Understanding Commodity Risk Factors In The Transition Towards A Net-Zero Carbon Economy

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Abstract

This paper provides novel evidence of a risk premia in the cross-section of commodity returns arising from the green transition. Extending the standard three factor model for commodity returns to include climate risk, we show how commodity returns have started to incorporate a risk premium to compensate for this risk since the 2015 Paris Agreement. We estimate the risk premia associated with both risk factors to be both statistically and economically significant, controlling for known risk factors.

Keywords: Commodity asset pricing models; Climate risk; Energy transition; High-frequency data.

JEL classification: D81, G11, G12, G14, Q02.

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1 Introduction

Climate change and the ongoing low-carbon energy transition are expected to have significant long-term effects on commodity markets and investment decisions (Davidson, Karplus, Lewis, Nahm and Wang, 2022; Pommeret, Ricci and Schubert, 2022). Green transition is taking place in a context of heightened geopolitical uncertainty. This is especially relevant as key transition commodity supplies are subject to concentration in just a few countries (OECD, 2022), exacerbating commodity market exposure to geopolitical factors. While there is increasing attention on the implications of climate-related risks for investors and financial institutions, and overall for the financial system stability and economic growth in general (European Systemic Risk Board, 2022; Igan, Rungcharoenkitkul, Takahashi et al., 2022; Financial Stability Board, 2023), relatively less is known about the exposure of commodity markets to climate risk implied in the green transition. We contribute to the understanding of these emerging new risks by empirically measuring new risk factors related to climate risk. We show that climate risk is priced in the cross-section of commodity returns, especially in the period following the 2015 Paris Agreement.

Climate change and the transition from fossil fuels to zero-carbon sources of energy add a new dimension to the uncertainties that roil commodity markets. Extreme weather events are becoming increasingly common and affect the production of many commodities. The current transition towards a carbon-neutral economy—intended to minimize the worst effects of climate change—is altering patterns of commodity production and consumption. The climate crisis poses a host of different risks, which fall under two main categories: physical risks and transition risks. Physical risks refer to the direct and indirect impacts of climate change on assets. These risks arise from changing climate conditions, such as extreme weather events, rising temperatures, sea-level rise, and other environmental changes. Physical risks can manifest in various ways, including changes in demand and supply of different commodities, damage to assets, disruption of supply chains, increased operational costs, and decreased asset values. Transition risks are associated with the process of transitioning to a low-carbon economy and adapting to new climate policies and regulations. These risks arise from changes in government policies, technological advancements, market preferences, and other factors that influence the shift towards carbon neutrality. Transition risks can include regulatory changes, carbon pricing, shifts in consumer preferences, likewise the emergence of low-carbon technologies, which affect commodity markets, market players, and the value and competitiveness of assets.

Although economic transitions have historically been slow and cumulative, the ongoing transition paradigm is leading to a shift in fuel type, access, production, delivery, reliability, and end-use of different commodities, thus challenging the overall orientation of our economic systems (e.g. Araújo, 2014; Semieniuk, Campiglio, Mercure, Volz and Edwards, 2021) while bringing structural changes in commodity markets (Baffes and Nagle, 2022). Understanding what drives developments in commodity markets is therefore critical to the design of policy frameworks supporting the ongoing transition towards a low-carbon economy while facilitating the economic objectives of sustainable growth, inflation stability, poverty reduction, food security, and the mitigation of climate change (Baffes and Nagle, 2022).

In this paper, we study a set of 24 commodities for the period 2000-2022. We rely on high-frequency data on future commodity contracts to build commodity log return series. We focus on commodity future markets as these markets have become increasing popular for portfolio diversification by institutional investors, since the so-called financialization of commodity markets that took place in 2014 (Cheng and Xiong, 2014) and they are strongly related to commodity spot markets . We extend previous work by including a climate risk factor in a standard asset pricing exercise, controlling for well-known commodity risk factors. We find that climate risk factors are priced in the cross-section of commodity returns, especially in the period post 2015, when the Paris Agreement brought the climate risk and green transition to the attention.

We contribute to the literature on asset pricing in commodity markets. The literature has identified few key factors that influence commodity pricing. These factors include inventory levels (Gorton, Hayashi and Rouwenhorst, 2013), roll-yield (Erb and Harvey, 2016), hedging pressure (Basu and Miffre, 2013), past returns (Gorton and Rouwenhorst, 2006; Miffre and Rallis, 2007), skewness (Fernandez-Perez, Frijns, Fuertes and Miffre, 2018; Fuertes, Liu and Tang, 2022), liquidity (Szymanowska, De Roon, Nijman and Van Den Goorbergh, 2014), basis-momentum (Boons and Prado, 2019), and relative-basis (Gu, Kang, Lou and Tang, 2019). While previous research has also drawn attention on the relationship between asset prices and geopolitical risks (Caldara and Iacoviello, 2022), only a limited number of studies address this relationship in commodity markets (Cheng, Liao and Pan, 2023), mostly with a particular focus on oil (Kollias, Kyrtsou and Papadamou, 2013; Brandt and Gao, 2019) or precious metals (Smales, 2014; Smales and Lucey, 2019; Baur and Smales, 2020). Only a few papers study the cross-section of the returns for a broad set of commodity futures markets (Daskalaki, Kostakis and Skiadopoulos, 2014; Koijen, Moskowitz, Pedersen and Vrugt, 2018). Bakshi, Gao and Rossi (2019) explore the presence of standard risk factors, namely an average commodity factor, a carry factor, and a momentum factor, in the cross-section of commodity returns. Our contribution to this strand of the literature is to explore the implications of the ongoing energy transition for commodity pricing factors and identify new risk factors associated with climate risk.

The paper is structured as follows...

2 Data

This section describes the commodity data used in the empirical analysis, the construction of portfolios and associated excess returns, our main proxies for climate-related risk. We also provide some basic descriptive statistics.

2.1 Data on commodity futures returns

The data for commodity futures contracts cover the sample period from January 2000 to December 2022, and are obtained from LSEG (formally Refinitiv). We focus on the front-end and second nearest continuous rolling futures contracts, which exhibit significantly higher trading volume and liquidity, making them more relevant for asset pricing and risk premium evaluations (e.g. Amihud and Mendelson, 1986; Fernandez-Perez et al., 2018). The empirical analysis is carried out at the monthly frequency, although we start from 5-minute frequency data to construct portfolios and associated excess returns (Menkhoff, Sarno, Schmeling and Schrimpf (2012) and Bakshi, Gao and Rossi (2019) also use monthly data).

Our sample consists of 23 commodities spanning the major categories (energy, metals, agriculture, and livestock) across different exchanges (NYMEX, CBOT, COMEX, ICE, LME). We also consider the Goldman Sachs Commodity Index (GSCI). The regular trading sessions for commodity futures vary based on the exchange and the specific commodity being traded. Many commodities trade almost 24 hours electronically, with short breaks for maintenance. Some commodities also have traditional floor trading hours, which are typically shorter than electronic sessions.

In order to maximize liquidity across all commodities and capture the most active trading periods across global exchanges, mid-quotes were extracted at 10:05 AM Eastern Time (3:05 PM London Time) for each trading day. This time point aligns with peak trading activity in both U.S. and European markets, thereby ensuring high liquidity across exchanges. Thus, in line with Gorton, Hayashi and Rouwenhorst (2013), for each month, we constructed rolling commodity futures monthly excess returns by selecting, at the end of each month, the nearest contract that did not expire in that month. We computed the total returns under the assumption that the futures position was fully collateralized. Therefore, the excess return from the end of one month to the end of the following month were calculated as:

$$\ln\left(\frac{F_{t+1,T}}{F_{t,T}}\right) \tag{1}$$

where $F_{t,T}$ is the futures price at the end of month t on the nearest contract whose expiration date T is after the end of month $t+1$ and $F_{t+1,T}$ is the price of the same contract at the end of month $t+1$. Following the extant literature since Fama (1965), we use logarithms for ease of exposition and notation. We report descriptive statistics of monthly commodity futures excess returns in Table 1. All commodities exhibit Sharpe ratios (SR) below 0.25, indicating that stand-alone investments in commodities are not particularly attractive. Nevertheless, the Skewness (Skew) and Kurtosis (Kurt) reveal significant deviations from normality, thereby complicating the interpretation of the Sharpe ratios. Commodity returns are mostly serially uncorrelated (the absolute first- order autocorrelations is not significant for 15 out of 23 commodities) and typically negatively skewed. To address the varying availability of data across the time series of the different commodities (variable N in Table 1), we restrict the sample in our empirical analysis to the period from January 2007 to December 2022.

2.2 Measuring climate risk

The literature has identified a number of measures for climate risk. We review some of this work in Table 2. A class of measures captures the physical aspect of climate risk and are based on the instances and severity of climate-related disasters and extreme temperatures. However, analyses based on historical climate events may not accurately reflect shifts in risk perception (Jung, Engle, Ge and Zeng, 2023).[1] Market expectations can change without direct experience of climate change events, leading current asset prices to reflect future climate risks that may not manifest for decades. Second, both the climate risk itself and the market responses to perceived risks evolve over time. Third, the scarcity of reliable data on a systematic evaluation of climate-related risks is a major obstacle. Although voluntary climate-related disclosures are available, they are often incomplete and inconsistent in quality (European Systemic Risk Board, 2020; Financial Stability Board, 2021).

In our analysis we capture climate risk with a set of forward-looking, time-varying measures that can be estimated in real time. First, we rely on the *climate policy uncertainty index* built by Gavriilidis (2021). Based on Baker, Bloom and Davis (2016) methodology for the economic uncertainty index, Gavriilidis (2021)'s climate policy uncertainty index builds on text searches of key terms related to climate risk as well as uncertainty and regulation in eight large US newspapers. In addition to a measure based on the perception of climate policy uncertainty in the press, we consider a measure of climate risk that reflects stock market perception of carbon emissions (Bolton and Kacperczyk, 2021). Following Jung et al. (2023) we consider a *stock market emission factor* that is the carbon emission value-weighted S&P 500 stock returns. To build the emission factor, we first calculate the industry stock market returns with the value-weighted stock returns

[1] We consider standard measures of physical climate risk and report the results of the asset pricing analysis with these measures in the section 4.5.

of the constituents of the S&P 500. Then, we calculate the market weighted average with the scope 3 industry carbon emissions as weights. Finally, we consider climate risk based on the occurrence of *transition climate risk events* building on Barnett (2019). The index represents the number of events that are related to transition risk every month. We extend the index by Barnett (2019) extended by Jung et al. (2023) to 2022, the end of our sample period.

As shown in Table 3, although there is some overlap, measures proposed in the literature tend to capture distinct aspects of climate risk in the green transition. When looking at the correlation between the measures in Table 4, we find that the comovement between them is generally low. An interesting exception is the *climate policy uncertainty index* that correlates positively and relatively strongly with the measures based on the occurrence of climate related news developed by Ardia, Bluteau, Boudt and Inghelbrecht (2023). The correlation coefficient of the *climate policy uncertainty index* is around 60% with both the physical and transition climate risk components. These measures of media climate change concern developed by Ardia et al. (2023) are highly correlated, with a correlation coefficient at 83%. This indicates that although different, these measures effectively tend to capture a similar aspect of climate risk related to the news coverage of events related to climate.

In an attempt to reconcile the various measures developed in the literature, we conduct a principal component analysis on the standardized climate risk measures. We find that the first 3 principal components (PCs) around 70% of the variance. What do these components represent? We present a correlation matrix between the 3 PCs and our climate risk measures in Table 5. Overall, the correlation coefficients suggest that the first principal component is related to the climate-related news coverage. The second principal component correlates positively with the physical climate risk, both the occurrence of climate disasters and extreme temperatures, and negatively to the climate policy events index. This suggests that the second component is likely to be capturing the physical aspect of climate risk, as opposed to the transition one. Finally, the third component correlated with all climate related events, either physical or transition. We do not find evidence of significant correlation between the stock market emission factor and the PCs.

Figure 1 shows the dynamics of climate risk captured by by the climate policy uncertainty index, the stock market emission factor, and the transition climate risk events index during our sample period 2007-2022. In line with the correlation analysis and the PCA presented above, the figure clearly shows that the dynamics of climate risk vary substantially depending on the measures used to capture it. In panel (a), climate risk associated with policy uncertainty exhibits an upward trend since the 2016 Trump election. The stock market emission factor in panel (b) reflects the market price of industry emissions, and as such it reflects the large drops and high volatility of the 2007-09 Global Financial Crisis. Volatility in the emission factor increases again in the most recent period. Finally, in panel (c) transition climate risk events are well spread across our sample period, with a slightly larger concentration of events in the most recent period following the Covid-19 pandemic.

3 Asset Pricing Approach

In order to determine whether the risks associated with the energy transition are priced in commodity returns, we augment the standard three-factor model by Bakshi, Gao and Rossi (2019) with a climate risk factor, CL. We employ the various measures in turn.

Our model includes the three standard risk factors that have been documented to contribute in explaining the cross-section of commodity returns by Bakshi, Gao and Rossi (2019). The average factor is the demeaned cross-sectional average of commodity excess returns, $f_t^{AVE} = AVE_t - \mu_{AVE}$. The momentum factor is the demeaned return of a portfolio long in the top commodity performers in the past 6 months, and short in the bottom performers, as $f_t^{MOM} = MOM_t - \mu_{MOM}$ with $MOM_t = MOM_{1,t} - MOM_{5,t}$. The carry factor is the demeaned return of a portfolio long in the most backward commodities ($ln(F_1/F_0) < 0$) and short in the most contango ones ($ln(F_1/F_0) > 0$), as $f_t^{CARRY} = CARRY_t - \mu_{CARRY}$ with $CARRY_t = CARRY_{1,t} - CARRY_{5,t}$.

Our test assets are 19 commodity portfolios. We follow previous work by Bakshi, Gao and Rossi (2019) and include 4 category portfolios (agriculture, livestock, metals, and energy), 5 momentum portfolio, and 5 carry portfolios. Moreover, given our focus on climate risk, we include 5 additional climate portfolios. We build the category portfolios by averaging the monthly excess returns across the commodities in each category. The momentum portfolios are based on the ranking of the past 6-month performance of the commodities. We link the returns of the portfolios every 6 month to obtain the excess return series for 5 momentum portfolio, $MOM_{1,t}$ to $MOM_{5,t}$. Similarly, we build the carry portfolios by ranking commodities based on their future curve spread, given by $ln(F_1/F_0)$. We link the returns of the portfolios based on this ranking and obtain excess return series for the 5 carry portfolios, $CARRY_{1,t}$ to $CARRY_{5,t}$. Finally, the climate portfolios are based on the ranking of the sensitivity of commodity returns to climate risk of the past 12-month period. Linking the returns of the portfolios every 12 months, we obtain excess return series for the 5 climate portfolios $CL_{1,t}$ to $CL_{5,t}$.

We follow a standard Fama and MacBeth (1973) procedure and we start our empirical asset pricing exercise by estimating the sensitivities of the portfolios' excess returns to the risk factors estimating the following equation:

$$er_{p,t} = \alpha_p + \beta_p^{CL} f_t^{CL} + \beta_p^{AVE} f_t^{AVE} + \beta_p^{MOM} f_t^{MOM} + \beta_p^{CARRY} f_t^{CARRY} + \epsilon_{p,t} \quad \text{for} \quad p = [1, ..., 12] \tag{2}$$

We estimate the time-series regression for each portfolio p and the β_p are the portfolios' sensitivities to each risk factor.

We proceed to estimate the exposure of the portfolio excess returns to the sensitivities at each point in time, in the second step, as follows:

$$er_{p,t} = \beta_p^{CL} \lambda_t^{CL} + \beta_p^{AVE} \lambda_t^{AVE} + \beta_p^{MOM} f_t^{MOM} + \beta_p^{CARRY} \lambda_t^{CARRY} + \epsilon_{p,t} \quad \text{for} \quad t = [1, ..., T] \tag{3}$$

where the λ_t is the market price of each risk factor at each point in time. Finally, we average the λ_t to obtain the risk premium, as $\hat{\lambda}^{CL} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_t^{CL}$.

If investors require compensation for holding assets exposed to the risks related to energy transition, we expect to find a positive and significant risk premia associated with the climate risk factor $\hat{\lambda}^{CL}$, controlling for the other known risk factors. In order to consider the dramatic shift towards the energy transition of the past decade, we estimate risk premia for the period following the 2015 Paris Agreement, as well as the full period 2007-2022. We expect the risk premia to be especially relevant in the period post 2015.

Furthermore, we ask whether the dramatic shift towards the energy transition of the past decade has affected the pricing of risk. We do so by analysing whether there is time variation in these risk premia and whether this time variation is related to the business or the financial cycles. Specifically, we estimate our augmented regression with the new risk factors λ^{CL} in 5-year rolling windows.[2] If the energy transition process is structurally changing the commodity market, we expect to find time variation in the risk premia, and we expect this variation to be positively related to the dynamics of global business and financial cycles.

4 Climate risk premium in commodity returns

4.1 Climate sorted portfolios

We start by studying the returns of the climate sorted portfolios to provide preliminary evidence for the presence of a priced climate factor. If climate risk is priced in the cross-section of commodities, portfolios

[2] Our results remain qualitatively similar with an alternative window of 4 years. Results are unreported for brevity but available upon request from the authors.

that are more sensitive to climate risk would yield higher excess return than the less sensitive portfolios.

We start by focusing on the *climate policy uncertainty index*. Descriptive statistics of the climate-sorted portfolios are reported in Table 6. Average and median values of portfolios excess returns decrease almost monotonically from the more sensitive portfolio to climate risk (P1) to the less sensitive portfolio (P5). Moreover, the Sharpe ratios are higher for the more sensitive portfolios. This is evident in the whole sample period (panel a), as well as in the post 2015 period (panel b).

We report the cumulative excess returns of the high minus low climate portfolio in Figure 2 (panel a). The high minus low portfolio is long in the portfolio with the more sensitive commodities, and short in the less sensitive portfolio. The portfolio exhibits a positive and largely increasing cumulative returns, indicating positive excess returns of a strategy long in most sensitive and long on least sensitive commodities to climate risk. Thus, there is indication that positive exposure to climate risk yields higher returns, pointing to a priced climate risk factor related to the uncertainty in climate policies.

Next, we turn to the market-based assessment of the exposure of firms to the green transition with the *stock market emission factor*. Although the high minus low portfolio does exhibit a somewhat upward trend (Figure 2, panel b), we find less clearcut evidence for the presence of a priced climate risk factor (Table 7, panel a). Furthermore, there is no evidence of regularities in the returns of commodities sorted based on their exposure to transition climate events, as measured by the *climate transition related events* index (Table 7, panel b, and Figure 2, panel c).

4.2 Climate risk premium

Next, we turn to the empirical test for the presence of climate risk premium in the cross-section of commodities. Table 8 reports the results of the asset pricing exercise for the full sample period 2007-2022. Panel a reports the results of the estimations with the climate policy uncertainty index. We find that the climate risk premia is positive as expected, although not statistically significant. We confirm previous findings that the carry risk and momentum risk are both priced in the cross-section of commodity returns. The magnitude of the prices of risks are in line with those estimated by Bakshi, Gao and Rossi (2019).

We then turn to the climate risk measure based on the stock market emission factor in Table 8 (panel b). Similarly to the previous measure, we find that the climate risk premia is positive, but not statistically significant. Turning to the climate transition related events measure in panel c, we confirm that the factor is not priced in the cross-section of commodity returns in our full sample period 2007-2022.

4.3 The green transition period

We now focus on the period post 2015 following the Paris Agreement that brought climate change and the need for a green transition to the fore of the public attention.

We report the results in Table 9. In panel a, we report the results for the climate policy uncertainty index and we show that the climate risk premium is positive and significant in the post-2015 period. The significance is confirmed considering the Shanken adjustment of the standard errors. The p-values of the pricing error tests confirm we can reject misspricing. In panel b, we show that the stock market emission factor is not priced in the cross section of commodity returns in the period post 2015 when correcting the standard errors with the Shanken adjustment to consider that betas are estimates. Turning to the transition related events in panel c, the results are weaker and we do not find a significant climate risk premium associated with this measure based on the occurrence of transition related events. Also we can reject the null of the pricing error test in this specification.

Overall, our results in this section confirm that it is the forward looking component of the uncertainty related to climate risk that the market prices in the cross-section of commodity returns, as opposed to the exposure of firms to the transmission or the occurrence of events related to the transition per se. The magnitude of the lambda associated with the climate policy uncertainty has doubled from the estimate for the full period, indicating that climate risk is an emerging new significant factor that is now priced in commodity returns. These results indicate that since the Paris Agreement, commodities more exposed to climate risk demand higher return to compensate for the climate-related transition risk.

4.4 Rolling windows

Our findings so far are supportive for the presence of a climate risk premium related to climate policy uncertainty in the post-2015 period, but not in the overall sample period 2007-2022. In this section, we explore the time variation in our estimates and we turn to the rolling window estimation of the climate risk premium.

Figure 3 (panel a) reports the rolling window risk premium estimates for the climate risk with moving windows of 5 year. The climate risk premium exhibits significant time variation, from low levels in the first part of the sample period to the positive and significant levels in the period post 2015. This exercise provides additional evidence that the 2015 Paris Agreement marked a dramatic shift in the perception of climate risk in commodity markets.

Is this trend evident in other climate risk measures related to the green transition? The results presented in Figure 3 confirm that the stock market emission factor is priced (panel b), while the transition events index is not (panel c). Moreover, similarly to the climate policy uncertainty, the emission factor is priced in the post 2015 period, but not before, confirming the dramatic impact of the 2015 Paris Agreement on commodity markets.

4.5 Is physical climate risk priced?

In this section, we turn to the measures of climate risk related to its physical manifestations. As we argue above, we do not expect physical climate risk to be relevant for commodity returns. To test our prediction, we first employ a measure that captures temperature rising above long-term levels, so called temperature anomalies, globally. The index is built by the National Oceanic and Atmospheric Administration (NOAA) and combines land and ocean data.[3] Moreover, we consider an alternative measure of climate risk based on the severity of disaster events worldwide from the Emergency Events Database (EM-DAT) at the Centre for Research on the Epidemiology of Disasters (CRED) of the University of Louvain (Gu and Hale, 2023).

We estimate the climate augmented factor model with these alternative measures and report the results in Table 10. We focus on the green transition period, post 2015. The results for both climate risk measures confirm that physical risk is not priced in the cross-section of commodity returns. Taken together, our findings suggest that commodities more exposed to climate risk associated with the green transition process demand a higher excess returns, whereas the physical aspects of climate risk such as rising temperatures and climate related disasters are not incorporated in commodity prices.

5 Robustness tests

5.1 GMM

TBA

5.2 Excluding metals

We now test whether our results are driven by the inclusion of metals in the test assets that are likely to be more exposed to the green transition as key resources for the green technology. We reestimate our augmented factor model with the exclusion of metals and we confirm the main results with a qualitatively

[3] NOAA National Centers for Environmental information, ”Climate at a Glance: Global Time Series”, published May 2024. Available from https://www.ncei.noaa.gov/access/monitoring/climate-at-a-glance/global/time-series.

similar climate risk premium (Table 11).

In conclusion, our results are robust to the exclusion of metal commodities from test assets of the asset pricing exercises.

6 Conclusion

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Table 1: Descriptive statistics of monthly commodity futures excess returns

	Mean	SD	Skew	Kurt	Median	Q_{25}	Q_{75}	ρ_1	SR	N
Agriculture										
Cocoa	0.05	8.65	-0.28	2.85	0.63	-5.40	6.10	-0.31***	0.01	176
Corn	0.49	9.77	-0.45	4.26	1.25	-4.03	6.41	-0.11	0.05	196
Coffee	0.12	9.56	0.08	3.25	-0.70	-5.14	6.86	-0.17**	0.01	176
Canola	0.44	6.54	-0.49	4.99	0.49	-3.24	4.30	0.00	0.07	275
Sugar	0.29	9.41	-0.02	4.55	-0.31	-4.61	5.75	0.11	0.03	176
Soybean	0.46	7.65	-0.62	3.89	0.78	-3.61	5.45	0.01	0.06	196
Wheat	0.32	9.73	0.04	3.48	0.27	-5.95	6.57	-0.11	0.03	196
Livestock										
Livecattle	0.29	5.22	-0.62	4.65	0.87	-2.55	3.52	-0.03	0.05	274
Leanhog	0.14	12.04	-0.29	4.50	0.26	-6.89	8.25	-0.14**	0.01	274
Metals										
Aluminium	0.38	5.92	0.08	3.64	0.06	-3.03	4.35	0.01	0.06	92
Copper	0.36	5.87	-0.04	3.55	0.20	-2.71	3.77	-0.04	0.06	92
Nickel	1.56	9.95	0.06	2.78	1.37	-6.37	8.45	-0.03	0.16	68
Zinc	0.41	7.28	-0.05	2.55	0.23	-5.48	5.91	-0.09	0.06	92
Gold	0.53	4.77	-0.05	3.34	0.29	-2.34	3.50	-0.11	0.11	192
Steel	0.08	11.03	0.81	4.70	-0.85	-5.80	5.06	0.33***	0.01	65
Palladium	0.91	10.31	-0.60	6.85	1.62	-3.89	6.44	-0.06	0.09	192
Platinum	0.05	6.94	-0.17	3.45	0.00	-4.07	4.99	-0.24***	0.01	167
Silver	0.26	9.32	0.04	4.74	0.14	-5.71	5.28	-0.08	0.03	192
Energy										
EUA	1.20	14.29	-0.11	6.03	0.00	-3.19	8.73	-0.13*	0.08	158
WTI	0.09	11.95	-0.46	9.98	0.63	-5.25	7.04	0.15**	0.01	195
Brent	0.46	10.46	-0.91	7.19	1.73	-5.08	6.96	0.11*	0.04	275
Natural Gas	0.08	13.62	0.07	4.43	0.00	-5.66	6.55	-0.02	0.01	275
Blendstock	0.15	12.75	-1.73	12.83	2.36	-6.16	7.54	0.08	0.01	195
GSCI	0.17	7.50	-0.93	6.08	1.36	-3.98	4.45	0.18**	0.02	189

Notes: The monthly excess returns are computed using Eq.1, which incorporates the interest earned on a fully collateralized futures position. Displayed are the mean, standard deviation (SD), the Skewness (Skew), the Kurtosis (Kurt), the median, the 25^{th} and 75^{th} percentile, the first-order autocorrelation (ρ_1), the Sharpe ratio (SR) and the number of observations (N). ***, **, * denote significance at the 1%, 5% and 10% level. Our sample starts in January 2000 and ends in December 2022.

Table 2: Climate risk measures in the literature (work in progress)

Reference	Measure	Data	Type of Risk	Findings
Engle, Giglio, Kelly, Lee and Stroebel (2020)	WSJ Climate Change News Index	Intensity of use of certain terms in the Wall Street Journal compared to authoritative texts on climate change by public bodies	Physical and transition risks	Build climate change hedge portfolios to manage climate risk
?	Climate risk measure	Textual analysis of Reuters climate-change news	Physical and transition risk	US climate policy factor is priced in US equity returns, while physical risk is not
Gavriilidis (2021)	Climate policy uncertainty index	Text mining on US newspapers	Transition risk	Climate policy uncertainty is associated with lower emissions in the US
Ardia et al. (2023)	Media climate change concerns index	Text mining on US newspapers and newswires	Physical and transition risk	Green (brown) firms' stock prices tend to increase (decrease) with unexpected increase in climate change concerns for both transition and physical climate change risk
Bua, Kapp, Ramella and Rognone (2024)	Physical and transition risk indices based on media attention	Extend Engle et al. (2020) measure on textual analysis of scientific texts on climate change by public bodies	Physical and transition risk	Significant transition and physical risk premia post-2015 in EU stocks
Bolton and Kacperczyk (2021)	Firm-level carbon emissions	Scope 1, Scope 2, Scope 3	Transition risk	Positive carbon premium in the US stock market
Jung et al. (2023)	Stock market emission factor	Carbon emission value-weighted S&P500 stock returns	Transition risk	Negatively associated with movement toward a less carbon-intensive economy
Barnett (2019)	Climate policy events index	List of major US climate, climate policy, and energy events	Transition risk	Higher risk of stranded assets
Gu and Hale (2023)	Occurrences of climate-related policy changes	International Energy Agency	Transition risk	Little evidence of policy impact
Jung et al. (2023)	Stranded asset factor by Litterman (2016)	Portfolios that are expected to rise in value as climate risk increases	Transition risk	Significant and time-varying climate beta

Table 3: Taxonomy of climate transition risk measures

Aspect of climate transition risk covered by measure:	CPU index	Emission factor	Climate-related event	Media Climate Change Concerns index (transition risk)	Occurrences of climate-related policy changes
Media coverage of uncertainty in climate policy/events	X			X	
Market assessment of carbon tax in US industries (assessment of the impact of future policies)		X			
Occurrences of climate policy related events			X		X

Table 4: Correlation of the climate risk measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Transition risk measures:							
Climate policy uncertainty index (1)	1.00						
Stock market emission factor (2)	0.02	1.00					
Climate policy events index (3)	0.06	-0.02	1.00				
Media climate change concerns index (transition) (4)	0.61	0.05	0.09	1.00			
Physical risk measures:							
Extreme temperatures (5)	-0.09	-0.01	-0.01	-0.02	1.00		
Media climate change concerns index (physical) (6)	0.60	0.05	0.11	0.83	-0.02	1.00	
Occurrences of climate disasters (7)	0.06	-0.02	-0.13	0.05	0.02	0.21	1.00

Notes: The table reports the correlation coefficients between the climate risk measures reviewed in Table 2. Sample period is 2007-2022.

Table 5: Correlation between the principal components and the climate risk measures

	PC 1	PC 2	PC 3
Transition risk measures:			
Climate policy uncertainty index	0.855	0.003	-0.144
Stock market emission factor	-0.143	-0.001	0.096
Climate policy events index	0.182	-0.648	0.735
Media climate change concerns index (transition)	0.928	-0.044	-0.084
Physical risk measures:			
Extreme temperatures	-0.055	0.305	0.274
Media climate change concerns index (physical)	0.935	0.054	0.004
Occurrences of climate disasters	0.144	0.800	0.487

Notes: The table reports the correlation coefficients between the 3 principal components (PCs) and the climate risk measures reviewed in Table 2. Sample period is 2007-2022.

Table 6: Descriptive statistics of climate-sorted portfolios (*climate policy uncertainty*)

	P1	P2	P3	P4	P5
a. 2007-2022					
mean	8.51%	8.85%	1.68%	-1.79%	-4.26%
median	13.83%	7.90%	3.74%	5.15%	-2.72%
st dev	23.80%	19.49%	20.16%	24.14%	29.93%
Sharpe ratio	0.3576	0.4543	0.0832	-0.0740	-0.1424
b. 2015-2022	P1	P2	P3	P4	P5
mean	7.74%	6.28%	5.60%	3.51%	-2.32%
median	13.13%	8.21%	5.72%	6.24%	-2.25%
st dev	20.15%	17.53%	18.24%	19.03%	30.83%
Sharpe ratio	0.3844	0.3583	0.3072	0.1845	-0.0752

Notes: The table reports the descriptive statistics of the climate-risk sorted portfolios where climate risk is measured by the climate policy uncertainty index. Sample period is 2007-2022 in panel a, and the post Paris Agreements period 2015-2022 in panel b.

Table 7: Descriptive statistics of climate-sorted portfolios (other transition risk factors)

a. *Stock market emission factor*					
	2007-2022				
	P1	P2	P3	P4	P5
mean	3.11%	3.95%	2.22%	6.07%	-3.81%
median	6.21%	5.02%	9.54%	11.82%	-3.33%
st dev	20.78%	22.07%	23.22%	24.27%	25.87%
Sharpe ratio	0.1499	0.1790	0.0954	0.2499	-0.1474
	2015-2022				
	P1	P2	P3	P4	P5
mean	4.06%	5.25%	2.34%	7.80%	2.45%
median	7.65%	3.77%	4.91%	11.65%	0.93%
st dev	19.75%	16.85%	18.11%	20.12%	24.55%
Sharpe ratio	0.2054	0.3116	0.1291	0.3878	0.0997
b. *Climate transition related events*					
	2007-2022				
	P1	P2	P3	P4	P5
mean	2.74%	1.28%	2.38%	4.13%	2.58%
median	13.87%	8.55%	2.67%	11.97%	6.77%
st dev	21.39%	21.70%	21.95%	21.95%	31.24%
SR	0.1281	0.0588	0.1085	0.1880	0.0826
	2015-2022				
mean	0.89%	3.30%	3.48%	7.15%	3.84%
median	8.77%	7.43%	3.84%	12.32%	5.67%
st dev	18.50%	19.47%	17.61%	18.37%	28.03%
SR 0.0481	0.1696	0.1973	0.3891	0.1369	

Notes: The table reports the descriptive statistics of the climate sorted portfolios where climate risk is measured by the stock market emission factor (panel a), and the climate transition related events index (panel b).

Table 8: Cross-sectional pricing exercise

	a. Climate policy uncertainty			
	AVE	MOM	CARRY	CLIMATE
λ	0.0024	0.0205	0.0118	0.1780
t-stat	(1.0424)	(4.5601)	(2.0741)	(1.3957)
χ^2	1.000			
	b. Stock market emission factor			
	AVE	MOM	CARRY	CLIMATE
λ	0.0022	0.0215	0.0103	0.0027
t-stat	(0.9684)	(4.8897)	(2.3881)	(1.4172)
χ^2	1.000			
	c. Climate transition related events			
	AVE	MOM	CARRY	CLIMATE
λ	0.0024	0.0198	0.0129	0.1835
t-stat	(1.0816)	(4.3890)	(2.5169)	(1.1906)
χ^2	1.000			

Notes: Results of the Fama and MacBeth (1973) pricing test of commodity portfolios monthly excess returns on a set of factors. The model includes an average factor, a momentum factor, a carry factor, and a climate risk factor. Climate factors related to the green transition are the climate policy uncertainty (panel a), the stock market emission factor (panel b), and the climate transition related events (panel c). A constant is included in the cross-sectional regression only. The sample period is 2007-2022. t-stats with and without Shanken (1992) adjustments are reported in parenthesis. The last row reports the p-values of the χ^2 test for the null hypothesis of zero pricing errors.

Table 9: Cross-sectional pricing exercise - the green transition period (2015-2022)

	AVE	MOM	CARRY	CLIMATE
a. Climate policy uncertainty				
λ	0.0030	0.0391	0.0166	0.4553
t-stat	(0.6739)	(4.8192)	(1.9304)	(2.4570)
t-stat (SH)	(0.6711)	(4.5762)	(1.8163)	(1.9881)
χ^2	0.3373			
b. Stock market emission factor				
	AVE	MOM	CARRY	CLIMATE
λ	0.0033	0.0410	0.0229	0.0102
t-stat	(0.7392)	(4.9749)	(2.7638)	(2.1755)
t-stat (SH)	(0.7347)	(4.4554)	(2.5456)	(1.4769)
χ^2	0.6386			
c. Climate transition related events				
	AVE	MOM	CARRY	CLIMATE
λ	0.0033	0.0332	0.0229	0.4474
t-stat	(0.7561)	(3.9537)	(2.8432)	(1.3433)
t-stat (SH)	(0.7548)	(3.6701)	(2.7594)	(1.0415)
χ^2	0.0090			

Notes: Results of the Fama and MacBeth (1973) pricing test of commodity portfolios monthly excess returns on a set of factors in the post 2015 Paris Agreement period. The model includes an average factor, a momentum factor, a carry factor, and a climate risk factor. Climate factors related to the green transition are the climate policy uncertainty (panel a), the stock market emission factor (panel b), and the climate transition related events (panel c). A constant is included in the cross-sectional regression only. The sample period is 2015-2022. t-stats with and without Shanken (1992) adjustments are reported in parenthesis. The last row reports the p-values of the χ^2 test for the null hypothesis of zero pricing errors.

Table 10: Pricing of physical climate risk

	AVE	MOM	CARRY	CLIMATE
a. Frequency of global temperature anomalies				
λ	0.0033	0.0364	0.0214	0.0772
t-stat	(0.7475)	(4.5539)	(2.6209)	(1.7200)
t-stat (SH)	(0.7437)	(4.2275)	(2.4763)	(1.2163)
χ^2	0.0003			
Climate related disaster events				
	AVE	MOM	CARRY	CLIMATE
λ	0.0029	0.0390	0.0205	0.0391
t-stat	(0.6555)	(4.7390)	(2.5546)	(0.0928)
t-stat (SH)	(0.6543)	(4.5999)	(2.5221)	(0.0823)
χ^2	0.0222			

Notes: Results of the Fama and MacBeth (1973) pricing test of commodity portfolios monthly excess returns on a set of factors, including an average factor (AVE), a momentum factor (MOM), a carry factor (CARRY) and a climate risk factor (CLIMATE) based on global temperature anomalies (deviations from a long-term level) in panel a, and climate related total damages from disasters in panel b. A constant is included in the cross-sectional regression only. The sample period is 2015-2022. t-stats with and without Shanken (1992) adjustments are reported in parenthesis. The last row reports the p-values of the χ^2 test for the null hypothesis of zero pricing errors.

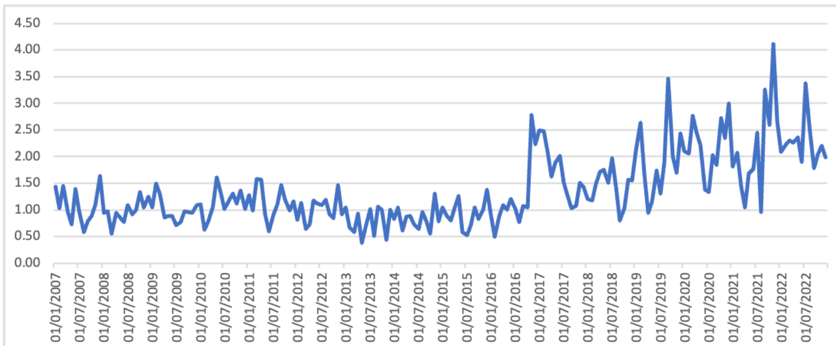
Table 11: Excluding metals (2015-2022)

	AVE	MOM	CARRY	CLIMATE
λ	0.0028	0.0396	0.0166	0.4472
t-stat	(0.6382)	(4.9019)	(1.9261)	(2.4297)
t-stat (SH)	(0.6346)	(4.6635)	(1.8132)	(1.9703)
χ^2	0.7790			

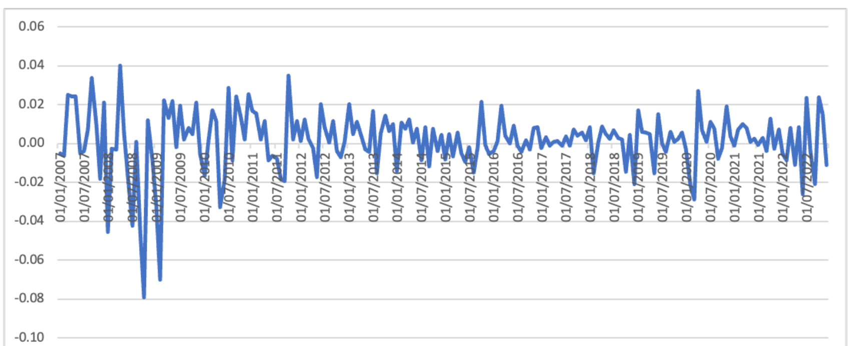
Notes: Results of the Fama and MacBeth (1973) pricing test of commodity portfolios monthly excess returns on a set of factors in the post 2015 Paris Agreement period excluding the metal portfolio from the test assets. A constant is included in the cross-sectional regression only. The sample period is 2015-2022. t-stats with and without Shanken (1992) adjustments are reported in parenthesis. The last row reports the p-values of the χ^2 test for the null hypothesis of zero pricing errors.

Figure 1: Climate risk factors

(a) Climate policy uncertainty



(b) Stock market emission factor



(c) Transition climate risk events

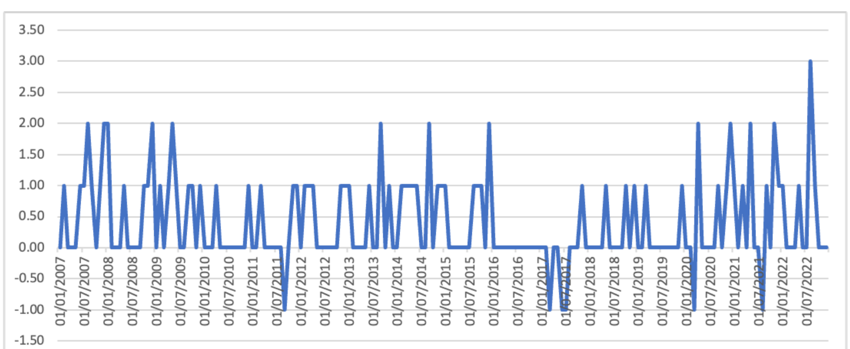
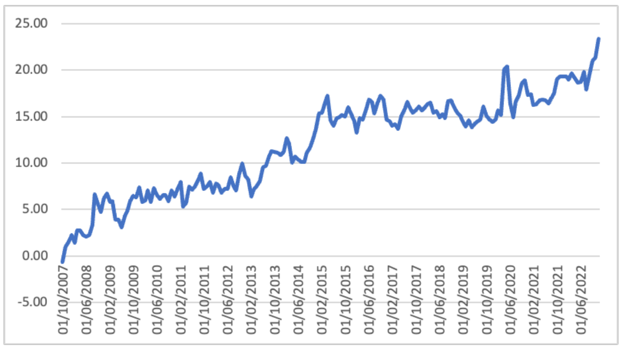
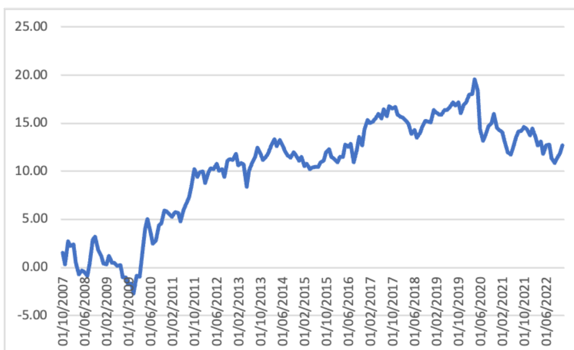


Figure 2: Climate sorted portfolios. The plot reports the excess returns of the climate-sorted portfolio. Climate risk factor is the climate policy uncertainty (panel a), the stock market emission factor (panel b), and the transition climate risk events (panel c). Sample period is 2007 to 2015.

(a) Climate policy uncertainty



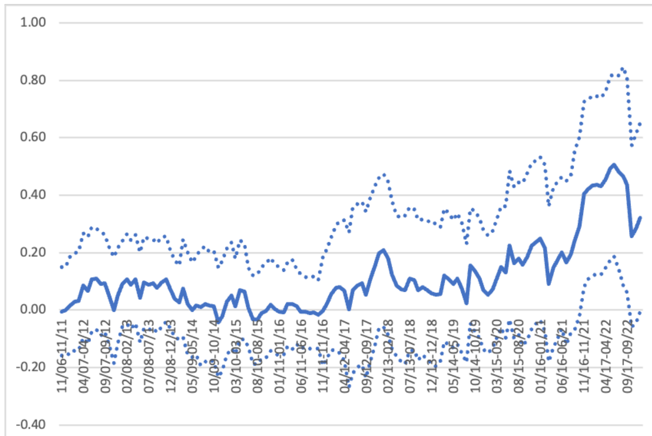
(b) Stock market emission factor



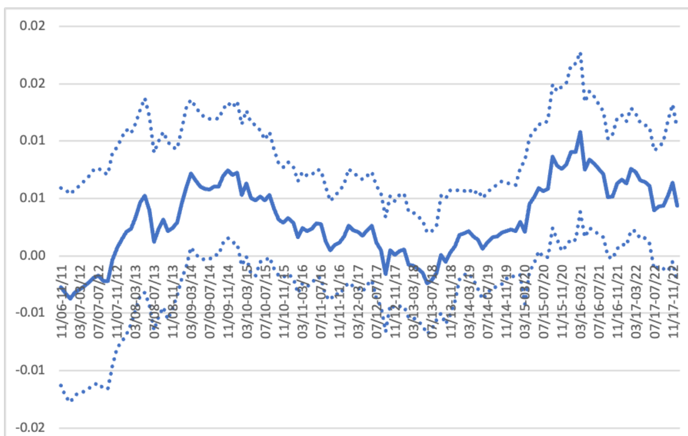
(c) Transition climate risk events

Figure 3: Time-varying climate risk premium. The plot reports the moving rolling window estimations of the lambdas for the augmented model with climate risk. The x-axis reports the 5-year windows.

(a) Climate policy uncertainty



(b) Stock market emission factor



(c) Transition climate risk events