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Look up! A Market-Measure of the Long-Term Transition Risks in Equity Portfolios

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Abstract

The transition to a low-carbon economy generates new regulatory, technological, market and reputational risks for the financial sector. These climate transition risks are mainly analysed by portfolio managers through bottom-up fundamental approaches such as prospective scenario analysis and company scores. In order to overcome the difficulty of linking climate transition risks with financial risks and the lack of data, recent research has investigated the impact of these risks on market prices by constructing dedicated factors. This paper contributes to this literature in two ways. First, we propose a new climate transition factor that captures both the sectoral and intra-sectoral dimension of the transition to a low-carbon economy. Second, instead of trying to add this factor to a multi-factor model, we propose to disentangle the effect of climate transition risks from traditional risks. Our approach thus enables investors to quantify and optimise the amount of risk coming from their exposure to transition sensitive instruments.

Key Takeaways

- We propose a climate transition factor that captures both the sectoral and intra-sectoral dimension of the transition to a low-carbon economy by relying on the climate-policy relevant sector classification and on GHG emissions intensity.
- Consistent with the literature, we do not find that the addition of such a factor significantly improves the power of an asset pricing model. However, we present an approach that enables us to disentangle the risk attributed to financial risk from those stemming from climate transition risks.
- Over the recent period (2017-2020), this risk associated with the transition factor already represents a significant part of the active risk of some funds.

Keywords: climate transition risks, factor investing.
JEL codes: G11, G12, G23, Q54.

1. Introduction

1. Introduction

Through the Paris agreement, the international community has committed to keep global average warming below 2°C, along with a more ambitious objective of 1.5°C. In addition to the physical effects of climate change, the economic transformations required to reach this objective will affect (positively or negatively) certain economic sectors more than others (IPCC, 2022). From an investor perspective, these transformations will generate new transition risks and it is therefore necessary to identify the companies that best anticipate regulatory, technological and market developments to manage them.

Transition risks are difficult to estimate using fundamental approaches. First, despite reinforced regulatory requirements[1] and recommendations[2], persistent gaps in climate-related data remain (NGFS, 2022). Secondly, the radical uncertainties associated with transition scenarios are difficult to incorporate into fundamental valuation models (Bolton et al., 2020). As a result, transition risk metrics display a significant degree of diversity (Bingler, Senni and Monnin, 2021).

Against this backdrop, academics have sought to measure transition risks directly from market prices, which reduces the data and model barriers mentioned above. So far, the effort has focused on building climate transition (CT) factors. These factors are designed on the same principle as traditional factors (e.g., size, value): they are portfolios constructed in such a way that their price changes are representative of the dynamics of the stocks affected by the transition risks. This approach relies on the assumption that markets integrate information related to transition risks. However, the literature presents contrasting results regarding the current integration of transition risks, both on the *significance* and the *direction* (e.g. Bolton & Kacperczyk, 2021; Alessi, Ossola and Panzica, 2021). Thus, our approach does not assume that prices already incorporate transition risks but that prices will do so over time.

The methodology we present aims to contribute to this literature on price-based analysis of transition risks by addressing two main conceptual issues. The first one is related to the design of a CT factor. While some papers rely solely on carbon intensity, i.e., the greenhouse gas (GHG) emissions of a company divided by its revenues, others use up to 10 metrics to build their representative portfolio (Görgen et al., 2020). The type and number of metrics raises questions regarding their current availability, quality, and their relevance to assess *long-term* transition risks. Our approach departs from previous attempts at producing a CT factor based solely on individual company characteristics. Instead, we utilise what is likely to be the most robust information regarding a company's exposure to transition risks: its industrial sector. We introduce a new CT factor that relies on i) the climate-policy relevant industrial sectors (CPRS) classification developed by Battiston et al. (2017), and ii) the carbon intensity to differentiate companies within these CPRS sectors.

The second issue of price-based analysis of transition risks is related to the use of a CT factor in a risk model. Investors have started considering transition risks relatively recently: 2015 was a pivotal year with the Paris Agreement and the warning by Bank of England Governor Mark Carney (Carney, 2015). Because the traditional tests to validate the relevance of a factor rely on long timeframes, CT factors usually do not pass these tests and are therefore not qualified as "proper" risk factors (Amenc, Esakia & Goltz, 2021; Görgen et al., 2020). We propose a different approach that focuses on the practical

1 - E.g., with the EU corporate sustainability reporting directive or taxonomy regulation.
2 - E.g., from the task force on climate-related financial disclosures (TCFD).

1. Introduction

management of transition risks by disentangling the links between a portfolio's exposure to the CT factor and the traditional ones.

Our goal is to give priority to the long-term robustness and to avoid what we call the "Don't Look-Up" syndrome. In this movie, the discovery of a world-killing comet serves as a metaphor for the (lack of) reaction of our society to climate change. What if this comet was not to destroy the world, but only one city? How would you design a "comet" factor? As in the first part of the movie, if the comet's trajectory is known only to scientists, the effect on market prices will be negligible. However, this effect will increase dramatically once the public becomes aware of the comet's trajectory and believes it to be true. The risk is therefore real, but its impact on prices is not observable for a long time; testing the validity of such a "comet" factor on historical prices is not relevant. In this case, the factor validation should focus on the inclusion of the most robust information about the comet: where it will crash. Therefore, we believe that the use of industrial sectors in the construction of a CT factor is crucial.

2. From a Fundamental to a Market Measure of Transition Risks

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Since 2015, several articles have investigated how transition risks are already reflected in asset prices (Giese, Nagy & Rauis, 2021). Their methodologies fall broadly into two categories: fundamental and price-based. The fundamental approach consists in studying whether the climate-related characteristics of companies have an influence on their cost of capital and therefore on their asset price. The price-based approach consists in constructing transition risk factors based on the prices of baskets of assets representative of companies exposed to the transition risks.

2.1 Fundamental Measure of Transition Risks

This first series of studies using a fundamental approach examines the impact of companies' non-financial characteristics related to transition risks on their financial performance through panel or cross-sectional analyses. For example. Bolton & Kacperczyk (2021) analyse 3,421 US firms over the period 2015-2017. They show that firms with higher GHG emissions and changes in GHG emissions are valued at a discount, suggesting that investors demand compensation for their exposure to transition risks (consistent with Görgen et al., 2020). The authors trace this effect at least in part to exclusionary screening performed by institutional investors to limit their transition risks.

By contrast, Engle et al. (2020) document that stocks of firms with high E-Scores – which the authors argue capture *lower* exposure to transition risks – show higher returns during periods with negative news about the future path of climate change. Choi, Gao and Jiang (2020) also find that stocks of carbon-intensive firms underperform during times with abnormally warm weather, a period when investors' attention to climate risks are likely to be particularly high.

These panel analyses are based on environmental and climate-related company data. These capture only some dimensions of the transition risks, and both their quality and coverage still need to be improved. To overcome these limitations, other approaches have favoured measures based on market prices.

2.2 Market Measure of Transition Risks

This series of studies is based on the construction of a transition factor, i.e., a price signal from companies with similar transition risk profiles. The main advantage of prices over characteristics is that they integrate information that has been processed by market participants. Scores and characteristics, by contrast, are based on sub-optimal data and ad-hoc models. Prices reflect the opinion of market participants who process information broader than extra-financial data (e.g., the evolution of climate-related industrial regulations or controversies related to the climate impact of certain companies). Prices thus have a richer informational content that is, moreover, updated over time.

For example, In, Park and Monk (2017) build a carbon efficient-minus-inefficient (EMI) portfolio based on GHG emissions intensity (considering Scope 1+2+3) within each of the 11 GICS[3] sectors. They find positive alphas for the EMI portfolio that cannot be explained by the Fama-French five-factor model between 2010 and 2015 in the US. According to the authors, these abnormal returns, which can be

3 - Global Industry Classification System.

2. From a Fundamental to a Market Measure of Transition Risks

seen as a green premium, might reflect mispricing or that transition risks are not fully captured by traditional factors[4].

In contrast, Alessi, Ossola and Panzica (2021) find a brown premium, but their studies differ from In, Park and Monk (2017) in at least two ways. Firstly, they not rely only on GHG emissions intensity but also on a combination of environmental transparency scores and GHG emissions intensity. Secondly, they build and analyse their factor based on the EU market (which has different non-financial disclosure requirements from the US market), and on a more recent period (2006-2018) when awareness of climate risks has increased (after the 2015 Paris Agreement). Cheema-Fox et al. (2021) provide a comparative analysis between US and EU regions over a similar period (2009-2018) and observe stronger positive alphas for "green" factors in Europe compared with the US.

The previous studies find opposite but *significant* green or brown premiums. On the other hand, the existence of this "green" premium is disputed by Alessi, Ossola and Panzica (2021) and Amenc, Esakia & Goltz (2021) who find that the premium disappears entirely when accounting for estimation error (consistent with Görgen et al., 2020).

The literature on the consideration of transition risks by equity markets thus presents contrasting results, both on the significance and the direction of the alpha generated by strategies designed to hedge against transition risks.

Roncalli et al. (2021) propose a different approach. Instead of focusing on the possible outperformance of a transition factor or its additional contribution to a multi-factor risk model, they study the variations in the transition exposure of stocks depending on their sector and region, and then compare the market-based approach with the fundamental one. They show that the correlation between the betas obtained through the market-based approach and the carbon intensity obtained through a fundamental approach is weak (only around 17%) and therefore suggest that the market-based approach captures more information. Finally, they propose a way to take a transition risk factor into account into minimum variance portfolios. Our paper aims to complement this approach by better understanding the interaction of the CT factor with the traditional ones.

4 - Gurvich and Creamer (2022) find similar results on a broader sample (MSCI ACWI).

3. Data and Model

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1. Climate-TransitionFactor

A climate transition (CT) factor does not provide an understanding of the cause of transition risks but it does provide a measure of the exposure of a portfolio to a signal that is positively correlated with companies that might suffer from an abrupt transition, and negatively correlated with companies that might benefit from this transition.

The energy transition has both a sectoral and a company-specific dimension. First, the extent of the transformations brought by the transition depends on the sectors, as the abatement cost of GHG emissions is directly related to the sector technologies (IPCC, 2022). Sector treatment in the construction of the CT factor is therefore a major concern. On the one hand, energy transition cannot be expected to wipe out entire branches of the economy, which argues in favour of a sector-neutral approach. On the other hand, some sectors will be affected more than others by the energy transition. In order to address both concerns, we design our factor as follows.

First, we narrow down the investment universe[5] to climate-policy relevant sectors (CPRS) as defined by Battiston et al. (2017). This classification identifies sectors whose primary economic activities "*could be affected, either positively or negatively in a disorderly low-carbon transition [...] considering (i) the direct and indirect contribution to GHG emissions; (ii) their relevance for climate policy implementation [...] (iii) their role in the energy value chain*" and has been used by several financial regulators to assess the exposure of financial institutions to transition risks (ECB, 2021; EIOPA, 2018). This first source of information for the design of our CT factor is both robust (the sectoral affiliation is easily accessible) and forward-looking (the classification is established based on disorderly transition scenarios).

The goal of the second step is to identify companies within these sectors that may benefit (or suffer) from a disorderly transition in the long run. Ideally, this step would be carried out based on multiple company climate-related data. For example, Görgen et al. (2020) compute a "Brown Green Score" from 10 variables containing company specific information related to value chain, adaptability, and public perception. However, these data remain scarce and are not available for all sectors (NGFS, 2022). Moreover, Roncalli et al. (2020) showed that the composite indicator built by Görgen et al. (2020) is well captured by a factor based on the GHG emissions intensity only. We therefore consider GHG emissions intensity as a robust and still relevant metric for identifying companies exposed to transition risks *within* the climate-policy relevant sectors.

This brings up the question of the scope of the emissions to be considered. Our factor is built, within the CPRS sectors, on the emissions intensity of Scopes 1 and 2. Our choice not to use Scope 3 GHG emissions is motivated by two reasons. The first is related to the data quality. The objective of our factor is to capture a market signal that is expected to evolve as new information becomes available, in particular when companies' greenhouse gas emissions are updated. It is therefore important that the granular design of the CT factor is based on consistent data regardless of the data provider used by market participants. By comparing seven data providers, Busch et al. (2022) highlighted strong inconsistencies in indirect (Scope 3) data, whether reported by companies or estimated by external

5 - Our universe consists of the 500 largest companies in the US market.

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parties. To be as robust as possible, our CT is therefore only built on the GHG emissions intensity on the direct (Scope 1) and energy consumption (Scope 2) perimeters, for which there are higher levels of data consistency. The second reason is related to our sectoral approach. As pointed out by Ducoulombier (2021), reporting standards are not intended to support comparisons between firms. An alternative would therefore have been to use estimated Scope 3 emissions. However, we found that the correlations between Scope 12 and Scope 123 emissions intensity are greater than 0.9 within each CPRS. As we only use GHG emissions intensity to rank the companies *within* a CPRS (to determine whether they belong to the short or long leg of the factor), adding Scope 3 to Scope 12 would have a negligible effect.

Finally, our CT factor is constructed as follows: the long ("brown") leg is built as an equally weighted (EW) portfolio of the 50% most GHG emissions intensive stocks selected within each of the six CPRS sectors. Symmetrically, the short ("green") leg is built as an EW portfolio of the 50% least GHG emissions intensive stocks selected within each of the six CPRS sectors. Then, the weight of each leg is set so that the factor is market neutral. In this way, we assume that the CT factor should not contain any market risk. This approach is consistent in the context of asset management, where the market serves as a benchmark for risk.

2. Risk Model

As discussed in the literature review, most of the existing studies integrate a transition factor into multi-factor models as an additional factor. In this subsection, we argue that this approach is problematic, both from an asset pricing and risk perspective. All calculations are performed on a universe of 1,277 US based funds and ETFs denominated in USD between 2012 and 2022.

From an asset pricing perspective, a risk factor is worth adding to a model when it helps to better explain the cross-section returns (Lewellen et al., 2010). As proposed by Fama and French (2015), we performed an ordinary least-square regression of the CT factor against traditional risk factor models to measure the regression intercept (α below).

$$F_{CT} = \alpha + \sum_{f} \beta_f F_f + \varepsilon$$

Here, the factors F_f belong to a set of traditional risk factors. We found that for different sets of risk factors, the intercept of these regressions is close to zero and statistically not significant (Exhibit 1). This indicates that the CT factor does not possess a premium that is not explained by already existing factors (consistent with Görgen et al., 2020 and Amenc, Esakia & Goltz, 2021).

Exhibit 1: Regression between the CT and traditional factors

	Intercept (%)	t-stat	R-squared
Fama French 5-factor model (2x3)	-0.03	-1.47	0.25
Industry portfolios (10)	-0.02	-0.78	0.33
Industry portfolios (48)	-0.01	-0.39	0.59

Note: the regression is realized between 2012 and 2022 using weekly returns.

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From a risk perspective, a risk factor might be worth adding to a model if it helps to better explain the variance of the returns. To decide whether this is the case, we evaluate the semi-partial correlation between the returns of a sample of funds and a set of risk factors including the CT factor (see Cohen and Cohen, 1975). The semi-partial correlation determines how much of the return variance is explained uniquely by the CT factor. Exhibit 2 shows that the addition of the CT factor does not improve the model's ability to explain risk in a significant manner, as it contributes very insignificantly to the model's R-squared.

Exhibit 2: Semi-partial correlation between the funds returns and sets of fundamental risk factors

	Fama French 5-factor model (2x3)	Industry portfolios (10)	Industry portfolios (48)
Avg R-squared of the instrument active returns	0.33	0.36	0.48
Contribution from CT factor	0.01	0.02	0.01

Note: The semi-partial correlation is computed for 1,277 US-based funds and ETFs between 2012 and 2022. Because the CT factor is market neutral, we have focused on active risk, that is, the returns of each instrument that are not due to its market exposure.

These tests confirm that the addition of the CT factor does not improve the performance of existing asset pricing models: the information contained in the transition factor is already spanned by existing financial risk factors (Alessi, Ossola and Panzica, 2021; Amenc, Esakia & Goltz, 2021).

However, a risk factor does not need to improve the power of an asset pricing model to be relevant for risk management (Grinold and Khan, 1994). The transition factor, as we defined it, is indeed representative of stocks that are sensitive to the energy transition. As such, especially for institutional investors with long-term horizons, it is useful to understand how they are exposed to this segment of the market, and to be able to disentangle the resulting risk from other financial risks. To do this, we propose to filter the CT risk from traditional risk factors.

$$r_i = \beta_{i,CT} F_{CT} + r_i'$$

Here, the residual return denoted by r'_i corresponds to the returns of the i-th instrument that have been filtered from the effect of the CT factor. These returns are not exposed to CT risk. The CT risk associated with this instrument is thus given by measuring the part of the risk that is due to the exposure to the CT factor, that is,

$$Active\ CT\ risk\colon \sqrt{Var(r_i - \mathrm{r}_i')} = \sqrt{\beta_{i,CT}^2\, Var(F_{CT})}$$

Because we have made the factor market neutral, this risk does not include any market risk, hence the "active" denomination. If we now regress the returns and filtered returns of each instrument on traditional financial risk factors, we obtain two sets of exposures. One set corresponds to the exposures β_{if} of the i-th instrument's returns to the f-th traditional risk factor.

$$r_i = \sum_f \beta_{if} F_f + \varepsilon_i$$

3. Data and Model

The other set (denoted by β'_{if}) corresponds to the exposures of the instrument's filtered prices to the same traditional risk factors.

$$r'_i = \sum_f \beta'_{if} F_f + \varepsilon_i$$

These two sets of exposures yield a new relationship for the CT risk that involves only financial factors.

$$Active\ CT\ risk: \sqrt{Var(r_i - \mathrm{r}'_\mathrm{i})} = \sqrt{\beta_{i,CT}\Sigma_F\beta^T{}_{i,CT} + \frac{1}{T}\sum_t(\varepsilon_{i,t} - \varepsilon'_{i,t})^2}$$

where Σ_F is the covariance matrix of the financial risk factors and the components of the vector $\beta_{if,CT}$ are given by $\beta_{if,CT} = \beta_{if} - \beta'_{if}$. The CT beta $\beta_{if,CT}$ is the difference between the traditional beta and the filtered beta. It corresponds to the financial exposure of an instrument that comes from the part of its returns that are exposed to CT risk[6]. The CT beta thus actually helps to disentangle financial risks from CT risk. There is indeed a straightforward relationship between the $\beta_{if,CT}$ and financial factors,

$$\beta_{if,CT} = \beta_{if} \times \varrho_{f,CT}\frac{\sigma_{CT}}{\sigma_f}$$

where $\varrho_{f,CT}$ is the correlation between the f-th financial risk factor and the CT factor.

Importantly, the definition of CT risk connects the CT factor to existing financial risk models. It shows that it is possible to measure transition risks using already available financial time-series models. It only requires the simple step of computing an extra set of betas from filtered returns. The above definition also allows the derivation of a method to minimise the CT risk of a portfolio by solving the following minimum variance problem.

$$min\ w^T \Sigma_F^{CT} w$$

where $\Sigma_F^{CT} = \beta_{CT}\Sigma_f\beta^T{}_{CT} + D_\varepsilon$ and the elements of the diagonal matrix D_ε are equal to $(1/\mathrm{T})\sum_t(\varepsilon_{i,t} - \varepsilon'_{i,t})^2$.

Because the market-based CT factor is of the same nature as the financial factors, it can be managed with the same tools. This is one of the greatest practical advantages of a market-based estimation of the CT factor from a portfolio management viewpoint.

6 - For instance, if many Value stocks of a portfolio are located in CPRS sectors, the CT beta associated with the Value factor will be high. It also means that if a portfolio's exposure to CT were to be completely eliminated, its exposure to the f-th financial factor would be reduced (or increased) proportionally to $\beta_{if,CT}$.

4. Results

4. Results

In this section, we first show how the CT factor is better designed to capture sensitivity to the long-term energy transition than a factor based solely on carbon intensity. Using the risk model, we then show how this factor is related to traditional ones and illustrate how these interactions can be considered in portfolio risk management.

4.1 Transition Factor Consistency

The relevance of a factor to capture the sensitivity of a portfolio to the energy transition is difficult to establish. In fact, energy transition periods of sufficient length are not available to test the robustness of CT factors with the statistical tools used for traditional risk factors. In contrast with financial risk factors, whose drivers have been present in markets for decades, the sample available to assess climate transition risks is not long enough to perform the usual statistical tests based on long-term returns. Here, the size of the historical sample forbids to posit that the significance of past behaviour provides sufficient likelihood of future relevance. In the case of climate transition risks, robustness must thus be supported by the data used for its construction. This is why industry membership, one of the most stable and reliable indicators of climate transition risks, is used on top of the more common carbon emissions.

We propose to compare three candidate factors:
a) the climate transition factor (CT) described above,
b) a sector-relative intensity factor based on a traditional sectoral classification (IOS), and
c) an intensity-only factor (IO).

The IOS factor is based on the GHG emissions intensity relative to its Refinitiv Business Classification (TRBC) sector (at the first level, i.e., 10 sectors) while the IO factor is built on a long-short strategy based on the GHG emissions intensity only.

A first test to assess the robustness of these factors is to compare their compositions. Since the objective is to construct a signal centred on transition risks, it is important that the composition be representative of companies sensitive to the transition: the various sectors concerned should be represented, and both “green” and “brown” activities should be included. The composition of each factor shows that considering only carbon intensity leads to large weights outside of climate-sensitive sectors (Exhibit 3). Indeed, in the considered universe (US), 49% of the stocks are not considered as climate policy relevant according to the CPRS classification. In the IO factor, while the long leg contains mostly CPRS stocks, the short leg contains less than 20% of CPRS stocks (26% for the short leg of the IOS factor).

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Exhibit 3: Weights of different CT factors in climate sensitive sectors

CPRS clean	Universe	IO short	IO long	IOS short	IOS long	CT short	CT long
1-fossil-fuel	6%	0%	20%	3%	4%	9%	9%
2-utility	3%	0%	25%	5%	7%	10%	11%
3-energy-intensive	31%	8%	20%	8%	31%	51%	51%
4-buildings	3%	5%	12%	5%	22%	15%	15%
5-transportation	7%	1%	9%	2%	12%	15%	14%
6-agriculture	0%	0%	0%	0%	0%	0%	0%
7-other	1%	3%	2%	3%	2%	0%	0%
no CPRS	**49%**	**83%**	12%	**74%**	21%	0%	0%

Note: (IO) factor is built on a long-short strategy based on the GHG emissions intensity only; (IOS) factor is built on the GHG emissions intensity relative to its Refinitiv Business Classification (TRBC) sector; (CT) is the climate transition factor.

In the future, the signal from these factors will therefore be driven mainly by companies with little concern for transition risks while companies that might benefit from the transition (best-in-class within the CPRS sectors) will remain out of scope. For example, the two NACE[7] sectors most represented in the short leg of the IO factor are the Financial and IT sectors, which are not directly concerned by the energy transition (Exhibit 4). This holdings-based analysis thus shows the importance of restricting the construction of factors to the CPRS universe to target where the transition risks are likely to occur.

Exhibit 4: Main sectors represented in the short leg of the intensity only (IO) factor

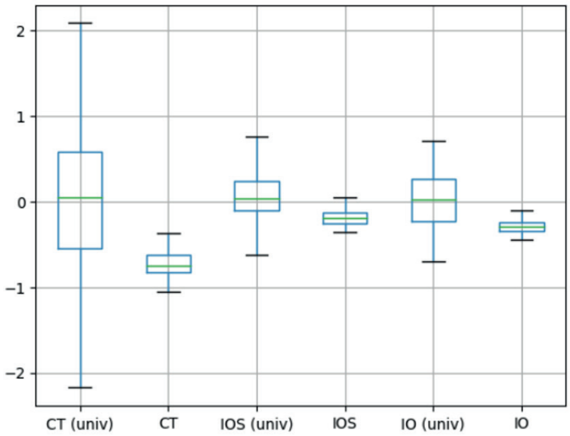
NACE sector	IO short
Non-life insurance	19%
Other software publishing	10%
Other activities auxiliary to financial services	6%
Other monetary intermediation	6%
Other credit granting	4%
Total	**45%**

While the first goal of the CT factor is to capture sensitivity to the long-term transition, such a factor should already allow for the identification of funds considered as "green" or "brown". A second test then consists in measuring the extent to which the sensitivity of a fund to the various factors is consistent with its current "green" or "brown" characteristic (estimated by a third party). Since there is no homogeneous definition of such funds, we consider a sample of "green" funds as the top decile of funds of our universe[8] based on the average share of corporate revenues that contribute positively to the climate mitigation. Conversely, we define a sample of brown funds as those with the highest transition risk score. We show that the betas of the "green" (respectively "brown") funds to the CT factor are significantly lower (respectively higher) than the average betas of the funds of our universe (Exhibits 5 and 6). This confirms the ability of the CT factor to identify "green" and "brown" funds from their prices. In order to validate the robustness of these tests, we also performed them with correlations rather than betas. We find that the CT factor has higher correlations with green funds than the IO and IOS factors.

7 - The Statistical Classification of Economic Activities in the European Community.
8 - Our fund universe consists of 600 funds and ETFs offered in the US market.

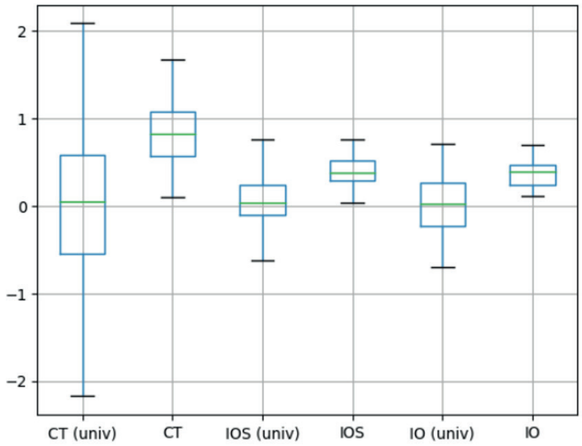
4. Results

Exhibit 5: Beta distribution of "green" funds to different transition factors



Note: The distribution of betas is done on 615 active funds and on a selection of the 10% of funds with the highest share involved in climate action according to Morning Star (representing 62 "green" funds).

Exhibit 6: Beta distribution of "brown" funds to different transition factors

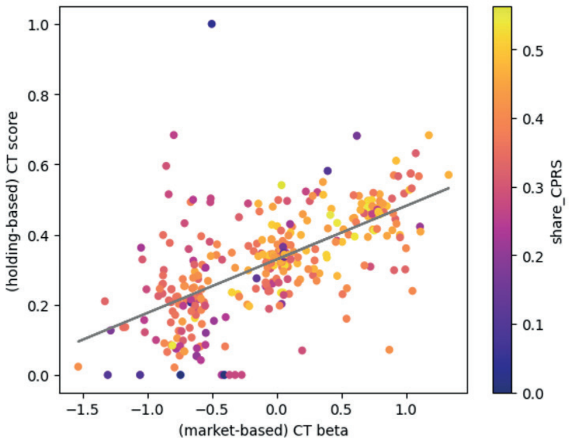


Note: The distribution of betas is done on 615 active funds and on a selection of the 10% of funds with the highest "carbon risk score" according to Morning Star (representing 53 "brown" funds).

A final test is to check the consistency between our market-based approach and a holdings-based approach built on the same metrics as those used to design the CT factor. On the one hand, it is important to ensure consistency between these two approaches, which have the same ultimate objective: to measure the sensitivity of a portfolio to the energy transition. On the other hand, the use of a price signal is motivated by the fact that it can indirectly integrate more information than a holdings-based score, which can therefore explain the different results between the two approaches. To do this, we regress a holdings-based risk metric constructed for each fund as the weighted share of constituents with carbon intensity above the median carbon intensity of their related CPRS main sector (only considering CPRS weights) against the beta of the fund to the CT factor. The coefficient is positive and significant, which confirms the consistency of the market-based approach (Exhibit 7).

4. Results

Exhibit 7: Consistency between holdings-based and market-based measures of transition exposure



Note: The (holdings-based) CT score is constructed for each fund with the same metrics used to design the CT factor. The coefficient of the regression line is positive (0.15) and significant (t-stat 15.23).

Several reasons can explain the remaining different results between the two approaches. First, we observe that the outliers are essentially funds where the share of securities belonging to the CPRS sectors is low and where transition risks are therefore not a concern. Moreover, the market-based approach is based on prices, which represent a large amount of information "digested" by market participants and can therefore capture more information than sector and carbon intensity. Two companies with the same carbon intensity and belonging to the same sector may indeed be impacted differently by the energy transition, for example, if the regulations applicable in their respective countries of activity differ (presence or absence of carbon taxes) or if one of them has been the subject of climate change controversy. A market-based approach captures these kinds of differences, whereas a holdings-based approach only focuses on a small number of transition-related metrics.

4.2 Disentangling Climate Transition Risks from Traditional Risks

In this section, we present estimates of the active risk associated with the CT factor and the correlations between the CT and traditional factors. One advantage of the price-based approach is that it produces risk estimates, not scores, so its interpretation and management are similar to those of financial risks.

The distribution of the annualised climate transition risk (in percent) estimated on a sample of 1,277 US based funds and indices between 2017 and 2022 is displayed in Exhibit 8. Exhibit 9 provides descriptive statistics on the distribution of CT risk across a universe of funds with active risk for different CT factors. The fraction of active risk associated with the CT factor represents an important part of the total active risk (last column).

4. Results

Exhibit 8: Distribution of the annualised CT risk between 2017 and 2022 within a universe of active funds

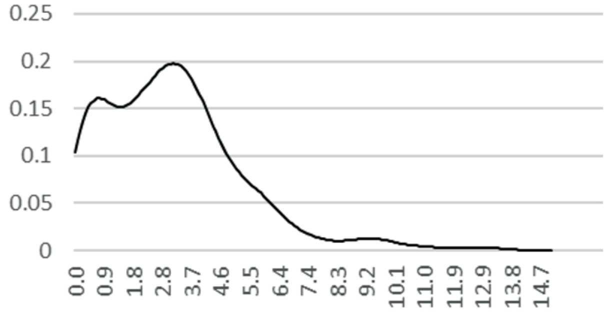


Exhibit 9: Distribution of the CT risk between 2017 and 2022 within a universe of active funds

(%) p.a.	CT	IO	IOS	Active risk
mean	3.12	3.37	1.69	9.95
std	2.22	3.20	1.38	5.81
min	0.00	0.00	0.00	3.00
25%	1.47	1.47	0.74	6.06
50%	2.93	2.96	1.31	8.68
75%	4.17	4.30	2.45	11.79
max	13.43	26.56	10.38	60.41

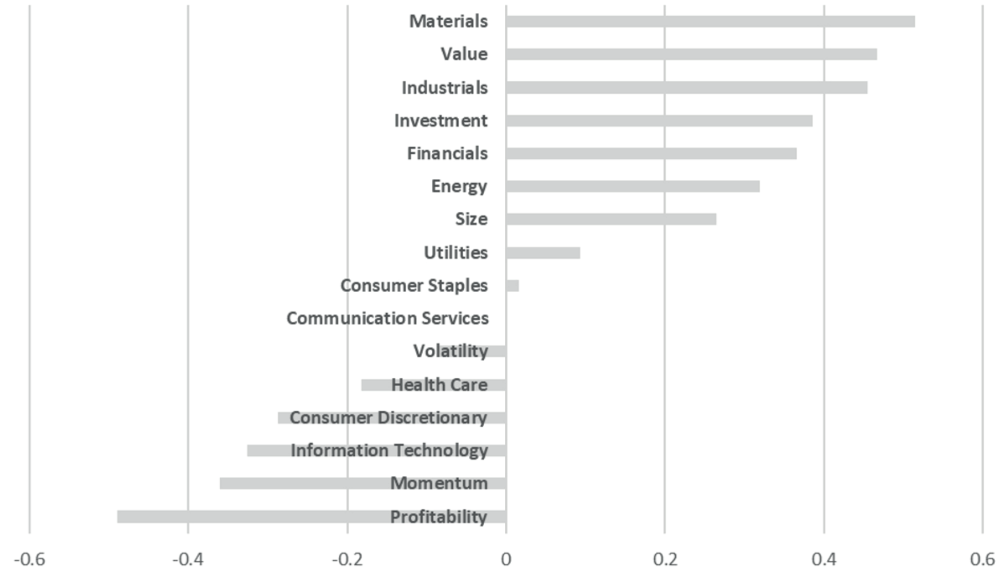
Note: Distribution of CT risk over a universe of 1,277 funds and ETFs with an active risk greater than 3% p.a.

The relative contribution of CT risk to financial exposures directly stems from correlations $\varrho_{f,CT}$ of the CT factor with financial risk factors. The correlations with a set of fundamental financial factors are shown in Exhibit 10. Notably, the CT factor exhibits important correlations to the sectoral factors "Industrials" and "Materials", and to the "Value" and "Investment" factors. Although our factor is designed as a long-short factor within transition sensitive sectors, the two sectoral biases "Industrials" and "Materials" can be explained by the fact that these two sectors are grouped within the same "Energy-intensive" sector in the CPRS classification. This relationship suggests that a portfolio optimisation aiming at reducing the CT factor exposure will also tend to reduce the exposure of the portfolio to these factors if it is performed without controlling for factor exposures.

However, the portfolio obtained by seeking to reduce its exposure to the IO factor will differ from the portfolio seeking to reduce its exposure to the CT factor. Because the carbon intensity is heavily correlated to the fossil fuel sectors, reducing exposure to the IO factor will lead to divestments concentrated in these sectors, as well as investments in non-CPRS sectors such as Retail and IT. On the other hand, reducing exposure to the CT factor is obtained by performing divestments in a more diverse set of sectors including Mining, Steel Production, Shipping, and Agriculture, while moving less capital to non-CPRS sectors. While using the IO approach might be more efficient in the context of a strict carbon reduction strategy, reducing a portfolio's exposure to the CT factor will likely affect a more diverse range of companies that are affected by transition risks, not only high carbon producers. The use of either factor thus depends on the strategy objective.

4. Results

Exhibit 10: Correlation between the CT factor and traditional factors



Note: The long(short) leg of each factor corresponds to an equally weighted portfolio of stocks with the 20% highest(lowest) performance expectations with respect to a given fundamental characteristic ("Size": free-float adjusted market cap; "Value": book-to-market ratio; "Investment": total asset growth over the last two years; "Profitability": gross profit to total asset ratios; "Volatility": weekly volatility estimated over the last two years; "Momentum": price momentum over the past 12 months without the last month). The relative weight of each leg in the final portfolio is calculated so as to cancel the exposure of the factor to the market factor. The long leg of the factors associated with industrial sectors simply correspond to the cap-weighted stocks belonging to this sector, while the short leg is the market factor whose weight is adjusted to make the factor market neutral.

Conclusion

Conclusion

This article contributes to the growing literature on price-based transition risks (Bolton et al. 2020, Görgen et al. 2020). To overcome the climate-related data gaps and to take advantage of the ability of market participants to integrate broader information in asset valuation, we propose a market-based measure of transition risks. In order to avoid the "Don't look up" effect associated with validating a factor only from a historical perspective, we focus on the design of a relevant and robust climate transition (CT) factor sensitive to the long-term energy transition shocks.

We propose a CT factor that captures both the sectoral and intra-sectoral dimensions of transition risks by relying on the climate-policy relevant sectors classification (Battiston et al., 2017) and on GHG emissions intensity. By construction, this leads to a reduction in the eligible universe of 50%, and thus avoids the factor signal being disrupted by companies little affected (negatively or positively) by transition risks, as opposed to a factor based solely based on the GHG emissions intensity. While the main goal of our CT factor is to be forward-looking, we show that this factor is already able to efficiently identify funds considered as "green" or "brown".

We also highlight that exposure to certain traditional factors such as "Value" and "Investment" are associated with greater transition risk. Without control, reducing exposure to transition risks may therefore lead to undesirable biases on other factors.

Our market-based approach of transition risks allows for the practical management of transition risks via portfolio optimisation. These techniques are straightforward to implement as they only require already existing sets of financial factors. Climate transition risks are not only measurable; they are also manageable with the same tools as those used to manage financial risks.

One of the major avenues for future research would be transposing this methodology to other complex environmental issues such as biodiversity, where important data gaps remain but where the recent development of specific indicators would permit to build such a factor.

4 - For example, the public database ENCORE provide a first approximation of economic activities dependencies on ecosystem services. Source: https://encore.naturalcapital.finance/en/data-and-methodology/data

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Scientific Portfolio Publications

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2023 Publications

- Herzog, B. ,Jones, J., and Safaee, S. Remember to Diversify Your Active Risk: Evidence from US Equity ETFs (March).
- Scientific Portfolio's Investment Philosophy (April).
- Scientific Portfolio's Investment Philosophy ANNEX - Summary of Functionalities (April).
- Bouchet, V. Decomposition of Greenhouse Gas Emissions Associated with an Equity Portfolio (May).
- Herzog, B. ,Jones, J., and Safaee, S. The Perceived Advantages of Self-Indexing for Institutional Equity Investors. (September).
- Bouchet, V., Vaucher, B., and Herzog, B. Look up! A Market-Measure of the Long-Term Transition Risks in Equity Portfolios. (November).

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