Pricing Climate Geopolitical Risks

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Abstract

Climate geopolitical risk (CGR) captures cross-border frictions that arise in the context of the energy transition and shape economic and financial outcomes. We construct a text-based measure of CGR and study its asset pricing and macro-financial implications. CGR does not affect the aggregate market risk premium but instead reallocates risk premia across firm characteristics. High-exposure assets earn significantly higher returns. Countries more exposed to global supply chains for critical inputs exhibit stronger, yet heterogeneous, responses in their term spreads. CGR thus operates as a state variable that is priced in the cross-section and linked to macro-financial vulnerability.

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1. Introduction

Climate finance and asset pricing literature identify two primary channels through which climate risk affects asset prices: physical risk (Baldauf et al., 2020; Bansal et al., 2019; Adduom et al., 2023; Bernstein et al., 2019) and transition risk (Ilhan et al., 2021; Hong et al., 2023; Sautner et al., 2023; Bolton & Kacperczck, 2021; 2023; 2025; Alekseev et al., 2022). While both channels are well-established, they abstract from the geopolitical frictions that increasingly shape the climate transition (see Giglio et al. 2021; Stroebel and Wurgler 2021; Hong et al., 2020 for recent reviews). Recent developments suggest that climate-related risks are increasingly mediated and shaped by cross-border strategic interactions. First, climate-related supply shocks have triggered policy responses with international spillovers, including export restrictions on key inputs. For example, following flooding-related concerns over domestic supply, India imposed restrictions on rice exports in 2022 and expanded them in 2023.[5] In parallel, China introduced export controls on gallium and germanium in 2023[6]. These are two critical minerals essential among other things, for semiconductors and battery production. Second, the energy transition has intensified strategic competition over clean technologies. Policies such as the U.S. Inflation Reduction Act (2022) and the European Union's Carbon Border Adjustment Mechanism have been accompanied by subsidy competition and trade tensions across major economies. These developments indicate that geopolitical responses to both climate shocks and transition policies have cross-border effects that extend beyond the originating country. These responses propagate across borders, contribute to the fragmentation and reorganization of global supply chains (Leonelli & Clora, 2024), and shape the pace and structure of the energy transition.

We argue that an important dimension of climate risk arises from this interaction between geopolitical competition and the economic infrastructure of the energy transition. We refer to this dimension as climate geopolitical risk (CGR): the systematic risk arising from geopolitical frictions—kinetic and non-kinetic—that affect inputs and infrastructure critical to the energy transition. Unlike physical and transition risks, which primarily operate through domestic damages and policy adjustments, CGR captures cross-border transmission channels through which climate-related shocks interact with strategic competition over resources and supply chains. This paper studies its asset pricing and macro-financial implications.

[5] https://www.theguardian.com/business/2023/jul/21/india-ban-on-rice-exports-raises-fear-of-global-food-price-rises

[6] https://www.usitc.gov/publications/332/executive_briefings/ebot_germanium_and_gallium.pdf

There are multiple channels through which climate geopolitical risk affects stock returns. We conceptualize CGR as a time-varying risk state reflecting geopolitical frictions that affect the availability, cost, and strategic control of inputs critical to the energy transition. In this environment, both cash flow and discount rate channels are affected. On the cash flow side, CGR influences expected profitability through input cost volatility, supply disruptions, and shifts in relative competitiveness. On the discount rate side, higher CGR increases uncertainty about future economic conditions and policy regimes. This raises the compensation investors require for bearing transition-related geopolitical risk. Because CGR exposure varies over time across firms, sectors, and countries, its effects are heterogeneous. As a result, CGR reallocates risk premia across characteristics rather than shifting the aggregate market premium.

To test these hypotheses, we construct a novel text-based measure of climate geopolitical risk using a large corpus of global news data. The index captures time variation in narratives linking geopolitical tensions to climate-relevant economic channels. The construction combines a broad keyword-based retrieval with a semantic filtering procedure that isolates climate-geopolitical content. A natural concern is that such a measure may proxy for existing sources of risk. We show that CGR is not spanned by standard proxies for climate risk, including policy uncertainty, transition risk, and physical risk, and captures distinct variation relative to conventional measures of geopolitical risk.

Our first set of results shows that CGR does not shift the aggregate market price of risk. Instead, it reallocates risk premia across characteristics. Periods of elevated CGR are associated with an increase in the price of size risk and a decline in the price of profitability risk, while the market premium remains unchanged. This pattern indicates that CGR affects how risk is priced across firms rather than the overall level of compensation for risk.

Consistent with this interpretation, we find evidence of firm-level reallocation. Firms with high CGR exposure earn significantly higher returns than firms with low exposure. CGR spread portfolios deliver economically large and statistically significant premia of approximately 40 to 50 basis points per month, comparable to standard cross-sectional anomalies. These results indicate that exposure to climate-geopolitical risk is associated with higher expected returns. At the same time, CGR acts as a conditioning variable. Periods of elevated CGR are associated with a higher price of commodity risk, while other characteristics such as value and profitability remain relevant in augmented specifications. These results indicate that exposure to climate-geopolitical risk is priced in the cross-section, while also conditioning the pricing of other risk characteristics.

At the sector level, CGR is associated with systematic differences in returns across industries. Portfolios that are long high-CGR sectors and short low-exposure sectors generate economically large and statistically significant out-of-sample returns, with positive risk-adjusted alphas relative to standard factor models. These results indicate that sector-level exposure to climate geopolitical risk is associated with return premia not captured by conventional risk factors. They also suggest that CGR influences the allocation of capital across sectors, consistent with shifts in comparative advantage linked to resource access and supply chain positioning.

If supply chains and access to critical inputs constitute a transmission channel for climate geopolitical risk, then its effects should be stronger in countries more exposed to disruptions in these inputs. Using country-level trade data on critical minerals, we construct measures of extraction and refinement dependence for G7 countries and China. We find that elevated levels of CGR are associated with a steepening of the yield curve on average. This effect is significantly stronger in countries more reliant on downstream processing and refining, indicating amplification through exposure to constrained segments of the supply chain.

This paper makes three contributions. First, we introduce a novel measure of climate geopolitical risk that captures cross-border frictions related to the energy transition and orthogonal to standard climate risk proxies. Second, we show that CGR acts as a state variable that reallocates risk premia across firms and sectors rather than shifting the aggregate market price of risk. Third, we document that the macro-financial effects of CGR depend on countries' exposure to global supply chains and provide evidence of an amplification channel operating through critical mineral dependencies.

Existing work primarily focuses on physical and transition risks and their implications for asset prices, firm outcomes, and expected returns (Giglio et al., 2021; Pástor et al., 2021, 2022; Bolton & Kacperczyk, 2021, 2023; Pankratz et al., 2021). This literature shows that climate-related risks are priced in the cross-section, although the existence and interpretation of a carbon premium remain debated (Aswani et al., 2022; Zhang, 2022). Related work uses news and attention-based measures to capture climate risk, showing that climate-related news and concerns affect both credit and equity markets (Engle et al., 2020; Huynh & Xia, 2021; Ardia et al., 2023). However, this line of research largely treats climate risk as either a domestic production shock or a policy-driven transition.

Second, this paper relates to the literature on geopolitical risk and political uncertainty. Geopolitical and policy-related risks have been shown to affect macroeconomic outcomes and asset prices (Caldara & Iacoviello, 2022; Pástor & Veronesi, 2012, 2013; Kelly et al., 2016;

Belo et al., 2013; Brogaard and Detzel, 2015). More recent work shows that geopolitical tensions are priced in the cross-section using text-based measures of conflict intensity (Hirshleifer et al., 2025; 2024), and that conflict-related events have measurable effects on financial markets (Guidolin & La Ferrara, 2010). However, this literature treats geopolitical risk as largely exogenous and focuses on its effects on expected returns. However, this literature treats geopolitical risk as largely exogenous and focuses on its effects on expected returns. Climate geopolitical risk instead arises from the interaction between climate-related shocks—both physical and transition—and geopolitical responses. It captures how climate conditions reshape cross-border interactions between sovereigns and economic agents. As a result, its effects operate through multiple economic channels and will generate heterogeneous impacts depending on firms' and countries' exposures.

Third, the paper contributes to the literature on text-based measures of economic uncertainty and risk. News-based and firm-level textual measures capture forward-looking information about policy, political, and economic risks (Baker et al., 2016; Hassan et al., 2019). A related literature shows that news content and narrative-based measures predict macroeconomic outcomes and asset returns (Manela & Moreira, 2017), and that text-derived factors can price a broad cross-section of assets (Bybee et al., 2024). Other applications extend these approaches to climate-related risks (Engle et al., 2020; Addoum et al., 2020). This paper connects these strands by introducing a climate-geopolitical state variable that captures cross-border frictions linked to the energy transition and studies how this dimension of risk shapes the propagation of shocks and the allocation of risk across firms and markets.

2. Data sample

Our primary database covers the 2005 - 2025 period and is largely a result of matching several datasets. We obtain news headlines data from ProQuest, Fama-French factors from the Kenneth French Data Library, sovereign macro factors from the Federal Reserve Economic Data (FRED) database, historical information on imports and exports of critical minerals from the UNComtrade database, S&P500 sector returns from Bloomberg and firm level information from Compustat.

2.1 The CGR index

We construct a monthly index of climate geopolitical risk (CGR) using global news headlines obtained from the ProQuest News Database. The raw dataset comprises 42,643 headlines from 475 major international news outlets over the period January 2005 to July 2025.

We restrict the sample to English-language newspaper articles classified as news to ensure consistency in source type and reporting format. The index is constructed using a two-step procedure. First, we apply a broad keyword search to article titles to obtain a high-recall corpus capturing geopolitical, macroeconomic, climate, and resource-related developments. The search is deliberately inclusive and does not require the joint presence of climate and geopolitical terms, allowing for comprehensive coverage of the broader risk environment. Climate relevance is more strictly imposed in a second step using a semantic filtering procedure. Following recent approaches to the construction of text-based risk sentiment measures (Giglio et al., 2026; Baker et al., 2016), we compute cosine similarity scores between each headline and a predefined set of climate-geopolitical risk definitions[7]. We retain headlines with positive cosine similarity scores and obtain a filtered corpus of 4,980 observations. This two-step procedure is key for our identification strategy. The initial keyword search ensures broad coverage of potentially relevant content, while the semantic filtering retains only headlines exhibiting at least some conceptual proximity to climate geopolitical risk. This approach is consistent with recent text-based methodologies that aim to reduce noise while preserving the economic relevance of the final corpus.

We then process the filtered corpus using standard natural language processing techniques. Text is cleaned, tokenized, deduplicated and analyzed using Latent Dirichlet Allocation (LDA), which we prefer for its interpretability in identifying coherent topics. We complement LDA with sentiment scores derived from a FinBERT model to capture variation in the intensity of climate-geopolitical narratives. The CGR index is constructed by aggregating the frequency and sentiment-weighted relevance of filtered headlines at the monthly frequency.

Figure 1 plots the CGR index and its AR(1) innovations. Higher values of CGR correspond to periods in which climate-related geopolitical tensions are more prominent in the information environment. The level of CGR evolves smoothly over time, indicating gradual shifts in the underlying risk environment, while the innovation series captures higher-frequency fluctuations around this trend. The CGR index construction is subject to some measurement limitations. The construction depends on the choice of keywords and semantic filtering, which may introduce noise or omit relevant events expressed in different terms. In addition, media coverage may reflect reporting intensity rather than underlying risk. Accordingly, CGR should

[7] More specifically, rather than comparing each headline to an abstract textual definition, we compute its cosine similarity with a set of 30 reference headlines selected (see appendix B) to capture the semantic content of climate-geopolitical risk. This anchor-based approach makes it possible to operationalize the concept through concrete textual exemplars rather than through a single stylized definition or one keyword, two keywords or several words.

be interpreted as a proxy for perceived climate-geopolitical risk rather than a direct measure of underlying shocks.

2.2 Variables in cross-sectional and timeseries regressions

Table 1 reports summary statistics for the variables used in the analysis at the monthly frequency. Firms in our sample report average monthly returns of 0.8% per and a standard deviation of 5.6%. The CGR index exhibits appreciable time-series variation, with a standard deviation of 0.183. Its distribution is slightly left-skewed, with a mean of −0.046. Innovations in CGR capture unexpected changes in the index and are, by construction, centred around zero.

To benchmark CGR, we include standard measures of geopolitical and climate-related risks including geopolitical risk (GPR), climate policy uncertainty (CPU), and transition and physical risk factors. GPR and CPU exhibit higher dispersion, while transition and physical risk measures are tightly distributed around zero. [8]

The variables used in the time-series regressions are defined as follows. MKTRF_t denotes the monthly excess return on the market portfolio. SMB_t, HML_t, RMW_t, and CMA_t are the Fama–French factors corresponding to size, value, profitability, and investment, respectively. $\text{SMB}_t$is the monthly return on a portfolio that is long small-cap stocks and short large-cap stocks; HML_t is the monthly return on a portfolio long high book-to-market stocks and short low book-to-market stocks; $\text{RMW}_t$is monthly return on a portfolio long firms with robust profitability and short firms with weak profitability, and $\text{CMA}_t$is monthly return on a portfolio long firms with conservative investment and short firms with aggressive investment. MOM_t denotes the return on a portfolio that is long past one-year return winners and short past one-year return losers. To capture broader macro-financial conditions, we include changes in implied volatility and oil prices. We proxy these by the volatility index (VIX) and the oil price (West Texas Intermediate, WTI) to capture broader macro sentiment and commodity dynamics linked to geopolitics respectively.

2.3 Is CGR spanned by existing risk measures?

A key requirement for the CGR index is that it captures variation in climate-related geopolitical risk that is not spanned by existing climate or geopolitical risk measures. While the semantic filtering step is designed to isolate climate-relevant content, this concern cannot be meaningfully resolved at the construction stage and requires empirical validation. Table 2

[8] Physical Risk, Transition Risk and Climate Policy Uncertainty are obtained from Baker et al., (2016).

reports pairwise correlations across the main risk measures. CGR, as well as its innovations, exhibits low correlations with existing proxies, including geopolitical risk (GPR) and climate policy uncertainty (CPU). This outcome suggests CGR captures a dimension of risk distinct from benchmark proxies. By contrast, transition and physical risk are more strongly correlated, consistent with shared underlying climate dynamics.

Next, we relate CGR to a set of commonly used climate and geopolitical risk proxies and examine the extent to which its variation can be explained by these variables. Specifically, we estimate time-series regressions of the form:

$$\mathrm{CGR}_t = \alpha + \beta' \mathrm{Z}_t + \varepsilon_t \qquad (1)$$

where Z_t includes transition risk, physical risk, climate policy uncertainty (CPU) and geopolitical risk (GPR). We estimate analogous specifications using CGR innovations obtained from an AR(1) process. Limited explanatory power in these regressions would suggest CGR contains information distinct from existing measures. The results are reported in Table 3. Across specifications, the explanatory power of regressions with CGR as the dependent variable is negligible. Adjusted R^2 is effectively zero for both level and innovation specifications. Compared to other specifications, coefficient estimates are small and statistically insignificant in levels, while limited evidence of an overlap with GPR appears when CGR innovation is dependent. By contrast, the other risk measures exhibit substantial co-movement among themselves. Transition and physical risks are strongly related (coefficients around 0.6), and both load on broader policy and geopolitical uncertainty measures. Similarly, GPR and CPU display significant cross-dependence. These patterns suggest that benchmark proxies share common variation, whereas CGR does not load meaningfully on this space.

3. Results

3.1 Does CGR condition factor risk premia?

Climate geopolitical risk may affect asset prices not only through expected cashflow shocks, but also through the compensation investors require for bearing systematic risk. Periods of elevated CGR are associated with increased uncertainty over critical inputs to the energy transition—such as disruptions to supply chains, trade restrictions, and policy fragmentation—all of which can amplify aggregate shocks and their propagation through the economy. To the extent that these shocks are difficult to hedge and coincide with states of high marginal utility, they can affect the stochastic discount factor by altering the covariance between returns and

investors' marginal utility. Under this mechanism, CGR does not constitute a separate priced factor. Instead, it would operate as a state variable that shifts the price of risk. When geopolitical frictions intensify, investors would demand higher compensation for exposure to systematic risks that are sensitive to the net-zero transition. This implies that variation in CGR should be reflected in changed in factor risk premia, rather than solely in firms' exposures or expected cashflows.

Our empirical design follows a two-step procedure. First, we estimate rolling factor loadings for individual firms using trailing time-series regressions over 60-month windows, so that exposures at month t are based only on information available up to $t-1$. Second, we recover month-by-month prices of risk from cross-sectional regressions of excess returns on these predetermined exposures. This yields a time series of factor premia, which we then relate to lagged CGR and its innovations respectively. By construction, this framework separates time variation in quantities of risk (factor loadings) from prices of risk (factor premia) to isolate the latter. To assess whether CGR conditions factor premia, we estimate time-series regressions of the form:

$$\lambda_{k,t} = c_k + \phi_k CGR_{t-1} + \eta_{k,t} \qquad (2)$$

where $\lambda_{k,t}$is the estimated price of risk for factor k in month t, and CGR is lagged to align with the investor information set and to mitigate contemporaneous feedback from returns. Inference is based on a moving block bootstrap applied to the time series of estimated monthly premia. We implement 5,000 bootstrap replications and report 90% and 95% confidence levels across block lengths of 24 months.

Table 4 reports the estimated sensitivities of factor premia to lagged CGR across alternative factor specifications. Several patterns emerge. First, there is no evidence that CGR conditions the market risk premium. The estimated coefficient on CGR in the λ_{MKT}regression is small and statistically indistinguishable from zero across all specifications for both level and innovation measures. This indicates that CGR does not operate as a broad market-wide conditioning variable for aggregate market risk. Second, CGR systematically affects the pricing of cross-sectional style factors, particularly size, value, and profitability. The premium on SMB increases with CGR, with positive and statistically significant estimates for both the level and innovation specifications ($\phi_{\text{SMB}} \approx 0.032$). This pattern implies that exposure to the size factor commands higher compensation in periods of elevated climate geopolitical risk. One interpretation is that risks associated with smaller firms become more strongly priced in high-

CGR states, potentially reflecting their greater sensitivity to disruptions in supply chains, financing conditions, or input costs. In contrast, the profitability premium (RMW) declines with CGR, with consistently negative and statistically significant coefficients. This suggests that profitability-related risk becomes less strongly priced in periods of elevated CGR. A reasonable explanation is that investors place relatively greater value on firms with more resilient cashflows in high CGR states. As a result, the cross-sectional spread in expected returns associated with profitability narrows when CGR is high. For the value factor (HML), the evidence is more modest but points to a weakly positive relation between CGR and the value premium, particularly in augmented specifications. This is consistent with value-oriented exposures becoming more strongly priced in high-CGR states. One interpretation is that the value premium is linked to sectors with greater exposure to tangible assets, commodities, or regulated industries which either become exposed, for example due to access restrictions, or physical damages as kinetic targets.

Augmenting the factor space with macro-financial variables such as the VIX and WTI provides insight into potential transmission channels. When changes in the VIX level are included, the estimated price of VIX risk is negative and becomes significant for CGR innovations (−0.080). Similar to the profitability factor, this result suggests that assets with positive exposure to volatility shocks serve as hedges and command lower expected returns. The WTI specification is more revealing. The estimated price of WTI risk rises with CGR, with coefficients of 0.084 for the lagged level and 0.100 for innovations, indicating that oil-related risk commands higher compensation in high-CGR states. At the same time, SMB and RMW effects attenuate, while HML remains conventionally significant. This suggests that part of the baseline conditioning effect may operate through energy and commodity-related risk, although the persistence of CGR effects after controlling for WTI indicates that this channel is not exhaustive.[9]

We note that the results are qualitatively similar when using innovations instead of CGR levels. The persistence of the SMB, HML, and WTI patterns under the innovation specification indicates that both anticipated and unanticipated variation in climate geopolitical risk may be relevant for factor pricing, rather than results being driven solely by slow-moving trends.

[9] This result is economically plausible. The transition from fossil fuels to low-carbon energy sources is gradual and involves continued reliance on conventional energy as a transitional input. As a result, geopolitical frictions that disrupt fossil fuel markets—such as supply constraints, trade restrictions, or resource competition—can propagate into broader transition dynamics by affecting input costs, energy security, and the pace of capital reallocation. To the extent that these shocks are systematic and difficult to hedge, they increase the covariance between energy-related returns and marginal utility. This provides a natural channel through which climate geopolitical risk can raise the price of oil-related risk, even in the context of a long-run shift away from fossil fuels.

3.2 Firm-level reallocations on climate geopolitical risk

We next examine whether climate geopolitical risk is associated with systematic reallocation across firms. Rather than relating returns directly to the CGR index, we estimate firm-level sensitivities to CGR and test whether firms with different exposures earn differentiated returns in the cross-section. For each firm i, we estimate CGR exposure using rolling time-series regressions of excess returns R_i^e on CGR and benchmark risk factors over a 60-month trailing window:

$$R_{i,\tau}^e = \alpha_{i,t} + \beta_{i,t}^{\mathrm{CGR}}\,\mathrm{CGR}_\tau + \boldsymbol{\gamma}_{i,t}'\mathbf{F}_\tau + u_{i,\tau}, \tau \in [t-W, t-1] \qquad (3)$$

where $\mathbf{F}_\tau$denotes the Fama–French factors. To reduce estimation noise in firm-level exposures, we apply a simple shrinkage procedure toward the industry mean. Let $\hat{\beta}_{i,t}$ denote the estimated CGR exposure and $\bar{\beta}_{g(i),t}$the average exposure within industry $g(i)$. The shrunk beta is defined as

$$\tilde{\beta}_{i,t} = (1-\kappa)\hat{\beta}_{i,t} + \kappa\bar{\beta}_{g(i),t} \qquad (4)$$

to limit the influence of extreme estimates while preserving cross-sectional variation in CGR sensitivity. Each month, firms are sorted into terciles based on $\tilde{\beta}_{i,t}$. We form portfolios that are long firms in the highest tercile of CGR exposure and short firms in the lowest tercile. We consider both equal-weighted (EW) and value-weighted (VW) portfolio constructions. We evaluate whether CGR exposure is priced by estimating the average return of the long–short portfolio

$$HL_t = \mu + \varepsilon_t \qquad (5)$$

with heteroskedasticity- and autocorrelation-robust standard errors. Table 5 reports the average excess returns of the CGR exposure - sorted portfolios. The results indicate a positive and economically meaningful excess return differential between high- and low-exposure firms. In the baseline specification using CGR levels, the long–short portfolio earns 0.4% per month under equal weighting and 0.5% per month under value weighting.

Sorting on CGR innovations yields similar magnitudes. The value-weighted portfolio earns a statistically significant 0.5% excess return per month, while the equal-weighted estimate just misses conventional significance. Broadly, results across level and innovation specifications indicate that both persistent and unexpected components of CGR are associated with cross-sectional excess return differentiation. These results provide evidence of systematic

reallocation across firms based on exposure to climate geopolitical risk. Firms with higher sensitivity to CGR earn higher average excess returns.

3.3 Sector-level rotations: who benefits?

Next, we assess whether sectoral sensitivities to CGR translate into return differentiation in an out-of-sample asset allocation framework. The objective is to identify which S&P 500 sectors are systematically exposed to CGR and to test whether these exposures generate sector-rotation returns. At each rebalance date τ, we estimate sector-level sensitivities to CGR using expanding-window regressions of the form:

$$R_{s,t} = \alpha_s + \beta_{s,\tau}^{\mathrm{CGR}} \mathrm{CGR}_{t-1} + \boldsymbol{\gamma}_s' \mathbf{F}_t + \nu_{s,t},\ t \in \mathcal{T}_\tau \qquad (6)$$

where $R_{s,t}$ denotes the monthly return of sector s, $\mathbf{F}_t$ is a vector of the Fama–French five factors, and $\mathcal{T}_\tau = \{t < \tau\}$ is the expanding estimation window with at least 60 observations. We define eligible sectors as follows:

$$\mathcal{E}_\tau = \{s\text{: sector } s \text{ has at least 60 monthly returns in } \mathcal{T}_\tau\}.$$

At each rebalance, we rank sectors by their estimated exposure $\hat{\beta}_{s,\tau}^{\mathrm{CGR}}$. The long portfolio $\mathcal{L}_\tau$ contains sectors with the highest estimated CGR exposures, and the short portfolio $\mathcal{S}_\tau$ contains sectors with the lowest exposures. The target number of sectors in each leg is three, subject to the constraint[10]

$$K_{\max,\tau} = \left\lfloor \frac{|\mathcal{E}_\tau|}{2} \right\rfloor, K_{L,\tau}, K_{S,\tau} \le K_{\max,\tau}, K_{L,\tau}, K_{S,\tau} \ge 2 \qquad (7)$$

Between rebalances, portfolio membership is fixed and out-of-sample long–short returns are computed as

$$HL_t = \frac{1}{|\mathcal{L}_\tau|} \sum_{s \in \mathcal{L}_\tau} R_{s,t} - \frac{1}{|\mathcal{S}_\tau|} \sum_{s \in \mathcal{S}_\tau} R_{s,t} \qquad (8)$$

Within each leg, sectors are equally weighted. We evaluate performance using both raw returns and factor-adjusted alphas:

$$HL_t = \mu + u_t,$$

[10] The choice of three sectors per leg reflects the small cross section of sector portfolios. In an eleven-sector universe, this provides a compromise between diversification within each leg and maintaining a meaningful spread in estimated CGR exposure.

$$HL_t = \alpha + \boldsymbol{\delta}'\mathbf{F}_t + u_t \qquad (9)$$

where the Equation (9) is extended with the Fama–French five factors model and alternatively with a momentum-augmented specification. Standard errors are heteroskedasticity- and autocorrelation-robust. To assess practicality of implementing the strategy, we proxy portfolio turnover with the Jaccard distance between consecutive portfolio sets. For a given set $\mathcal{A}_\tau$ (long, short, or combined),

$$\text{Turnover}_\tau = 1 - \frac{|\mathcal{A}_{\tau-1} \cap \mathcal{A}_\tau|}{|\mathcal{A}_{\tau-1} \cup \mathcal{A}_\tau|} \qquad (10)$$

Equation (10) captures the extent to which sector membership changes across rebalancing dates. Table 6 reports the mean returns and factor-adjusted alphas of the sector rotation strategy. The first column in each specification report average returns. Subsequent columns report alphas relative the benchmark factor models. Across all specifications, the strategy delivers positive and statistically significant returns. Average returns range from 0.4% to 0.6% per month. Risk-adjusted alphas are of similar magnitude, typically between 0.5% and 0.6% per month, and remain significant across both FF5 and FF5+MoM specifications.
Performance is stable across rebalancing frequencies. Quarterly rebalancing yields modestly higher excess returns (up to 0.6% per month) than annual rebalancing (approximately 0.5% per month). Results are robust to using CGR innovations instead of levels.

Figure 3 presents sector compositions for the strategy (with quarterly balancing). The long leg is persistently tilted toward sectors such as financials and information technology, while the short leg includes sectors such as energy and materials. This pattern is stable across specifications and reflects systematic differences in how sectors load on CGR. At first glance, the presence of energy in the short leg may appear at odds with the conditional pricing results in Section 3.1, which show that CGR raises the price of commodity and energy-related risk. However, the two results capture distinct objects. Section 3.1 identifies time variation in the *price* of risk, whereas the sector rotation strategy sorts on the *exposure* of sector returns to CGR itself. A natural interpretation is that energy-sector returns are primarily driven by global commodity price dynamics, which are only partially aligned with CGR. While CGR increases the compensation required for bearing oil and commodity risk, it does not follow that energy-sector returns co-move strongly with CGR innovations. In fact, energy firms may benefit from certain CGR states—for example through higher fossil fuel prices, supply disruptions, or increased demand for energy security—thereby weakening or even offsetting their direct exposure to CGR shocks.

By contrast, sectors such as financials and information technology are more tightly linked to global production networks, capital flows, and supply-chain integration. These sectors are therefore more exposed to disruptions associated with geopolitical fragmentation and the reconfiguration of the energy transition. As a result, their returns load more strongly on CGR, placing them in the long leg of the strategy.

Full turnover statistics are reported in Table 7. Turnover is measured using the Jaccard distance between consecutive portfolio sets and should therefore be interpreted as a proxy for changes in portfolio composition rather than exact trading volume. The strategy exhibits moderate turnover and reflect time variation in estimated CGR exposures. Turnover is higher under annual rebalancing than quarterly rebalancing and is consistent with larger adjustments in portfolio composition at lower rebalancing frequencies. Results are similar across specifications based on CGR levels and innovations.

3.4 CGR transmission through supply chain exposure

The transmission of CGR is unlikely to be uniform across countries. Instead, its effects should, in part, depend on the degree and nature of exposure to global supply chains. For example, economies that rely more heavily on imported raw or refined critical and rare earth minerals could be more vulnerable to disruptions associated with climate geopolitical risk. This motivates an amplification hypothesis in which CGR has stronger effects on financing conditions in more exposed economies.

Particularly for critical minerals, a key distinction arises between upstream (extraction) and downstream (refining) stages of production. The economic mechanism operates through input-specific uncertainty and its implications for financing conditions. Downstream sectors rely on refined inputs that are often produced in a limited number of jurisdictions and are less easily substituted in the short-run. Geopolitical frictions - such as export controls, trade restrictions, or strategic stockpiling - therefore generate uncertainty over both availability and pricing of these inputs. This raises the volatility of expected cashflows and increases the covariance of firm outcomes with adverse aggregate states. In equilibrium, we expect this to be reflected in tighter financing conditions, such as steeper term spreads and borrowing costs. In contrast, upstream extraction is more exposed to global commodity price dynamics, where markets are deeper and substitution margins are broader. Although CGR may affect commodity prices, these effects are more likely to be absorbed through price adjustments rather than quantity constraints, resulting in a weaker impact on financing conditions.

We measure upstream and downstream exposure to critical minerals supply chains using country-level trade data obtained from UNComTrade. We define extraction dependence as a measure of a country's net import position in upstream (raw) materials, scaled by GDP. Positive values indicate reliance on foreign supply, while negative values indicate net exporter status. Refined dependence is defined analogously for downstream (processed) critical minerals. Net upstream dependence captures a country's relative position along the supply chain and distinguishes between economies that are more reliant on upstream versus downstream inputs.

More formally:

$$\text{Extraction Dependence}_c = \frac{\text{Raw Imports}_c - \text{Raw Exports}_c}{GDP_c} \quad (11)$$

$$\text{Refined Dependence}_c = \frac{\text{Refined Imports}_c - \text{Refined Exports}_c}{GDP_c} \quad (12)$$

$$\text{Net Dependence}_c = \text{Extraction Dependence}_c - \text{Refined Dependence}_c \quad (13)$$

In our sample raw minerals include nickel and cobalt ores, whereas refined products include lithium compounds, cobalt oxides, and rare-earth elements. Figure 3 plots net dependence over time for G7 countries and China. Beyond cross-sectional differences, the figure reveals substantial time variation and structural shifts in supply-chain positions. Several economies exhibit pronounced regime changes, including the post-2010 adjustment in China and the sharp increase in Japan's net dependence after 2015. European countries follow heterogeneous paths: France and Germany display early spikes followed by sustained declines, while the United Kingdom transitions from negative to positive net dependence. High volatility is particularly evident in Canada and China, in contrast to the more stable profiles of Germany and Italy.

China stands out as a structurally distinct case. Its persistently negative net dependence reflects its role as a global processing hub, characterised by large-scale imports of raw materials and extensive downstream refining capacity. The sharp decline around 2010 is consistent with a period of rapid expansion in refining activity and heightened reliance on imported inputs. The subsequent upward trend toward zero suggests a gradual rebalancing of the supply chain, potentially reflecting increased upstream integration and strategic efforts to reduce dependence

on foreign raw materials. Unlike China, the US does not display evidence of large structural shifts, indicating a more stable integration within global value chains over the sample period.[11]

These dynamics indicate that vulnerability to geopolitical risk is both time-varying and country-specific, and reinforces the need to model CGR transmission as interacting with evolving supply-chain positions. More specifically, we estimate the pooled regression:[12]

$$\text{TermSpread}_{c,t} = \alpha_c + \lambda_t + \beta_1 \,\text{Exposure}_{c,t} + \beta_2 \left(\text{CGR}_t \times \text{Exposure}_{c,t}\right) + \boldsymbol{\Gamma}'\mathbf{X}_{c,t-1} + \varepsilon_{c,t} \quad (14)$$

where the dependent variable is the country term spread, capturing variation in financing conditions and expected economic activity. $\text{Exposure}_{c,t}$ is one of extraction dependence, refined dependence or net dependence of country c at t. $\mathbf{X}_{c,t-1}$ contains lagged country macro variables: current account balance and debt-to-GDP. The coefficient of interest, β_2, measures the amplification effect of interacting CGR with exposure on financing conditions. Standard errors are clustered at the country level, and inference is based on wild cluster bootstrap (Rademacher) p-values.

Table 8 presents the results. The transmission of CGR to financing conditions depends on supply-chain exposure, with a clear asymmetry between upstream and downstream dependence. Refined (downstream) dependence is associated with a stronger response of term spreads to CGR. In Panel A, the interaction coefficient ($CGR_t \; x \; Exposure_{c,t}$) is positive and statistically significant (0.008 for levels and 0.006 for innovations). In Panel B, we exclude time fixed effects so CGR can be identified. Again, the interaction term achieves conventional significance (0.013 and 0.010) and CGR itself has a positive and statistically significant unconditional effect on term spreads. This implies that the interaction term captures amplification of an already adverse effect on financing conditions. By contrast, extraction (upstream) dependence does not exhibit a robust interaction effect once time fixed effects are excluded. The sensitivity of these results to the inclusion of time effects suggests that part of the transmission operates through common global shocks rather than purely cross-country heterogeneity.

Country-level regressions (Appendix Table A1) broadly align with the panel evidence, while highlighting substantial cross-country heterogeneity. The interaction between CGR and

[11] This stable position for the US also introduces vulnerability if there are sudden curtailments on supply, say from China on refined critical minerals.

[12] To isolate within-country dynamics, we also estimate country-specific time-series regressions of the same form without time fixed effects. See Table A2 for country level (G7+China) specification results.

refined dependence is positive and economically large in a subset of countries with pronounced downstream exposure, most notably Germany and the United States. In other economies, the interaction is generally small and statistically insignificant. On the other hand, extraction (upstream) dependence does not exhibit a consistent amplification effect. Interaction coefficients are typically insignificant and, in several cases negative, suggesting that upstream exposure does not systematically increase sensitivity to CGR.

Altogether, the results indicate that the amplification of CGR operates primarily through countries' exposure to downstream stages of production. Economies more reliant on refined inputs exhibit stronger increases in the term spread when geopolitical climate risk is elevated. This pattern is consistent with the geographic concentration of global processing capacity and limited substitutability of refined inputs. These factors make disruptions more biting for domestic economic activity. At the same time, the heterogeneity in country-level responses suggests that this transmission channel is not universal but depends on country-specific industrial structure and exposure to global supply chains.

4. Conclusions

Climate geopolitical risk refers to cross-border geopolitical frictions that arise in the context of the energy transition and affect the availability, cost, and strategic control of key inputs, technologies, and trade flows. This paper studies whether such frictions influence how risk is priced in financial markets and how they propagate to macro-financial conditions.

The evidence indicates that climate geopolitical risk operates as a state variable that shifts the price of risk rather than acting as a standalone factor. Periods of elevated CGR are associated with systematic variations in the compensation investors require for bearing specific risks. The price of size and commodity-related risks increase, the price of profitability and volatility risks decline, and the market risk premium remains largely unaffected.

At the same time, exposures to CGR vary meaningfully across firms and sectors, and these differences are priced. Firms with higher sensitivity to CGR earn higher average returns, and this pattern extends to the sector level in out-of-sample portfolio tests. Sector rotation results indicate that CGR exposure is not concentrated in traditional energy sectors alone but instead reflects broader sensitivity to disruptions that affect global production networks and capital allocation. Although CGR raises the price of commodity-related risk, the cross-sectional evidence shows that its effects are not reducible to an oil-risk channel.

To examine transmission to the macro-financial environment, we focus on countries' exposure to global supply chains for critical inputs. The results show that the effect of CGR on

financing conditions depends on the structure of this exposure. Economies with greater reliance on downstream processing and refining exhibit stronger responses of term spreads to increases in CGR. This is consistent with a mechanism in which disruptions to more concentrated and strategically controlled stages of production translate into tighter financial conditions.

Our findings indicate that climate risk in financial markets is not limited to physical damages or domestic transition policy. Geopolitical frictions linked to the energy transition influence both the pricing of risk and the distribution of exposures across firms, sectors, and countries. As dependence on global inputs and technologies associated with decarbonization increases, such frictions are likely to become more relevant for asset pricing and macro-financial stability.

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Figure 1 - Climate Geopolitical Risk (CGR) Level and Innovations

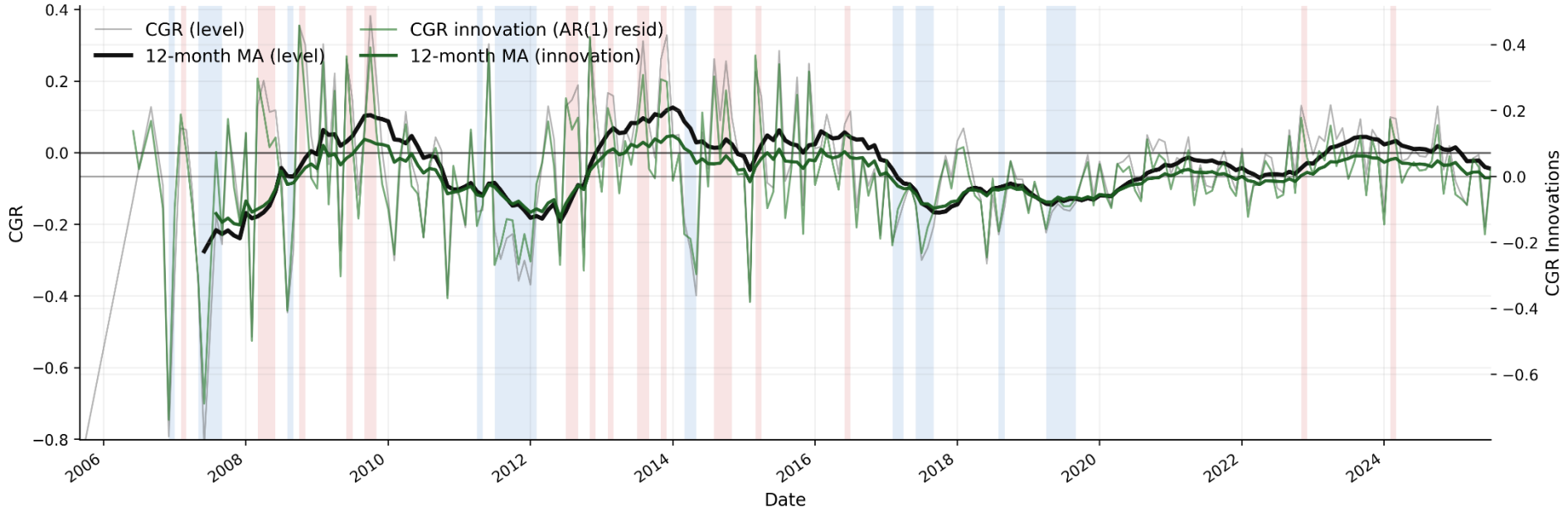


Figure 1 plots CGR levels and AR (1) innovations, with 12-month moving averages. Shaded areas indicate high (≥75th percentile in red) and low (≤25th percentile in blue) CGR regimes.

Figure 2. Out-of-sample performance and portfolio composition (CGR Innovations, quarterly rebalancing)

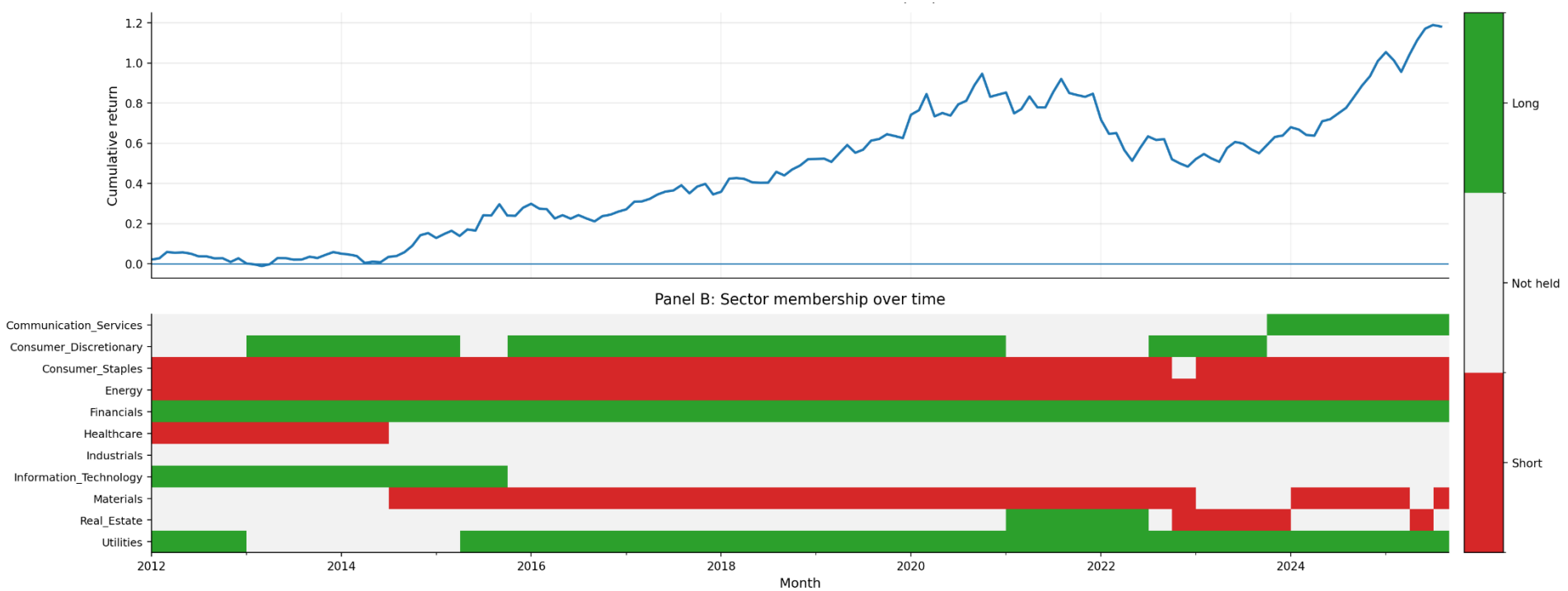


Figure 2 presents the out-of-sample performance and sector composition of high-minus-low portfolios formed on estimated CGR AR(1) innovation betas under quarterly rebalancing. Panel A plots cumulative excess returns of the equal-weighted high-minus-low portfolio. Returns are constructed using an expanding-window procedure in which CGR betas are estimated using all available data up to each rebalancing date, and sectors are sorted into portfolios accordingly. Panel B shows portfolio membership over time. At each rebalancing date, sectors are classified into long (high CGR exposure), short (low CGR exposure), or not held, based on tercile sorting of estimated betas.

Figure 3 - Net upstream dependence (extraction − refined) per $bn GDP

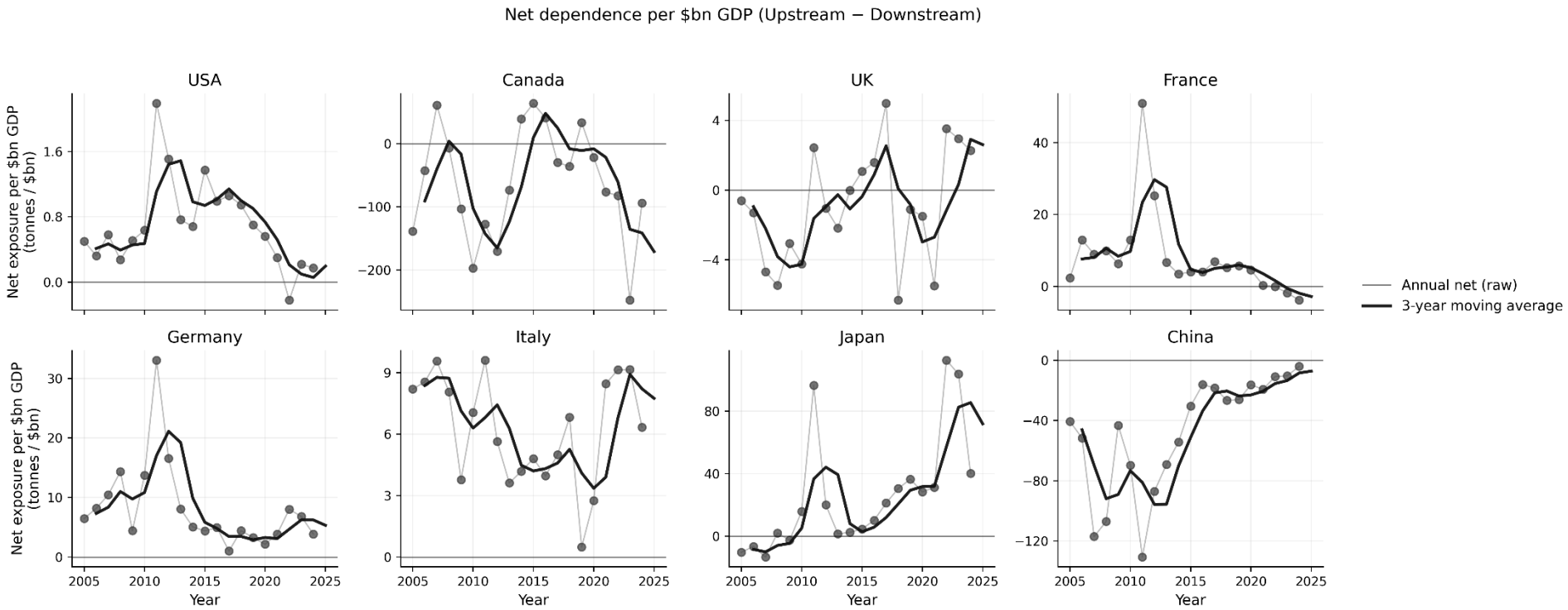


Figure 3 shows the evolution of net upstream dependence across major economies. Net dependence is defined as extraction dependence minus refined dependence, where each component is measured as (imports − exports) of upstream (raw) and downstream (refined) critical minerals, scaled by GDP (in $bn). Grey markers show annual values; the black line is a 3-year moving average. Positive values indicate net upstream dependence, while negative values indicate net downstream dependence.

Table 1. Summary statistics

Variable	N	q1	Median	μ	σ	q3
Ret	240	-0.021	0.010	0.008	0.056	0.039
Climate Geopolitical Risk Measures						
CGR	228	-0.132	-0.033	-0.046	0.183	0.057
CGR Innovations	223	-0.077	0.004	0.000	0.168	0.079
Benchmark Climate Factors						
GPR	246	81.609	92.381	100.254	29.699	110.404
CPU	246	88.430	116.194	146.275	89.933	189.138
Transition Risk	246	-0.007	-0.002	0.000	0.008	0.005
Physical Risk	246	-0.005	-0.001	-0.001	0.008	0.005
Climate PCA	246	-0.929	-0.057	0.000	1.271	0.800
Asset Pricing Controls						
MKT	234	-0.018	0.013	0.008	0.045	0.033
SMB	234	-0.019	0.000	-0.001	0.027	0.015
HML	234	-0.018	-0.003	-0.001	0.032	0.014
RMW	234	-0.008	0.003	0.003	0.019	0.013
CMA	234	-0.012	-0.001	0.000	0.019	0.011
MoM	234	0.000	0.002	0.002	0.023	0.003
VIX	212	-0.113	-0.013	0.001	0.204	0.083
WTI	201	-0.055	0.014	0.003	0.118	0.070

Table 1 presents summary statistics for the variables used in the analysis. Panel A reports the dependent variable. *Ret* denotes monthly excess returns. Panel B reports climate geopolitical risk measures. Climate Geopolitical Risk index (CGR) is a standardised measure of climate-related geopolitical tensions; *CGR Innovations* are defined as the residuals from an AR(1) process fitted to CGR. Panel C reports benchmark climate factors. *GPR* is the Geopolitical Risk index of Caldara and Iacoviello, (2022); *CPU* - Climate Policy Uncertainty index; Transition Risk and Physical Risk indices are the climate risk indices from Baker, Bloom, and Davis (2016). *Climate PCA* is the first principal component extracted from *Transition Risk*, and *Physical Risk*. Panel D reports the time-series variables. *MKTRF* is the monthly return on the value-weighted stock market net of the risk free rate; *HML* is the monthly return on the portfolio long value stocks and short growth stocks; *SMB* is the monthly return on the portfolio long small-cap stocks and short large-cap stocks; *CMA* is the monthly return of a portfolio that is long on conservative investment stocks and short on aggressive investment stocks; *VIX* is the monthly log change in the Volatility Index; *WTI* is the monthly log change in West Texas Intermediate crude.

Table 2: Cross correlations and autocorrelations in climate and geopolitical risk variables

Variable	CGR	CGR Innovations	Transition Risk	Physical Risk	GPR	CPU
CGR	1					
CGR Innovations		1				
Transition Risk	-0.076	0.021	1			
Physical Risk	-0.077	-0.027	0.611	1		
GPR	-0.058	-0.091	-0.133	-0.078	1	
CPU	-0.052	0.005	-0.218	-0.191	0.368	1

The sample period is 2005 – 2024. The table reports pairwise correlations between climate geopolitical risk (CGR), its AR (1) innovations, and benchmark climate and geopolitical risk measures at the monthly frequency. All variables are defined in Table 1.

Table 3 – Validation tests: is CGR spanned by climate and geopolitical risk factors?

Dependent	Transition Risk	Physical Risk	GPR	CPU	CGR Variant	Climate PCA factor	N	Adj R^2
Panel A: CGR at level								
CGR	-0.062	-0.051	-0.048	-0.056		0.092	227	0.000
	(0.112)	(0.122)	(0.050)	(0.057)		(0.086)		
Transition Risk		0.593***	-0.051	-0.107*	-0.04		227	0.383
		(0.061)	(0.065)	(0.054)	(0.071)			
Physical Risk	0.599***		0.018	-0.045	-0.033		227	0.368
	(0.119)		(0.069)	(0.061)	(0.079)			
GPR	-0.071	0.025		0.371***	-0.043		227	0.133
	(0.069)	(0.098)		(0.094)	(0.042)			
CPU	-0.139*	-0.059	0.347**		-0.047		227	0.163
	(0.077)	(0.081)	(0.139)		(0.051)			
Panel B: CGR AR (1) Innovations								
CGR Innovations	0.068	-0.063	-0.090**	-0.003		0.006	222	0.000
	(0.086)	(0.088)	(0.040)	(0.043)		(0.055)		
Transition Risk		0.634***	0.039	0.032	0.042		222	0.385
		(0.052)	(0.044)	(0.058)	(0.050)			
Physical Risk	0.617***		0.024	-0.071	-0.037		222	0.389
	(0.069)		(0.067)	(0.044)	(0.050)			
GPR	0.065	0.042		-0.033	-0.093**		222	0.001
	(0.081)	(0.123)		(0.067)	(0.042)			
CPU	0.055	-0.125	-0.033		-0.003		222	0.000
	(0.101)	(0.087)	(0.068)		(0.045)			

Table 3 presents results on validation tests of CGR and its innovations to benchmark risk factors. All variables are defined in Table 1. Standard errors are HAC robust (maxlags=6). Standard errors are reported in parentheses. * 10%, ** 5%, *** 1%. N denotes the number of observations, and Adj. R^2 is the adjusted R-squared.

Table 4: Does CGR condition factor risk premia?

Factor	**FF5**			**FF5 + VIX**			**FF5 + WTI**		
	Coef.	Low	High	Coef.	Low	High	Coef.	Low	High
Panel A: State Variable = Lagged CGR level									
λ_{MKT}	-0.023	-0.100	0.027	0.003	-0.018	0.029	-0.005	-0.026	0.025
λ_{SMB}	0.030*	-0.001	0.093	0.010	-0.015	0.035	0.005	-0.016	0.030
λ_{HML}	0.013	-0.003	0.039	0.013*	-0.002	0.036	0.009*	-0.003	0.027
λ_{RMW}	-0.013**	-0.034	-0.001	-0.006*	-0.014	0.000	-0.004*	-0.012	0.003
λ_{CMA}	0.004	-0.007	0.015	0.000	-0.012	0.015	0.000	-0.012	0.013
$\lambda_{\Delta \ln(VIX)}$				-0.081	-0.226	0.033			
$\lambda_{\Delta ln(WTI)}$							0.084*	0.000	0.173
Panel B: State Variable = Lagged CGR Innovations									
λ_{MKT}	-0.033	-0.114	0.021	-0.005	-0.035	0.032	-0.016	-0.049	0.027
λ_{SMB}	0.032**	0.002	0.093	0.013	-0.010	0.042	0.010	-0.011	0.037
λ_{HML}	0.012	-0.003	0.037	0.011*	-0.003	0.037	0.007*	-0.003	0.028
λ_{RMW}	-0.012*	-0.032	0.000	-0.006*	-0.015	0.001	-0.004	-0.012	0.003
λ_{CMA}	0.003	-0.006	0.016	0.000	-0.010	0.017	0.000	-0.011	0.013
$\lambda_{\Delta \ln(VIX)}$				-0.080**	-0.211	-0.012			
$\lambda_{\Delta ln(WTI)}$							0.100*	0.019	0.187

Table 4 reports estimates of conditional factor loadings from time-series regressions of factor returns on lagged CGR variables. The dependent variable is firm level excess returns. Panel A uses the lagged CGR level, while Panel B uses lagged CGR AR (1) innovations. Results are shown for three model specifications: FF5, FF5 augmented with $\Delta ln(VIX)$, and FF5 augmented with $\Delta ln(WTI)$. All variables are defined in Table 1. Coefficients are reported with confidence intervals based on block bootstrap inference (block lengths 6, 12, 18, and 24 months). Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively.

Table 5: CGR-sorted portfolio returns.

	High - Low CGR (EW)	High - Low CGR (VW)	High - Low CGR Innovations (EW)	High - Low CGR Innovations (VW)
Mean (α)	0.004*	0.005 ***	0.004	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
N	197	197	192	192

Table 5 reports average excess returns on high-minus-low portfolios formed by sorting firms into terciles based on estimated CGR exposure. *High – Low* denotes the return on a zero-cost portfolio that is long firms in the highest CGR tercile and short firms in the lowest tercile. Portfolios are constructed using equal weights (EW) and value weights (VW), and results are shown for CGR levels and CGR AR (1) innovations. Reported coefficients are average monthly excess returns in decimal form. Standard errors are reported in parentheses. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. N denotes the number of monthly observations.

Table 6: Out-of-sample CGR-sorted portfolio performance

Specification by CGR variant	Mean	Alpha (FF5)	Mean	Alpha (FF5 + MoM)
Expanding Window, Annual rebalance (Level)	0.005***	0.005***	0.004**	0.006***
	(0.002)	(0.001)	(0.002)	(0.002)
Adj. R^2		0.35		0.365
N	163	163	158	158
Expanding Window, Quarterly rebalance (Level)	0.006**	0.006***	0.005***	0.006***
	(0.002)	(0.002)	(0.002)	(0.003)
Adj. R^2		0.301		0.315
N	166	166	161	161
Expanding Window, Annual rebalance (Innovation)	0.005**	0.005***	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Adj. R^2		0.282		0.287
N	163	163	158	158
Expanding Window, Quarterly rebalance (Innovation)	0.005***	0.005***	0.005***	0.006***
	(0.002)	(0.001)	(0.002)	(0.002)
Adj. R^2		0.291		0.305
N	163	163	158	158

Table 6 reports out-of-sample mean excess returns and factor-model alphas for high-minus-low portfolios formed by sorting S&P 500 sectors on estimated CGR betas. In each rebalancing period, betas are estimated using all data available up to that date, sectors are ranked on the estimated exposure, and a zero-cost portfolio is formed by going long high-exposure sectors and short low-exposure sectors. Results are reported separately for CGR levels and CGR AR(1) innovations, under annual and quarterly rebalancing. Mean denotes the average monthly excess return on the high-minus-low portfolio. Alpha (FF5) and Alpha (FF5 + MoM) denote intercepts from time-series regressions of portfolio excess returns on the Fama–French five factors, and on the five factors augmented with momentum, respectively. Standard errors are HAC and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Adj. R^2 is reported for the factor regressions, and N denotes the number of monthly observations.

Table 7: Portfolio turnover summary

Specification	Avg turnover (all)	Avg turnover (long)	Avg turnover (short)	Rebalances
Annual rebalance (Level)	0.17	0.192	0.115	14
Quarterly rebalance (Level)	0.078	0.082	0.055	56
Annual rebalance (Innovations)	0.148	0.192	0.115	14
Quarterly rebalance (Innovations)	0.063	0.056	0.056	55

Table 8 reports average turnover for high-minus-low portfolios formed on estimated CGR exposure. Turnover is computed as the average fraction of portfolio weights traded at each rebalancing date. "Avg turnover (all)" refers to total portfolio turnover, while "long" and "short" denote turnover within the respective legs of the portfolio. Results are reported for specifications based on CGR levels and CGR AR (1) innovations, under annual and quarterly rebalancing. "Rebalances" denotes the total number of portfolio rebalancing events over the sample period.

Table 8: Term spread regressions: CGR and supply chain exposure

	Downstream (Level)	Downstream (Innovations)	Upstream (Level)	Upstream (Innovations)	Dependence (Level)	Dependence (Innovations)
Panel A						
Exposure	0.003	0.003	-0.005***	-0.005***	0.002**	0.002***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
CGR × Exposure	0.008***	0.006***	-0.011	-0.010	0.008	0.006
	(0.002)	(0.001)	(0.012)	(0.009)	(0.005)	(0.004)
Country FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Adj. R^2	0.653	0.664	0.648	0.66	0.649	0.66
N	1743	1714	1743	1714	1743	1714
Panel B						
CGR	0.518**	0.379**	0.342***	0.235***	0.630***	0.460**
	(0.167)	(0.137)	(0.100)	(0.084)	(0.158)	(0.129)
Exposure	0.000	0.000	-0.006*	-0.007**	-0.001	-0.001
	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
CGR × Exposure	0.013***	0.010***	-0.001	-0.002	0.015***	0.011***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
Country FE	yes	yes	yes	yes	yes	yes
Year FE	no	no	no	no	no	no
Adj. R^2	0.305	0.316	0.306	0.32	0.307	0.317
N	1743	1714	1743	1714	1743	1714

Table 8 reports panel regressions of the sovereign term spread (10-year minus 3-month government bond yields) on supply chain exposure and its interaction with CGR. Upstream exposure corresponds to extraction dependence, downstream exposure to refined dependence, and dependence denotes net upstream exposure (extraction minus refined) all in (net tons/bUSD GDP). Columns distinguish between CGR levels and CGR AR (1) innovations. All other variables are defined in Table 1. Panel A includes country and year fixed effects. Panel B includes country fixed effects only and reports the CGR main effect. Exposure variables are scaled by GDP. Standard errors are clustered at the country level and reported in parenthesis. Statistical significance is based on wild cluster bootstraps (Rademacher) at the country level. Statistical significance is denoted by *, **, and *** at the 10%, 5%, and 1% levels, respectively. Adj. R^2 denotes the adjusted R-squared and N the number of observations.

Appendix A

Table A1. Top 20 Journal News Sources

	Headlines		polarity			
Journal	N	%	mean	std	min	max
Asia News Monitor	620	12.600	0.039	0.140	-1.000	0.800
New York Times	185	3.700	0.015	0.171	-0.600	0.800
The Washington Post	122	2.500	0.035	0.191	-0.500	1.000
Washington Examiner	108	2.200	0.015	0.105	-0.500	0.500
The Straits Times	104	2.100	0.034	0.164	-0.333	0.800
Wall Street Journal	92	1.900	0.001	0.138	-0.500	0.400
Telegraph	90	1.800	0.008	0.167	-0.500	0.550
The Korea Times	88	1.800	0.040	0.143	-0.200	0.700
Financial Times	87	1.800	0.032	0.145	-0.500	0.600
The Christian Science Monitor	80	1.600	0.065	0.207	-0.800	0.800
Yerepouni Daily News	74	1.500	0.029	0.211	-0.600	0.800
The Australian Financial Review	72	1.500	0.082	0.194	-0.500	0.800
Los Angeles Times	68	1.400	0.022	0.221	-0.500	0.700
The Business Times	64	1.300	0.050	0.218	-0.600	0.800
China Daily	59	1.200	0.077	0.260	-0.600	1.000
The Canberra Times	59	1.200	0.032	0.188	-0.488	0.700
Pittsburgh Post - Gazette	52	1.100	0.060	0.206	-0.500	0.800

Table A2: Country level amplification tests regressions

Table A1 reports country-level regressions of the sovereign term spread (10-year minus 3-month government bond yields) on supply chain exposure and its interaction with CGR. Upstream exposure corresponds to extraction dependence, downstream exposure to refined dependence, and net dependence is defined as extraction minus refined dependence. Columns distinguish between CGR in levels and CGR AR(1) innovations. All specifications include Debt-to-GDP and current account balance as controls, lagged by one year. Exposure variables are scaled by GDP. Standard errors are Newey–West (HAC) with 6 lags and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels. Adj. R^2 denotes the adjusted R-squared and N the number of monthly observations.

Exposure Type	CGR Variant	Exposure (β_1)	Interaction (β_2)	N	Adj. R^2
		Panel A: Canada			
Refined Dependence	Level	-0.002	0.008	220	0.332
		(0.002)	(0.006)		
	Innovation	-0.002	0.006	216	0.327
		(0.002)	(0.004)		
Extraction Dependence	Level	-0.002	0.002	220	0.296
		(0.008)	(0.020)		
	Innovation	-0.002	-0.004	216	0.296
		(0.010)	(0.019)		
Net Dependence	Level	-0.002	0.008	220	0.336
		(0.002)	(0.005)		
	Innovation	-0.002	0.006	216	0.329
		(0.002)	(0.004)		
		China			
Refined Dependence	Level	0.018***	0.003	208	0.343
		(0.006)	(0.009)		
	Innovation	0.018***	0.003	204	0.34
		(0.006)	(0.006)		
Extraction Dependence	Level	-0.030***	-0.015	208	0.289
		(0.011)	(0.021)		
	Innovation	-0.030***	-0.018	204	0.288
		(0.011)	(0.018)		
Net Dependence	Level	0.019**	-0.001	208	0.31
		(0.007)	(0.013)		
	Innovation	0.020**	0.001	204	0.306
		(0.008)	(0.019)		
		France			
Refined Dependence	Level	-0.587***	-0.023	215	0.172
		(0.150)	(0.174)		
	Innovation	-0.583***	-0.004	214	0.172
		(0.145)	(0.105)		
Extraction Dependence	Level	-0.047***	-0.061**	215	0.24
		(0.013)	(0.027)		
	Innovation	-0.044***	-0.043*	214	0.224
		(0.013)	(0.022)		
Net Dependence	Level	-0.051***	-0.066**	215	0.279

		(0.014)	(0.028)		
	Innovation	-0.048***	-0.047**	214	0.259
		(0.014)	(0.024)		
		Germany			
	Level	0.508*	1.015**	220	0.086
Refined Dependence		(0.288)	(0.509)		
	Innovation	0.560*	0.964*	216	0.098
		(0.294)	(0.495)		
	Level	-0.023	-0.021	220	0.059
Extraction Dependence		(0.015)	(0.031)		
	Innovation	-0.021	-0.013	216	0.062
		(0.015)	(0.027)		
	Level	-0.02	-0.017	220	0.054
Net Dependence		(0.015)	(0.031)		
	Innovation	-0.018	-0.01	216	0.057
		(0.014)	(0.027)		
		Italy			
	Level	-2.306***	-0.979	220	0.642
Refined Dependence		(0.255)	(0.808)		
	Innovation	-2.302***	-0.888	216	0.646
		(0.249)	(0.645)		
	Level	0.186**	0.094	220	0.128
Extraction Dependence		(0.090)	(0.112)		
	Innovation	0.164*	0.066	216	0.114
		(0.098)	(0.096)		
	Level	0.064	0.022	220	0.063
Net Dependence		(0.100)	(0.121)		
	Innovation	0.042	0.007	216	0.061
		(0.107)	(0.104)		
		Japan			
	Level	0.006	0.011**	220	0.379
Refined Dependence		(0.011)	(0.004)		
	Innovation	0.003	0.010**	216	0.344
		(0.013)	(0.004)		
	Level	-0.005***	-0.005**	220	0.508
Extraction Dependence		(0.001)	(0.002)		
	Innovation	-0.005***	-0.003*	216	0.488
		(0.001)	(0.002)		
	Level	-0.004***	-0.002	220	0.488
Net Dependence		(0.001)	(0.001)		
	Innovation	-0.004***	-0.001	216	0.472
		(0.001)	(0.001)		
		United Kingdom			
	Level	0.214	-0.557	220	0.117
Refined Dependence		(0.197)	(0.441)		
	Innovation	0.276	-0.413	216	0.116

		(0.207)	(0.393)		
	Level	0.038	0.303	220	0.084
Extraction Dependence		(0.045)	(0.204)		
	Innovation	0.029	0.182	216	0.072
		(0.043)	(0.186)		
	Level	0.059	0.058	220	0.084
Net Dependence		(0.051)	(0.212)		
	Innovation	0.059	0.029	216	0.081
		(0.050)	(0.193)		
Panel G: USA					
	Level	-1.300***	1.709**	220	0.535
Refined Dependence		(0.422)	(0.824)		
	Innovation	-1.265***	1.163*	216	0.546
		(0.436)	(0.614)		
	Level	-0.509***	-0.841**	220	0.5
Extraction Dependence		(0.146)	(0.408)		
	Innovation	-0.476***	-0.633*	216	0.51
		(0.134)	(0.351)		
	Level	-0.441***	-0.519	220	0.518
Net Dependence		(0.109)	(0.325)		
	Innovation	-0.426***	-0.387	216	0.532
		(0.104)	(0.278)		

Appendix B.

1	Competition for critical natural resources creates tensions between states.
2	Climate instability increases the risk of geopolitical conflicts over raw materials.
3	Export restrictions on strategic minerals for the climate transition destabilize global markets.
4	Migrations caused by environmental disasters lead to political pressures.
5	Unequal access to green energy resources fuels rivalries among nations.
6	Misaligned climate policies trigger transboundary trade tensions.
7	Border protection has become a priority in response to climate-driven migration flows.
8	International and cross-border conflicts over water resources are becoming more frequent due to water stress.
9	Carbon border tariffs are seen as threats by some trading partners.
10	Sanctions on rare metal exports relevant for the carbon transition disrupt global supply chains.
11	Climate change causes population displacement across borders.
12	The global energy transition to net zero intensifies competition for strategic resources.
13	Diplomatic tensions rise when countries impose unilateral climate barriers.
14	Strategic alliances over green resources are becoming a major geopolitical issue.
15	Limited access to cobalt or lithium required for the net zero transition may trigger regional conflicts.
16	Border militarization is a response to increasing environmental migration.
17	Climate-vulnerable countries experience growing external geopolitical pressures.
18	Poorly coordinated green taxes may provoke trade retaliation.
19	Securing minerals critical for the energy transition has become a national priority for many countries.
20	Resource scarcity intensifies power dynamics on the international stage.
21	Foreign investments in transition-critical sectors are sometimes restricted to protect national energy sectors.
22	Stricter immigration policies often follow prolonged climate crises.
23	Conflicts of interest in climate negotiations reflect latent geopolitical stakes.
24	Disagreements over net-zero goals create regional tensions.
25	Food crises driven by climate disruptions fuel political instability and geopolitical alliances
26	Environmental taxation can be used as a protectionist tool.
27	Dependence on a few countries for green materials increases economic and geopolitical vulnerability.
28	Climate change acts as a risk multiplier in international relations.
29	Sovereign level trade disputes over renewable energy technologies are becoming more frequent.
30	The global ecological transition is reshaping geostrategic balances.