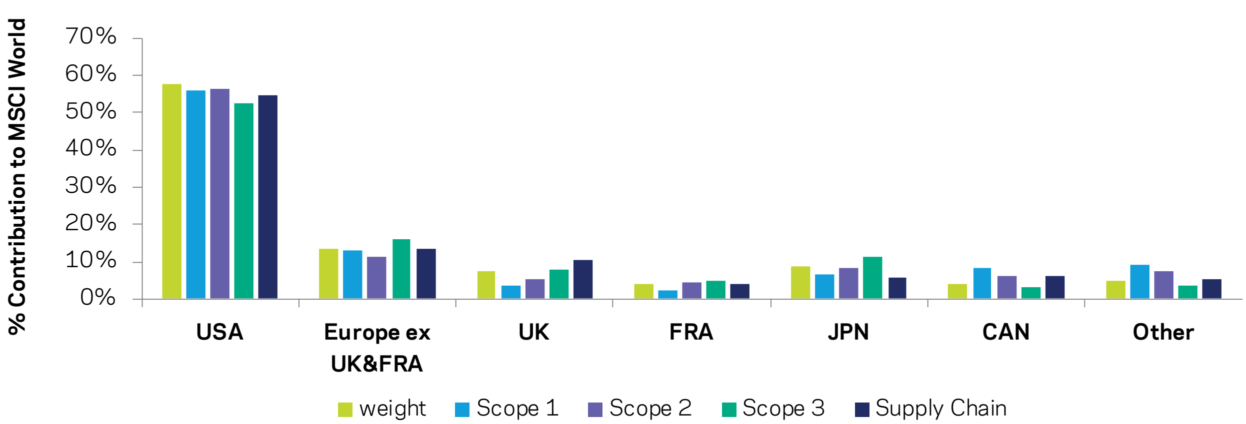
We now turn to the distribution of our measure across sectors and geographies, as presented in **Figure 3**. For ease of presentation, we show the results in terms of the contribution of each sector (in Panel A) and each region (in Panel B) to the overall index level. For comparison, we also show the index weight of each sector and region. We summarize this data by computing the contributions for each quarter in our sample, and then showing the contribution for the average quarter in **Figure 3**.

Figure 3: Sector and Country-Level Contributions to MSCI World-Level Carbon Emissions Metrics

Panel A: Sector Contribution to Various Carbon Emissions Metrics



Panel B: Country-Level Contribution to Various Carbon Emissions Metrics



Each sample quarter, percentage contributions to MSCI World are calculated from each sector (Panel A) and each country or broader region (Panel B), as of December 31, 2021. The charts above show the time series averages of these contributions. In Panel A, the historically deprecated Telecommunication is omitted from the chart. Source: AQR, Trucost, MSCI, Revere, Bloomberg.

In Panel A, we see that our supply chain measure spikes for Utilities, Energy, and Materials, the three sectors that are also associated with high scope 1 emissions, suggesting that their (revenue-weighted) average customer is just as brown. This may not be surprising: companies that are important customers for these sectors, and therefore likely use a lot of energy, oil, gas, or minerals, are likely companies that also have substantial greenhouse gas emissions – which is exactly what our measure captures.

The distribution by sector is also revealing with respect to the information additivity of the indirect carbon metric, and its differences versus scope 1, 2 and 3 carbon intensity metrics. For example, we see a relatively higher supply chain exposure for Industrials than one may expect from traditional emissions data. Similarly, Financials have relatively larger supply chain climate exposure relative to any of scope 1, 2 and 3 carbon intensities. This suggests that some industrials and financial companies provide goods and services to customers who may be subject to significant climate risk, despite these companies' standalone processes being relatively green. In contrast, the supply chain exposure is relatively less pronounced for Consumer Staples, at least compared to the scope 3 exposure of that sector. This is perhaps surprising. As we mentioned in our data section, our customer data does not include data on retail customers who may be relatively more important for Consumer Staples; however, for this to explain the patterns in **Figure 3**, retail customers would need to be more carbon-heavy than corporate customers. Finally, we note that supply chain climate exposure is relatively less concentrated at the sector level than scope 1 exposure.

Panel B of **Figure 3** repeats the analysis by geography, looking at the countries with the highest weight in the MSCI World index. We observe some variability related to size (e.g., USA stands out in absolute terms, but not when compared to the index weight of that region), but no significant concentration beyond that. A couple of countries stand out in that their supply chain exposure is noticeably different than the traditional scope 1, 2, or 3 exposure. For example, the UK contributes 4-8% to MSCI World overall scope 1, 2, 3 weighted average carbon intensity, but as much as 10% to the index's supply chain exposure (for comparison, the average index weight of the UK is about 8%). On the flipside, Japan contributes less to index-level supply chain exposure than it does to scope 1, 2, or 3 emissions, suggesting that it does business with relatively greener customers that its own emissions profile would suggest. Lastly, we see that commodity-based economies such as Canada contribute more to the supply chain exposure than their weight in the index, or their estimated scope 3 emissions may suggest. It seems intuitive that commodity producers have carbon-heavy customers, but it is perhaps more surprising that they score as "browner" on our supply chain measure than they do on scope 3 emissions. Canada's contribution to index-level supply chain exposure is twice as high as its scope 3 contribution (Australia, while lumped into "Other" in Panel B, also contributed twice as much to the supply chain exposure as it does to scope 3). One explanation for the pattern is that the customers of commodity-producing countries are relatively browner not just because of those countries' own scope 3 emissions, but also because of other sources of emissions; another is that scope 3 data may be missing some components of customers' scope 1+2 emissions that we explicitly account for here.

Validating the Measure

The intuition underlying our supply chain climate exposure measure suggests that the measure captures dimensions of climate risk that may well be material for the underlying portfolio companies. At the same time, we believe that the validity of such measures should be based not only on intuition and first principles, but to the extent possible also verified with data. Unfortunately, this is a big challenge for ESG measures broadly speaking, and for climate measures in particular. This is because the outcome variables we care about here, instances of climate risks affecting company valuations, are rare in historical data; the most severe climate events, whether related to physical or transition climate risks, may only occur in the coming years and decades. Necessarily, the tests we can implement here will give circumstantial rather than smoking gun type evidence. But, in our view, such circumstantial evidence is still preferable to no evidence at all.

Below we propose a series of tests that we believe are informative notwithstanding the data challenges. First, we relate our measure to more traditional climate data, including E pillar scores, carbon emissions and carbon transition scores data from third-party vendors. A positive correlation with related third-party climate risk data would certainly lend credibility to our measure. In contrast, if we saw zero correlation with "standard" climate data, it would be difficult for us, or for the investor community, to accept this measure, no matter how plausible the intuition behind it. Second, we test whether supply chain climate exposure correlates with climate sentiment. That is, we check whether the companies identified by our measure as relatively green or relatively brown experience returns, with intuitive signs, versus measures of market-wide sentiment following climate news. Third, we use an event study methodology to gauge the price behavior of stocks around meaningful macro-level climate news, as a function of such stocks' supply chain carbon exposure. While these tests are necessarily circumstantial, we believe that the preponderance of evidence we present here justifies the use of our proposed metric in investment practice.

Comparison to Third-Party Climate-Related Metrics

To compare our supply chain climate risk measure with other climate data, we regress it on scope 1, 2, and 3 emissions intensity, as reported by Trucost, and on Environmental (E-pillar), climate change theme, and Low Carbon Transition (LCT) scores, as reported by MSCI. **Table 2** summarizes the results from the Fama-MacBeth estimation method (pooled regressions produce similar patterns in estimates and statistical significance).

Table 2. Explaining Supply Chain Carbon Exposure with Traditional Climate Data

	(1)	(2)	(3)	(4)	(5)
ln CO2 intensity, scope 1	0.29***				0.08***
	(56.08)				(14.43)
ln CO2 intensity, scope 2	-0.09***				0.01
	(-8.63)				(1.76)
ln CO2 intensity, scope 3	0.15***				0.09***
	(13.03)				(6.83)
MSCI E pillar score		-0.05***			0.00
		(-4.16)			(0.90)
MSCI climate change score			-0.04***		0.02***
			(-5.40)		(3.93)
MSCI Low Carbon Transition score				-0.49***	
				(-934.18)	
Sector + region indicator	NO	NO	NO	NO	YES
Observations	77,194	84,249	65,727	11,135	55,970
R-squared	0.280	0.011	0.010	0.171	0.461
Number of x-sections	51	51	36	6	36

The table presents estimates from Fama-MacBeth regressions of the supply chain carbon exposure (in logs) on scope 1, 2, 3 carbon intensity (in logs) and on MSCI E pillar, climate change theme, and Low Carbon Transition (LCT) scores. Regression (5) also includes sector and regional dummy variables; it does not include LCT scores given their much smaller data coverage. The regressions are run quarterly from June 2009 to December 2021 for the developed large cap universe (MSCI World); the table presents time series estimates t-statistics adjusted for heteroskedasticity and auto-correlation with Newey-West procedure with 4 lags. Source: AQR, Trucost, MSCI.

Table 2 shows that supply chain climate exposure is strongly related to third-party measures of emissions, in most cases with the intuitive signs. For example, we expect a higher (riskier) supply chain climate exposure for those companies that also have high carbon emissions intensity, at least in terms of scope 1 and 3 emissions.[6] Similarly, we find intuitive signs for a range of climate-related measures from MSCI ESG data: higher supply chain carbon exposure correlates with lower (i.e., less attractive) overall Environmental characteristics in regression (2); lower climate change theme scores in (3); and less attractive Low Carbon Transition scores in (4). We note that data limitations lead to meaningfully lower number of observations in (3) and (4); this is particularly acute for (4), where we only have 6 quarterly cross-sections of data, as opposed to 51 quarters in regressions (1) or (2). Finally, we pool the explanatory variables and add sector and region indicators in regression (5) (we do not use the Low Carbon Transition score here given the much poorer data coverage). We again find strong positive correlations with scope 1 and 3 emissions. This

6 While scope 2 emissions show a negative sign in regression (1), this is likely driven by the interactions between scope 1, 2, and 3 emissions, and the strong correlation between these variables. When we regress our measure on scope 2 alone, with or without sector and regional controls, we find reliably positive coefficients.

time, surprisingly, we find a positive rather than a negative coefficient on the climate change theme, counterintuitively suggesting that with all the controls, issuers with a higher (i.e., more attractive) climate change score also have higher supply chain carbon exposure.[7]

Critically, while we find strong and mostly intuitive correlations to typical climate data from ESG data providers, these third-party variables only capture a small amount of variability in our measure. R^2s in **Table 2** range from 1% for high-level E and climate change scores to 20-30% when controlling for emissions-based measures (we note that greenhouse gas emissions are an important subcomponent of Low Carbon Transition scores). Even in our "kitchen sink" regression (5), where we also control for sector and region membership, traditional climate data and sector/country fixed effects capture less than half of the variability of our measure.

This combination of findings is encouraging for our measure. If we found no correlations whatsoever with third-party climate data, this might mean that our measure simply does not capture any climate-related information. The third-party measures we use here, and similar measures we did not have access to for this paper, come from well-known, reputable data providers who work with some of the most sophisticated investors and consultants. These measures may be noisily estimated, but we posit that they capture at least some climate-related information, meaning that we should expect at least some correlation with our own metric.

At the same time, it is comforting that the correlation is imperfect. Had we found R^2s close to 1.0, we would have concluded that our measure effectively conveys the same information as what is already captured by traditional providers. This would reduce the potential usefulness of our idea to those allocators who already subscribe to the standard climate data. Of course, finding correlations lower than 1.0 is not a sufficient condition for success: the low correlations might after all be attributable to white noise that carries no incremental information about climate. To test whether this may be the case, and to isolate the incremental information in our measure, we resort to sentiment analysis in the next section.

Correlation with Climate News Sentiment

While the most meaningful climate risk events may materialize only in the future, their likelihood of occurrence and potential impact are certainly discussed in the news media today. We can leverage such discussions to validate our measure: if it indeed captures climate risk, then stocks with relatively higher exposure should do poorly when negative climate news arrives; stocks with relatively lower exposure should do well. The advantage of this approach is that we rely on the overall market, rather than on individual analysts, to assess which stocks are more exposed to climate risks. Of course, we do not observe such market assessment directly, but we can infer it implicitly from price movements around climate news events, as explained in Engle et al. (2020) and AQR (2021). Moreover, we can use this insight to check whether our measure captures information not yet contained in standard climate data. We do this by sorting stocks on a version of supply chain exposure that is orthogonalized (residualized,

7 The sign flip is likely driven by the correlations between the various climate variables, and not by the somewhat different samples regressions (2) and (5) are estimated over (the changes are due to data coverage). When (2) is estimated using the same data as (5), the coefficient on MSCI Climate Change theme is clearly negative (-0.05, with a t-stat of -10.3).

or neutralized with respect to) to other climate data.

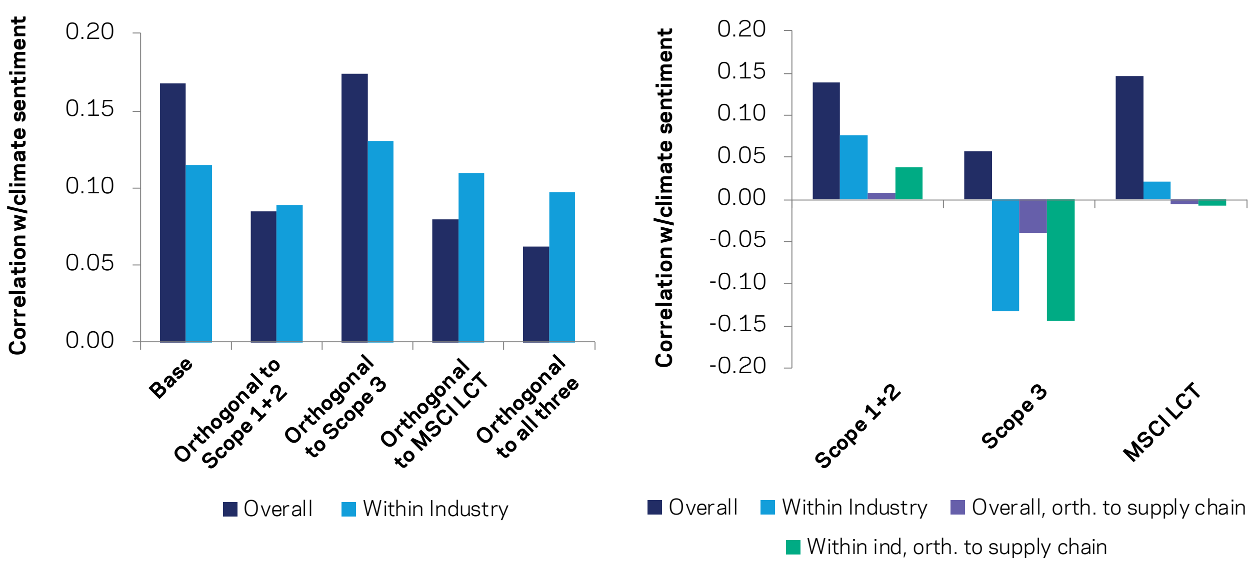
To carry out this analysis, we need data on climate sentiment. We utilize the data from Ardia et al. (2021), made publicly available from the authors. Specifically, we use their Media Climate Change Concern index (MCCC) and measure the arrival of climate news by looking at the monthly changes to the index over time. This climate news sentiment data was used in other papers as well, for example in Pastor et al. (2021), and is available until June 2018.[8]

To measure the relationship between supply chain climate exposure and climate news sentiment, we form hypothetical factor portfolios that are long in stocks with low supply chain climate exposure (green stocks) and short in stocks with large supply chain climate exposure (brown stocks). To avoid unintended bets, we form these portfolios in a country-neutral manner, with or without industry adjustments, and target zero beta (equity market neutral) and 7% ex ante volatility. As before, we use large cap developed market stocks for this analysis. **Figure 4** presents the (monthly) correlations between these factors and climate news sentiment.

Figure 4. Correlation of Market-Wide Climate Sentiment with Factors Built Using Supply Chain Carbon Exposure

Panel A: Correlations of Supply Chain Factors with Climate News Sentiment

Panel B: Correlations of Traditional Climate data with Climate News Sentiment



The top panel shows monthly return correlations with the monthly changes in climate news sentiment index of Ardia et al. (2021) for factors based on: supply chain climate exposure overall; as well as within-industry exposure, removing the commonality with other typical climate-related data. The bottom panel shows similar correlations for a hypothetical long-short portfolio based on typical climate-related data, removing the commonality with the supply chain measure, as indicated in the chart. The hypothetical portfolio ranks stocks on (negated) supply chain carbon exposure, neutralizes country and, as indicated, industry exposures, removes market exposures based on ex-ate beta and targets 7% ex ante volatility. This hypothetical portfolio is monthly rebalanced. Returns are gross of transaction costs, financing costs and fees. Given the available climate sentiment data, the sample period is June 2009 through June 2018. Hypothetical performance results have many inherent limitations, some of which, but not all, are described herein. No representation is being made that any fund or account will or is likely to achieve profits or losses similar to those shown herein. Hypothetical performance results are presented for illustrative purposes only. Hypothetical performance is gross of advisory fees, net of transaction costs, and includes the reinvestment of dividends. If the expenses were reflected, the performance shown would be lower.

8 We have repeated all analyses below also with a different source of sentiment data: the Crimson Hexagon series, used in Engle at al. (2020). The results are very similar to what we presented here. We chose to highlight the Ardia et al. data in our paper because the data is publicly available and because it has a somewhat longer time series (the Crimson Hexagon data at our disposal ends in mid-2017).

Figure 4 shows evidence that factors based on supply chain climate exposure co-move with the climate news sentiment, with the positive correlation of about 0.15-0.2. That is, the stocks we identify as greener outperform the stocks we identify as brown, at times of increased climate concerns measured as in Ardia et al. (2021). While the level of the correlation might seem low, we stress that these are correlations between news sentiment and returns of stocks sorted on a measure that does not utilize any news data. For comparison, portfolios that are explicitly optimized to correlate with climate news sentiment in Engle et al. (2020) also show out-of-sample correlations of about 0.2 with climate news.

We believe that these positive correlations are an important validation of our measure, indicating that supply chain climate exposure captures information that the market subsequently deems important in the climate context.

We still need to check if such information might simply be a function of some relatively obvious characteristics, for example sector or industry membership (for example, as we saw above, Utilities stand out on our measure). To address this, **Figure 4** also uses a version of the supply chain factor that is defined entirely within industry. We still see a positive correlation here, even if it is somewhat lower than before. Another potential concern is that our measures are to some extent correlated with traditional climate data (as we saw in the prior section) and the return correlations with climate news might be indirectly attributable to such 3rd party data and not to our supply measure per se. **Figure 4**, Panel A shows that this is not the case: we find similar levels of correlations also for factors that were orthogonalized to scope 1, 2, and 3 emission and to MSCI's Low Carbon Transition scores.

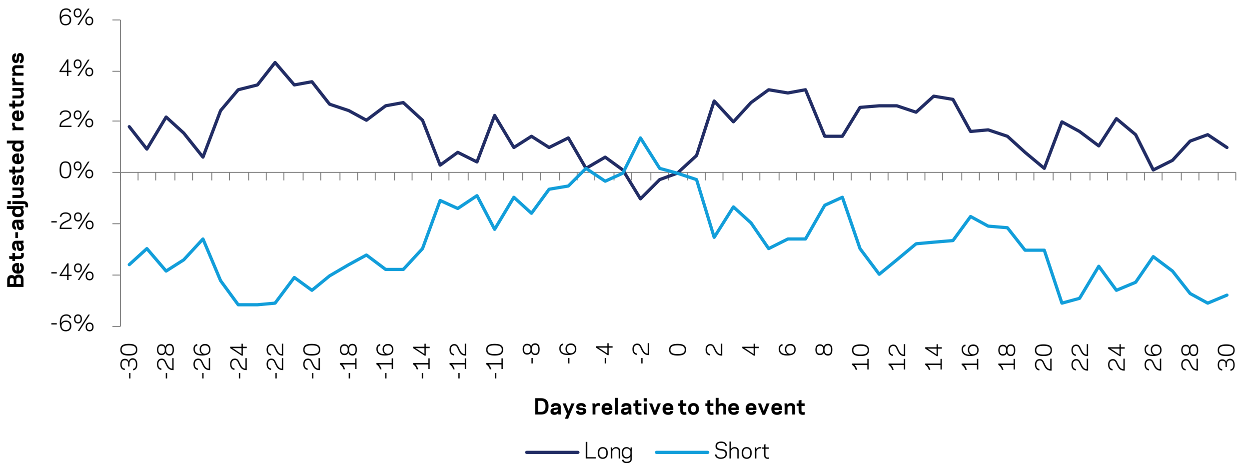
Strikingly, the reverse does not hold when we instead analyze factors based on traditional climate data in **Figure 4**, Panel B. On their own, factors based on greenhouse gas emissions, or on MSCI Low Carbon Transition scores, show correlations that are relatively similar to those we found in Panel A. However, as soon as we control for industry membership, these correlations disappear for LCT scores or even turn negative for scope 3 emissions. We still find low positive correlations for scope 1+2 emissions, but even they decrease to almost zero when we orthogonalize the factors to our supply chain climate exposure. We conclude that the correlations between traditional climate data and climate news are either due to industry membership or are subsumed by our supply chain metric.

Reaction to Macro-Level Climate Change News

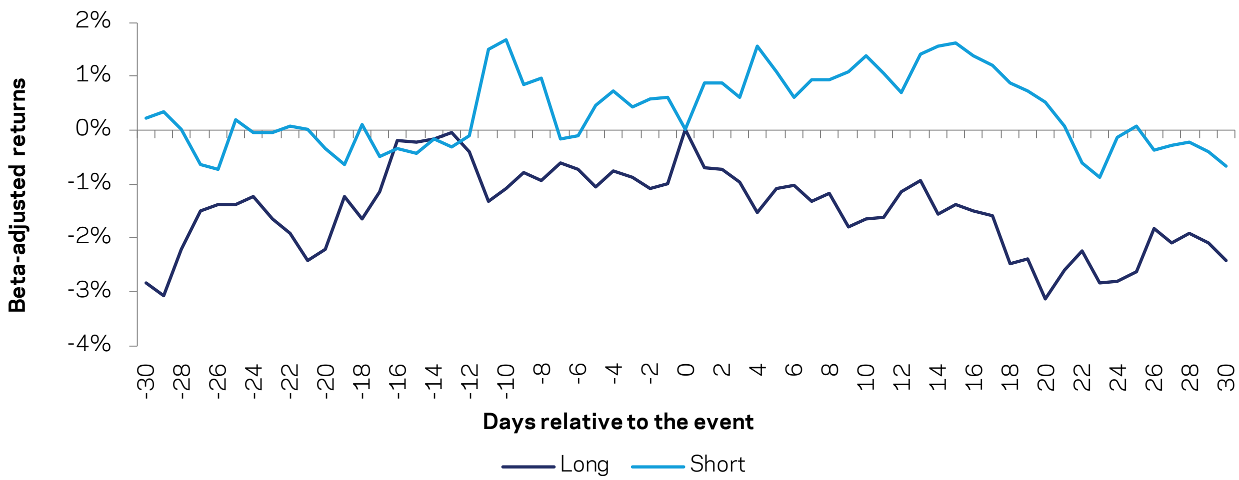
Our last validation test relies on a simple event study methodology: we utilize the long-short factors based on supply chain carbon exposure data, introduced above, and assess how they behave around major climate events. This experiment is obviously related to the climate sentiment analysis above and may be noisier in that the information about such macro events may have been telegraphed to the media, and thus also the market, before the event itself took place. At the same time, this approach has the benefit of strong and straightforward intuition, and is arguably more transparent than the more sophisticated NLP techniques behind sentiment measures. For this reason, we illustrate this approach with two sample events, choosing one that is positive for climate (G8 committing on 7/9/2009 to reduce greenhouse gas emissions by 80%, by 2050) and one that is negative (President Trump pulling the U.S. from the Paris Agreement on 6/1/2019). Given the construction of our factors, we would predict them to do well around positive climate news (i.e., we would expect the long leg of the factor to appreciate, relative to the short leg of the factor) and do poorly around negative climate news (longs depreciate relative to short). **Figure 5** tests whether this is the case, showing market beta-adjusted performance of the longs and shorts in the 30 day window around the two events in question (the "0" date on the x-axis corresponds to the event itself).

Figure 5: Stock Reaction to Climate News Events

Panel A: Example Positive Climate News Event: G8 Agrees to Reduce GHG Emissions by 80% by 2050



Panel B: Example Negative Climate News Event: President Trump Withdraws the US from Paris Agreement



Daily cumulative beta-adjusted-returns to the longs and shorts from the supply chain climate exposure factor, in the 30 day window surrounding two climate events: G8 committing to reducing emissions by 80% by 2050 on 7/9/2009 (Panel A) and President Trump withdrawing the U.S. from the Paris Agreement on 6/1/2019 (Panel B). The long and short side are beta-adjusted using the MSCI World benchmark. Universe of large cap developed markets stocks, similar to MSCI World constituents. The long-short factor portfolio ranks stocks on their (negated) supply chain carbon exposure, neutralizes country and, as indicated, industry exposures, removes market exposures based on ex-ate beta and targets 7% ex ante volatility. This hypothetical portfolio is monthly rebalanced. Returns are gross of transaction costs, financing costs and fees. Source: AQR.

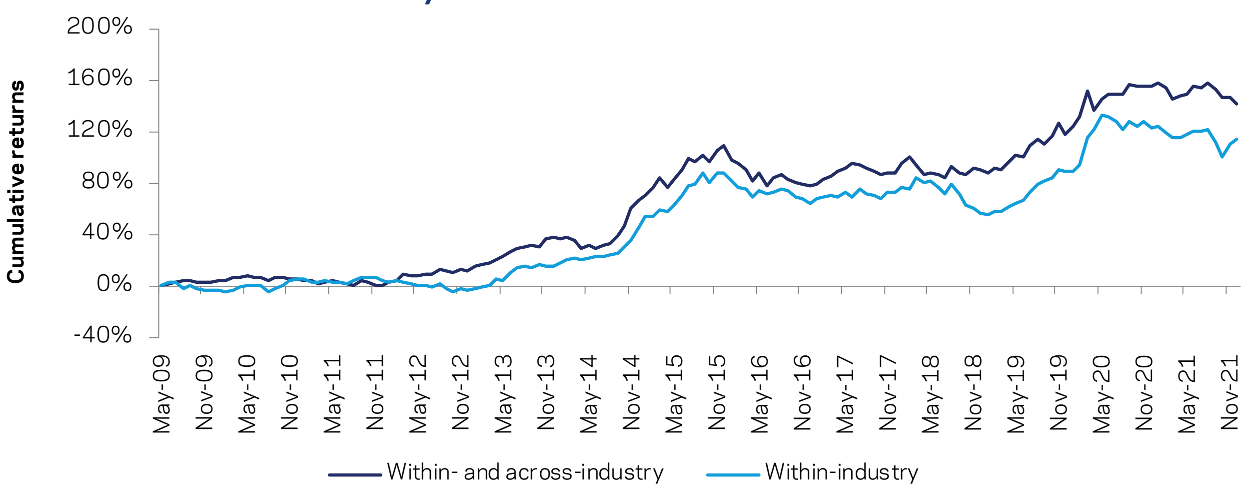
The results in **Figure 5** are more mixed, but we still observe some encouraging patterns. For positive news in Panel A, the short side of the factor (brown stocks) has negative market-adjusted performance after the event happens. The long side (green stocks) is more muted and noisier. For negative news, it is the long side that reacts more strongly, with more pronounced negative market-adjusted performance.

Of course, the two events we highlighted here are only a fraction of possible climate events one may consider. As we explained above, we showcase them here to illustrate the overall approach, but would argue that the news sentiment analysis in the previous section is a more informative way to validate the measure.

Factor Performance

Our final exhibit focuses on the performance of stocks sorted on the supply chain climate exposure measure. We utilize the industry-neutral factor we introduced in our climate sentiment analysis above. Hypothetical factor performance, gross of fees and transaction costs, is presented in **Figure 6**.

Figure 6: Cumulative Performance of the Long-Short Supply Chain Climate Exposure Portfolio and Its Within-Industry Version



Universe of large cap developed markets stocks, similar to MSCI World constituents. The long-short portfolio ranks stocks on (negated) supply chain carbon exposure, neutralizes country and, as indicated, industry exposures, removes market exposures based on ex-ate beta and targets 7% ex ante volatility. This hypothetical portfolio is monthly rebalanced. Returns are gross of transaction costs, financing costs and fees. The sample is June 2009 through December 2021. Source: AQR.

The factor based on the data we propose here has realized positive hypothetical performance over this sample period. Its annualized Sharpe Ratio is of the order of 0.7 and is not subsumed by typical style exposures. The performance is not driven by sector allocation (e.g., long Energy, short IT) and is relatively similar also for the industry-neutral version of the factor.

While this strong performance is arguably good news, but we do not view it as necessary for the validation of our measure. Our key objective in this research was to study supply chain climate exposure, and it is at least theoretically possible that such measures may not deliver performance as strong as what we observe here. Having said that, we note that this performance can be consistent with the market pricing in climate risks.

Arguably, markets have paid increasingly more attention to climate, so as long as markets care about the supply chain exposure, it may be intuitive that the prices of issuers with high exposure have fallen relative to prices of issuers with low exposure, leading to the positive performance of our factor. For example, Pedersen et al. (2021) show how such repricing occurs in response to changes in the preferences of, or the information available to market participants. At the same time, there are alternative explanations: for example, our climate exposure measure might be indicative of higher production efficiency and higher overall quality, as suggested in a related context in Garvey et al. (2018).

Conclusions

We propose a novel method leveraging economic linkages to improve the measurement of a firm's climate exposure. Traditional climate data rely on firm-level variables that likely correlate with climate outcomes: carbon emissions, fossil fuel reserves, revenue from restricted sources (e.g., thermal coal, oil sands), etc. We make a simple, but to our knowledge not-yet-proposed point that such metrics can be informative not only about the exposures of a given stock but also about the exposures of its customers and suppliers. For example, if a firm's customers are heavily exposed to climate change (e.g., they emit a lot of CO_2, have fossil fuel reserves, etc.), then the firm inherits this exposure indirectly, even if by itself it may seem "green." While there are similarities between our measure and the often discussed scope 3 emissions, our metric captures somewhat different information and has a meaningful advantage of being much easier to assess, using data many investors already have access to.

The flexibility of our intuitive methodology, good data coverage, and the additional validations we present here bode well for the broad usefulness of this approach to measure and report risks of both individual assets and broad portfolios. Moreover, while we focus on public equities in this article, investors can leverage our idea also in other asset classes. This is most obvious in credit, but also holds in sovereign fixed income, where one could consider trade-weighted exposure to countries that produce more emissions or are otherwise exposed to climate risks.

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