

ENVIRONMENT AND FINANCIAL MARKETS: ASSESSMENT AND RISK

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The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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ENVIRONMENT AND FINANCIAL MARKETS: ASSESSMENT AND RISK

ADITYA GUPTA

ABSTRACT

This dissertation examines how climate risk, decomposed into transition risk and physical risk, is priced across G7 equity markets and the US fixed income market over the period February 2016 to May 2025. Using a Transition Risk Index (TRI) and a Physical Risk Index (PRI) as the primary explanatory variables, alongside monthly benchmark equity index returns for all seven G7 countries and monthly US 10-year Treasury yield data, this study conducts six empirical analyses: pooled and fixed-effects panel OLS regressions, a time-series OLS of climate risk on bond yield changes, 24-month rolling regressions to capture time-varying sensitivity, individual country level regressions, portfolio level Climate Value at Risk (Climate VaR), and an analysis of bond-equity correlation dynamics under climate stress.

The results show that transition risk exerts a statistically significant and negative effect on G7 equity returns in pooled OLS ($\beta = -0.312$, $p < 0.001$), a finding that is robust to the inclusion of country fixed effects. In the bond market, higher transition risk is associated with rising yields, significant at the 5% level. Physical risk, by contrast, does not show significant pricing in either market, a finding consistent with the hypothesis that markets are slow to incorporate gradual climate trends. The Climate VaR analysis reveals that equity tail risk increases meaningfully during periods of high transition risk. Rolling regressions reveal that the sensitivity of equity returns to both risk indices is not stable over time, with notable shifts around the COVID-19 period and the Russia-Ukraine conflict.

Taken together, these findings suggest that while transition risk is increasingly priced into G7 financial markets, physical risk remains systematically underweighted, a market inefficiency with implications for portfolio construction and climate-related financial regulation.

Keywords: *climate risk, transition risk, physical risk, G7 equity markets, bond yields, panel OLS, Climate VaR, rolling regression, financial markets, market efficiency*

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CHAPTER 1

INTRODUCTION

Climate change has moved from being a scientific and policy concern to a defining issue for global financial markets. The moment that crystallised this shift for the financial community was Mark Carney's 2015 speech at Lloyd's of London, in which the Bank of England Governor framed climate change as a systemic threat to financial stability, introducing the distinction between **physical risks**, the direct financial damage from extreme weather events and long-term shifts in climate patterns, and **transition risks**, which arise from the policy, technological, and market adjustments needed to move toward a lower-carbon economy. In the decade since that speech, these two categories of climate risk have become central to how regulators, investors, and researchers think about the relationship between environmental change and financial outcomes.

Despite this growing recognition, the question of whether and how financial markets actually price climate risk remains unresolved. A large and rapidly growing body of academic research has examined individual asset classes in isolation, covering equity markets, corporate bond markets, and carbon credit markets, and has found evidence of both partial pricing and systematic mispricing depending on the type of risk, the time horizon, and the institutional context. However, what is much less common is a study that looks at how the same set of climate risk indicators affects multiple asset classes simultaneously, using a consistent methodology across a comparable time period. This is the central ambition of this dissertation.

Specifically, this study asks **three related questions**. **First**, does transition risk, as measured by a Transition Risk Index (TRI), have a statistically significant effect on equity returns across G7 markets, and if so, is the effect uniform across countries or does it vary by economy? **Second**, does either transition risk or physical risk, as measured by a Physical Risk Index (PRI), affect the US 10-year Treasury yield, the benchmark for global fixed income pricing? **Third**, has the sensitivity of financial markets to these climate risk measures changed over time, particularly around major shocks such as the COVID-19 pandemic and the Russia-Ukraine conflict?

To answer these questions, this dissertation uses three datasets covering February 2016 to May 2025: monthly benchmark equity index data for all seven G7 countries (the United Kingdom, the United States, Japan, France, Germany, Canada, and Italy), monthly US 10-year Treasury bond yield data, and monthly TRI and PRI observations. These are combined into a panel dataset of 567 country-month observations and a time-series dataset of 81 monthly observations, and six empirical analyses are conducted: pooled and fixed-effects panel OLS regressions, a bond market OLS, 24-month rolling regressions to track time-varying sensitivity, individual country regressions, portfolio-level Climate Value at Risk (Climate VaR), and an analysis of how climate risk affects the traditional bond-equity correlation.

The findings contribute to **three gaps identified in the existing literature**. The **first** is the absence of comparative cross-asset analysis: most prior studies examine equity markets or bond markets, but not both simultaneously using the same risk measures. The **second** is the lack of a unified framework that incorporates both physical and transition risk in the same regression, allowing their relative importance to be assessed directly. The **third** is the limited attention paid to time-varying dynamics: a static coefficient from a full-sample regression cannot reveal whether climate risk has become more or less important to market pricing over the course of the sample period, or whether major global events have altered the relationship.

The remainder of this dissertation is structured as follows. Chapter 2 reviews the existing literature on climate risk and financial markets, covering physical risk, transition risk, green bonds, and carbon markets. Chapter 3 describes the data sources, construction, and descriptive statistics. Chapter 4 sets out the methodology for each of the six analyses. Chapter 5 presents and discusses the results. Chapter 6 concludes with a summary of findings, limitations, and directions for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Physical Climate Risk and Market Efficiency

A central question in the climate-finance literature concerns whether financial markets correctly price the long-run physical risks associated with climate change. Hong, Li and Xu (2019) provide compelling evidence that they do not. Using the Palmer Drought Severity Index across 31 countries from 1985 to 2014, they demonstrate that worsening drought trends, driven by rising global temperatures, reliably forecast declining profitability in the food sector, yet stock prices fail to reflect this information in a timely manner. The resulting long-short portfolio strategy generates an annualised alpha of approximately 7%, consistent with systematic market underreaction to physical climate risk. Crucially, this finding holds across multiple risk-adjustment frameworks and is unique to the food industry, confirming that the mechanism is drought exposure rather than unobserved country-level differences. The study shows that stock markets are slow to price gradual but observable climate trends, challenging core assumptions of the Efficient Market Hypothesis in the context of environmental risk.

This market inattention to physical risk has important implications for asset pricing beyond the food sector. Physical climate shocks, including floods, droughts, and extreme weather events, are increasingly frequent, and Jan et al. (2026) illustrate their disruptive effects in an emerging market context. Using structural equation modelling with data from Pakistan and China, they find that uncertainties arising from climate

events negatively affect investor behaviour, reducing investment activity and pushing investors toward safer instruments. Financial stability moderates these effects, acting as a buffer that allows investors to stay engaged with climate-sensitive assets rather than pull back entirely. Taken together, these studies suggest that physical risk affects financial markets through both rational underpricing (Hong et al., 2019) and behavioural channels (Jan et al., 2026), with the latter being especially pronounced in emerging economies with weaker institutions.

Extending the physical risk literature to sector-specific firm performance, Bauri, Mondal and Fatma (2025) offer one of the first cross-country empirical studies of how climate physical risk affects the financial performance of energy companies. Using a panel of 48 listed energy firms from ten G-20 countries over the period 2017–2021, they use the Notre Dame Global Adaptation Initiative (ND-GAIN) climate vulnerability score, which captures country-level exposure, sensitivity, and adaptive capacity across six key sectors including food, water, health, and infrastructure, as a measure of physical climate risk. Pooled OLS and random-effect panel regressions consistently show that climate vulnerability negatively and significantly affects all four performance measures examined: return on assets (ROA), return on equity (ROE), return on capital employed (ROCE), and the price-to-book ratio. Firms based in more climate-vulnerable countries consistently underperform their peers in lower-risk countries across both accounting and market measures.

Adding further evidence on heat as a physical climate risk, Pankratz, Bauer and Derwall (2023) examine the direct financial effects of high temperatures across more than 17,000 firms in 93 countries from 1995 to 2019. They find that a one-standard-deviation increase in the number of extremely hot days reduces revenues by 0.6% and operating income by 1.8% of their respective quarterly averages. Importantly, the study also looks at analyst forecast errors and stock returns around earnings announcements, finding that markets consistently underestimate the financial damage caused by heat exposure. This suggests that investors are not fully pricing in heat as a material physical risk, reinforcing the market inefficiency identified by Hong et al. (2019) while extending it well beyond the food sector to a much broader cross-country sample.

At a more aggregate level, Dietz, Bowen, Dixon and Gradwell (2016) take a top-down approach to quantifying physical climate risk, applying an integrated assessment model to estimate the impact of 21st-century climate change on the present market value of global financial assets. They find that the expected climate value at risk (Climate VaR) of global financial assets is 1.8% under a business-as-usual emissions path, equivalent to roughly US\$2.5 trillion. The tail risk is considerably larger: at the 99th percentile, Climate VaR reaches 16.9%, or US\$24.2 trillion. This makes Dietz et al. (2016) one of the few early attempts to translate physical climate risk into a standardised, portfolio-level financial risk metric, and its approach is directly relevant to the quantification framework developed in this dissertation.

2.2 Transition Risk, Carbon Pricing, and Asset Repricing

While physical risks operate gradually, transition risks, stemming from policy shifts, regulatory changes, and the move toward a low-carbon economy, can trigger sudden asset repricing. Monasterolo and de Angelis (2020) examine the most significant recent

policy shock of this kind: the 2015 Paris Agreement. Applying a market model and Fama-French five-factor framework to low-carbon and carbon-intensive equity indices across the EU, US, and global markets, they find that the systematic risk of low-carbon indices declined significantly after the Agreement's announcement, while optimal portfolio weights for green assets increased. Carbon-intensive indices, however, showed a comparatively muted reaction, particularly at monthly frequency. This uneven response, markets beginning to reward low-carbon investment without yet penalising fossil fuel exposure, points to a partial and incomplete pricing of transition risk, which the authors describe as a form of market 'blindness' that has implications for financial stability.

Capasso, Gianfrate and Spinelli (2020) extend the transition risk analysis to the credit market, using Merton's distance-to-default model to show that higher carbon emissions and greater carbon intensity are negatively associated with corporate creditworthiness across a sample of 458 investment-grade firms from 2007 to 2017. Critically, using the Paris Agreement as a quasi-natural experiment in a difference-in-differences framework, they demonstrate that high-emitting companies experienced a significantly larger reduction in distance-to-default after 2015, evidence of a causal channel from regulatory climate shocks to credit risk. These findings carry direct implications for lending institutions, rating agencies, and bond investors, suggesting that carbon footprint is a material and underweighted input into credit risk assessments. The connection between Monasterolo and de Angelis (2020) and Capasso et al. (2020) is worth noting: while the former documents an equity market repricing of climate transition opportunities, the latter shows that the transition also increases default risk for high-emitting firms in the credit market.

2.3 Fixed Income Markets: Green Bonds and ESG Pricing

The green bond market represents a direct financial mechanism linking climate objectives with capital allocation, and its pricing dynamics have attracted considerable academic attention. Hachenberg and Schiereck (2018) provide one of the earliest systematic empirical analyses, comparing daily i-spreads of 63 green-labelled bonds against matched non-green bonds from the same issuers over a six-month period in 2015–2016. Their findings reveal that green bonds in the AA, A, and BBB rating categories trade marginally tighter than comparable non-green bonds, with single-A bonds showing statistically significant pricing differentials of approximately 3.88 basis points. However, the full-sample result is not statistically significant, and AAA-rated green bonds trade slightly wider, apparently reflecting these issuers' explicit commitment to price green bonds at parity.

The panel regression results indicate that industry classification and ESG issuer ratings, rather than maturity, volume, or currency, drive the observed pricing differentials. Financial sector green bonds trade consistently tighter than comparable non-green bonds, while government-related issuers show the opposite pattern, a gap the authors attribute to differing motivations and investor bases across sectors. Interestingly, the existence of an ESG issuer rating is associated with wider spreads for green bonds, suggesting that when the issuer itself is considered ESG-compliant, investors may not feel the need to pay a premium for the specific green label. This

study establishes a useful baseline for understanding the 'greenium' in fixed income markets, though the small sample size and single time window limit how far the findings can be generalised.

2.4 Carbon Markets and Cross-Market Connectedness

Understanding how climate-related financial instruments interact with mainstream financial markets is essential for risk quantification and portfolio management. Tan, Sirichand, Vivian and Wang (2020) provide the most comprehensive analysis of this question to date, applying a modified Diebold-Yilmaz spillover index methodology to examine return and volatility connectedness within a 'Carbon-Energy-Finance' system comprising the EU Emissions Trading System (EU ETS), energy commodities, equity indices, and bond markets over the period 2008–2018. Their results reveal that approximately 42% of forecast error variance in asset returns derives from cross-market spillovers. The European equity market (STOXX 600) is the dominant return transmitter in the system, while carbon allowances primarily function as a net return receiver, absorbing information from equity and commodity markets rather than generating it.

More recently, Lorente, Mohammed, Cifuentes-Faura and Shahzad (2023) extend the cross-market connectedness analysis to include green financial assets and renewable energy markets alongside a climate change index and a geopolitical risk index, covering June 2012 to June 2022. Using Quantile Vector Autoregressive (QVAR) analysis and wavelet coherence, they find that total connectedness across these markets varies considerably depending on market conditions, with the strongest links appearing in the upper quantile. The study also picks up important event-driven shifts: connectedness falls after the second wave of COVID-19 and rises sharply during the first 100 days of the Russia-Ukraine conflict, during which geopolitical risk acts as a net transmitter to the climate change index. These findings build on Tan et al. (2020) by bringing green finance and renewable energy into the connectedness framework, and by showing that spillover patterns are not stable over time but shift considerably depending on the broader political and economic environment.

2.5 Synthesis, Theoretical Foundations, and Research Gaps

Taken together, the existing literature shows that climate risk, both physical and transitional, affects financial markets across asset classes, but that this effect is uneven, incomplete, and varies by context. Several theoretical frameworks support these findings. The Efficient Market Hypothesis, as tested by Hong et al. (2019) and further supported by Pankratz et al. (2023), is consistently violated in the context of long-horizon physical climate risk. Modern Portfolio Theory, as applied by Monasterolo and de Angelis (2020), requires significant revision to account for the changing risk-return profiles of green and brown assets in the post-Paris landscape. Merton's structural credit risk model, used by Capasso et al. (2020), provides a practical quantitative framework for translating carbon exposure into default probability, but its current application remains limited to Scope 1 emissions and investment-grade firms in developed markets. The Climate VaR methodology introduced by Dietz et al. (2016) represents a promising step toward portfolio-level risk quantification, though its

reliance on aggregate macroeconomic modelling leaves room for more granular, asset-class-specific applications.

Several **gaps** remain in the literature. **First**, while individual asset classes have been examined separately, there is limited comparative analysis of how climate risk is priced, consistently or otherwise, across equities and bonds at the same time. **Second**, most empirical work uses a static, full-sample coefficient and does not examine whether market sensitivity to climate risk has changed over time, particularly around major shocks like the COVID-19 pandemic or the Russia-Ukraine conflict. **Third**, while Dietz et al. (2016) offer a useful starting point for portfolio-level climate risk quantification, the literature has not yet developed a shared methodology for combining physical and transition risks into a single, comparable set of risk metrics across asset classes. This dissertation addresses all three gaps directly.

CHAPTER 3

DATA

3.1 G7 Equity Indices

The equity market data consists of monthly closing price observations for the benchmark stock market index of each G7 country, spanning January 2016 to January 2026. The seven indices are the FTSE 100 (United Kingdom), the Dow Jones Industrial Average (United States), the Nikkei 225 (Japan), the CAC 40 (France), the DAX (Germany), the S&P/TSX Composite (Canada), and the Italy 40 (Italy). All data were sourced from Investing.com and represent end-of-month closing values.

From the monthly price series, monthly log returns are computed as $r_t = \ln(P_t / P_{t-1})$, where P_t is the closing index level at the end of month t . Log returns are preferred over simple percentage returns in financial econometrics because they are time-additive and more likely to follow an approximately normal distribution. The mean monthly log returns over the sample period are positive for all seven markets, ranging from +0.33% for the UK and Italy to +0.84% for the United States, reflecting the broadly positive equity market performance over the 2016-2025 period.

Country	Index	Mean Return (%/month)	Std Dev (%)	Min (%)	Max (%)
United Kingdom	FTSE 100	+0.33	3.49	-14.86	+11.65
United States	Dow Jones	+0.84	4.46	-14.78	+13.06
Japan	Nikkei 225	+0.69	4.61	-11.12	+14.01
France	CAC 40	+0.50	4.63	-18.89	+18.33
Germany	DAX	+0.80	4.76	-17.96	+13.99
Canada	S&P/TSX	+0.64	3.83	-19.52	+9.97
Italy	Italy 40	+0.69	5.69	-25.98	+20.94

Table 3.1: Descriptive statistics for G7 equity index monthly log returns, February 2016 to May 2025.

3.2 US 10-Year Treasury Bond Yield

The fixed income data consists of monthly observations of the US 10-year Treasury bond yield, also sourced from Investing.com, covering January 2016 to January 2026. The 10-year Treasury yield serves a dual role in this study: as a control variable in the equity regressions and as the dependent variable in the bond market OLS analysis. The yield ranged from a historic low of 0.53% in August 2020 to a high of 4.93% in October 2023, reflecting the extraordinary monetary policy cycle of the sample period. For the bond market OLS regression, the first difference of the yield level is used, expressed in basis points (bps), as this is more stationary than the level itself.

3.3 Transition Risk Index and Physical Risk Index

The Transition Risk Index (TRI) and Physical Risk Index (PRI) are the core independent variables in this study. Both indices are measured at monthly frequency and expressed as continuous numerical scores, with positive values indicating elevated climate risk and negative values indicating relatively low risk. The TRI captures the financial market pricing of risks associated with the transition to a low-carbon economy, reflecting policy announcements, regulatory changes, and shifts in investor sentiment. The PRI captures the market pricing of physical risks from actual or anticipated climate events.

The TRI and PRI data cover January 2016 to May 2025, yielding 82 monthly observations in total, though the coverage is not fully continuous, with 31 of the 113 calendar months missing. The gaps are scattered throughout the sample and do not cluster in any particular sub-period. After merging with the equity and bond datasets, the final usable sample consists of 81 date observations covering February 2016 to May 2025.

Variable	Mean	Std Dev	Min	Max	Observations
Transition Risk Index (TRI)	-0.0103	0.0236	-0.0782	+0.0532	82
Physical Risk Index (PRI)	-0.0063	0.0240	-0.0601	+0.0415	82
US 10Y Yield (%)	2.696	1.190	0.533	4.926	121
US 10Y Yield Change (bps)	+1.932	24.754	-59.60	+63.30	120

Table 3.2: Descriptive statistics for TRI, PRI, and US 10-year bond yield, 2016 to 2025.

3.4 Data Merging and Sub-Period Classification

The three datasets are merged on a common date variable, with TRI/PRI observations determining the final date coverage. For the panel regressions, the data are converted to long format with 567 observations (81 dates multiplied by 7 countries). For time-series analyses, the wide format is used with 81 date observations.

The sample is divided into four event windows: pre-COVID (February 2016 to December 2019, 34 observations), the COVID era (January 2020 to December 2021, 18 observations), the Russia-Ukraine conflict period (January to December 2022, 9 observations), and the post-conflict period (January 2023 to May 2025, 20 observations). These windows are chosen because the literature, particularly Lorente et al. (2023), identifies them as periods in which climate risk connectedness patterns change significantly.

CHAPTER 4

METHODOLOGY

This chapter describes the econometric methods used in each of the six analyses. HC3 heteroskedasticity robust standard errors (White, 1980) are preferred throughout because financial return data exhibit conditional heteroskedasticity, meaning the variance of the error term is not constant over time. HC3 corrects for this by using a leverage adjusted residual in the variance-covariance matrix, and is particularly conservative in small samples.

4.1 Analysis 1, Panel OLS: TRI and PRI on G7 Equity Returns

The core specification is a panel OLS regression where the monthly log return of country i 's equity index at time t is regressed on the contemporaneous TRI and PRI, with the US 10-year yield included as a macro control:

$$R_{it} = \alpha + \beta_1 \times \text{TRI}_t + \beta_2 \times \text{PRI}_t + \beta_3 \times \text{US10Y}_t + \varepsilon_{it}$$

The analysis is run in two specifications. The first is pooled OLS, which stacks all 567 country-month observations and estimates a single common intercept. The second is a country fixed-effects OLS, implemented via the within transformation: each variable is demeaned at the country level before estimation, which absorbs any time-invariant country-specific characteristics such as market size, regulatory environment, or energy mix.

4.2 Analysis 2, OLS: TRI and PRI on US Bond Yield Changes

To examine how climate risk affects fixed income markets, the following time-series OLS is estimated:

$$\Delta \text{Yield}_t = \alpha + \beta_1 \times \text{TRI}_t + \beta_2 \times \text{PRI}_t + \varepsilon_t$$

where ΔYield_t is the month-on-month change in the US 10-year Treasury yield expressed in basis points. A positive β_1 would indicate that higher transition risk is associated with rising bond yields, potentially reflecting that investors interpret transition risk as a signal of future policy-driven inflation or fiscal stress.

4.3 Analysis 3, Rolling Regressions: Time-Varying Sensitivity

A potential limitation of the full-sample OLS is that it imposes a constant coefficient on TRI and PRI across the entire 2016–2025 period. To address this, rolling OLS regressions are estimated using a 24-month window, moving forward by one month at each step. The 24-month window balances having enough observations for a

meaningful regression while being short enough to capture evolving dynamics. The rolling regression is run on an equal-weighted G7 average return series, by regressing average G7 returns on TRI, PRI and US 10-year yields:

$$G7_avg_t = \alpha + \beta_1 \times TRI_t + \beta_2 \times PRI_t + \beta_3 \times US10Y_t + \varepsilon_t$$

4.4 Analysis 4, Country-Level OLS

To examine heterogeneity in climate risk sensitivity across G7 economies, individual OLS regressions are estimated for each country using the same specification as Analysis 1, with 81 monthly observations per country. The TRI and PRI coefficients are then compared across countries to identify which G7 markets are most sensitive to each type of climate risk.

4.5 Analysis 5, Portfolio Climate VaR

An equal-weighted G7 portfolio return is constructed by averaging the monthly log returns of all seven equity indices. Portfolio Value at Risk (VaR) and Conditional VaR (CVaR, also known as Expected Shortfall) are computed using historical simulation at the 5% confidence level. VaR at 5% is the return level below which 5% of monthly portfolio returns fall. CVaR is the average of all returns in the worst 5% of cases, providing a measure of tail risk beyond the VaR threshold. These metrics are computed separately for periods when TRI and PRI are in their upper quartile versus the rest of the sample.

4.6 Analysis 6, Bond-Equity Correlation Under Climate Stress

A 24-month rolling Pearson correlation is computed between the G7 average equity return and the monthly change in the US 10-year yield. The rolling correlation series is then compared between periods when TRI is in its upper quartile and all other periods, and a two-sample t-test is used to assess whether the difference is statistically significant. This tests whether climate risk disrupts the traditional negative bond-equity correlation that portfolio managers rely on for diversification.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Panel OLS Results (Analysis 1)

Table 5.1 reports the results of the pooled OLS and country fixed-effects OLS regressions of G7 equity returns on TRI, PRI, and the US 10-year bond yield. The most important finding is the strongly significant negative coefficient on TRI in both specifications.

Variable	Pooled OLS Coeff.	Pooled p-value	FE OLS Coeff.	FE p-value
Intercept	+0.00539	0.188	-	-
TRI	-0.31162	0.000 ***	-0.31162	0.000 ***
PRI	+0.00457	0.957	+0.00457	0.957
US10Y Yield	-0.00101	0.493	-0.00101	0.492
R-squared	0.0309		0.0310	
N	567		567	

*Table 5.1: Panel OLS results. Dependent variable: monthly log equity return. HC3 robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

The TRI coefficient of -0.312 indicates that a one-unit increase in the Transition Risk Index is associated with a 31.2 percentage point reduction in the G7 equity return in the same month, significant at the 1% level ($p < 0.001$) in both specifications. The fact that the coefficient is virtually identical across pooled and fixed-effects models suggests it is not driven by time-invariant country-level characteristics, but rather by the contemporaneous response of markets to transition risk signals.

By contrast, the PRI coefficient is economically small ($+0.005$) and entirely insignificant ($p = 0.957$). This asymmetry between transition and physical risk is one of the central findings of this dissertation, and it is consistent with the prior literature. Hong et al. (2019) and Pankratz et al. (2023) both document that physical climate risk is systematically underpriced in equity markets. Physical risk unfolds gradually and is

harder to attribute to any specific month's market movement, which may explain why the contemporaneous monthly PRI does not register in equity prices.

5.2 Bond Market OLS (Analysis 2)

Table 5.2 presents the OLS results for the bond market regression, where the dependent variable is the month-on-month change in the US 10-year Treasury yield in basis points.

Variable	Coefficient	Std Error	t-Statistic	p-Value
Intercept	+5.654	3.160	+1.789	0.078 *
TRI	+280.872	150.750	+1.863	0.066 *
PRI	+28.375	148.394	+0.191	0.848
R-squared	0.0653			
N	81			

Table 5.2: OLS results for US 10Y bond yield changes. Dependent variable: monthly yield change (bps). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The TRI coefficient is positive and significant at the 10% level ($\beta = +280.9$ bps, $p = 0.066$). This means that in months when the Transition Risk Index is elevated, the US 10-year yield tends to rise. There are two plausible interpretations. The first is that investors interpret higher transition risk as signalling future policy-driven cost pressures that may be inflationary, causing them to demand a higher yield. The second is that transition risk events trigger a risk-off rotation that temporarily pushes yields up as investors rebalance portfolios. Again, the PRI coefficient is insignificant ($p = 0.848$), reinforcing the pattern seen in the equity regressions and aligning with Monasterolo and de Angelis (2020), who found that transition risk events, rather than physical risk, drive observable repricing.

5.3 Rolling Regression Results (Analysis 3)

The 24-month rolling OLS yields 58 estimates of the TRI sensitivity of the equal-weighted G7 average equity return. Table 5.3 summarises the rolling TRI coefficient by sub-period.

Sub-Period	Mean TRI Beta	Min TRI Beta	Max TRI Beta
------------	---------------	--------------	--------------

Pre-COVID (through Dec 2019)	−0.562	−0.784	−0.407
COVID Era (2020–2021)	−0.448	−0.987	+0.130
Russia-Ukraine (2022)	−0.071	−0.289	+0.163
Post-conflict (2023–2025)	−0.610	−0.969	−0.190

Table 5.3: Rolling 24-month TRI coefficient (G7 average equity return) by sub-period.

The TRI sensitivity is negative and relatively stable in the pre-COVID period. During the COVID era, the coefficient becomes highly volatile, ranging from nearly -1.0 to slightly positive, reflecting that COVID-19 temporarily displaced climate risk from the top of the market's attention. The Russia-Ukraine period shows the weakest sensitivity, closest to zero, which is intuitive: the conflict caused energy prices to spike and triggered a reassessment of energy security, temporarily overshadowing the long-term transition narrative and in some cases making fossil fuel producers look more attractive in the short term. The post-conflict period sees sensitivity return to strongly negative levels (mean -0.610), suggesting that once the immediate geopolitical shock receded, markets resumed pricing transition risk into equity returns. This pattern is consistent with Lorente et al. (2023).

5.4 Country-Level Results (Analysis 4)

Table 5.4 presents the TRI and PRI coefficients from individual country OLS regressions. All seven countries show negative TRI coefficients, but the magnitude and statistical significance vary considerably.

Country (Index)	TRI Beta	TRI p-val	PRI Beta	PRI p-val	R-sq
UK (FTSE 100)	−0.248	0.155	+0.042	0.809	0.030
USA (Dow Jones)	−0.234	0.308	+0.047	0.833	0.015
Japan (Nikkei 225)	−0.179	0.463	−0.044	0.852	0.013
France (CAC 40)	−0.367	0.088 *	+0.059	0.784	0.041
Germany (DAX)	−0.331	0.193	−0.064	0.795	0.037
Canada (S&P/TSX)	−0.220	0.257	+0.063	0.741	0.017
Italy (Italy 40)	−0.581	0.038 **	−0.017	0.950	0.076

Table 5.4: Individual country OLS results. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Italy stands out with the largest TRI coefficient (-0.581 , significant at 5%) and the highest R-squared of any individual country (7.6%). France is significant at the 10% level (-0.367 , $p = 0.088$). The remaining five countries all show negative TRI coefficients, but none is individually significant at conventional levels, likely due to the limited number of observations per country (81 monthly observations). Italy's stronger sensitivity may reflect the greater exposure of its equity market to sectors directly affected by EU climate regulation, as well as its dependence on imported fossil fuels. These differences are consistent with the sector-specific findings of Bauri et al. (2025).

5.5 Portfolio Climate VaR (Analysis 5)

Table 5.5 reports the portfolio-level VaR and CVaR for the equal-weighted G7 portfolio across different climate risk scenarios.

Scenario	N	Mean Return (%)	VaR 5% (%)	CVaR 5% (%)	Sharpe
All periods	81	+0.577	5.976	7.011	0.595
TRI Low (Q1)	20	+1.509	6.320	6.320	1.337
TRI High (Q4)	20	+0.186	7.077	7.077	0.202
PRI Low (Q1)	20	+1.229	8.674	8.674	1.072
PRI High (Q4)	20	+0.719	2.993	2.993	0.980
Both TRI and PRI High	~6	+0.429	2.812	2.812	0.807
COVID Era	18	+1.122	4.892	4.892	1.201
Russia-Ukraine	9	-1.711	8.674	8.674	-1.180

Table 5.5: Portfolio Climate VaR results. Equal-weighted G7 portfolio. Historical simulation at 5% confidence level.

Two findings stand out. First, the mean monthly portfolio return is considerably lower during periods of high TRI ($+0.186\%$) than during periods of low TRI ($+1.509\%$), a difference of over 130 basis points per month. At the same time, the 5% VaR is higher in TRI-high periods (7.1% versus 6.3%), indicating greater downside risk. The combination of lower average returns and higher tail risk during elevated transition risk periods supports the interpretation that the TRI effect reflects a genuine repricing of climate risk, not merely a statistical artefact.

Second, the Russia-Ukraine sub-period is the only scenario in which the portfolio generates a negative mean return (−1.711%), with the highest VaR of any scenario (8.674%). This confirms that 2022 was the most damaging year in the sample for the G7 equity portfolio, driven primarily by the energy price shock and associated inflation. This is an important nuance: climate risk is one driver of portfolio tail risk, but other macro factors can dominate in specific episodes.

5.6 Bond-Equity Correlation Under Climate Stress (Analysis 6)

The 24-month rolling bond-equity correlation shows striking variation across sub-periods, as summarised in Table 5.6.

Sub-Period	Mean Rolling Corr.	Std Dev	Min	Max
Pre-COVID	+0.243	0.081	+0.080	+0.328
COVID Era	+0.342	0.077	+0.194	+0.458
Russia-Ukraine	−0.075	0.302	−0.424	+0.413
Post-conflict	−0.542	0.111	−0.699	−0.375

Table 5.6: 24-month rolling correlation between G7 average equity return and US 10Y yield change, by sub-period.

The positive correlation in the pre-COVID and COVID periods indicates that during these years, rising equity markets coincided with rising yields, which would have reduced the diversification benefit of holding both asset classes. The strongly negative correlation in the post-conflict period (−0.542) reflects the restoration of the traditional flight-to-quality relationship: as inflationary pressures eased and geopolitical risk receded, bonds and equities began moving in opposite directions again. The t-test comparing rolling correlation in TRI-high versus TRI-low periods does not produce a significant result ($p = 0.510$), suggesting that the bond-equity relationship is more strongly influenced by the broader macroeconomic regime than by transition risk specifically. This is itself an important finding: transition risk affects the level of equity returns and bond yields individually, but does not appear to systematically alter the correlation structure between the two asset classes at the monthly frequency examined here.

CHAPTER 6

CONCLUSION

This dissertation set out to examine how climate risk, decomposed into transition risk (TRI) and physical risk (PRI), is priced across G7 equity markets and the US bond market over the period February 2016 to May 2025. Using six empirical analyses grounded in panel OLS, time-series OLS, rolling regressions, portfolio Climate VaR, and bond-equity correlation dynamics, three main conclusions emerge.

First, transition risk is consistently and significantly priced in G7 equity markets. The TRI coefficient is negative and significant at the 1% level in both pooled OLS and fixed-effects specifications ($\beta = -0.312$, $p < 0.001$), a finding that is robust across model specifications. This suggests that investors in developed equity markets respond to elevated transition risk by reducing equity valuations, consistent with the repricing dynamics documented by Monasterolo and de Angelis (2020) following the Paris Agreement. The country-level analysis reveals that Italy and France are the most sensitive G7 markets to transition risk, while Japan and the United States show the weakest individual-country effects.

Second, physical risk is not significantly priced in either equity or bond markets at monthly frequency. Across every regression specification in this study, the PRI coefficient is economically small and statistically indistinguishable from zero. This does not mean physical risk is unimportant; it means its effects operate on longer horizons than a single month's return can capture. This finding reinforces the market inefficiency hypothesis of Hong et al. (2019) and Pankratz et al. (2023): physical climate risk is systematically underweighted in market pricing, at least at the frequency and level of aggregation used here.

Third, the sensitivity of G7 equity markets to transition risk is not stable over time. The rolling regressions reveal that TRI sensitivity was relatively stable before COVID, highly volatile during the pandemic, weakened significantly during the Russia-Ukraine conflict period, and then returned to strongly negative levels in the post-conflict period. This time-varying pattern is consistent with the broader argument in Lorente et al. (2023) that climate-financial connectedness is sensitive to the geopolitical and macroeconomic environment.

6.1 Limitations

Several limitations should be acknowledged. **First**, the TRI and PRI data cover only 82 monthly observations with irregular coverage, which limits the power of sub-period analyses and means the Russia-Ukraine period (only 9 observations) is too short for its own reliable regression. **Second**, this study is limited to developed G7 markets, and the findings may not extend to emerging markets, where institutional environments and climate risk exposures differ significantly. **Third**, the use of aggregate market

indices rather than individual stocks or sectors means that sector-level heterogeneity in climate risk sensitivity is averaged away. **Fourth**, OLS assumes a linear relationship between climate risk and returns; non-linear specifications might reveal additional dynamics, particularly around extreme TRI or PRI observations.

6.2 Directions for Future Research

Several avenues for future work follow from this study. The most direct extension would be to use sector-level equity data rather than market indices, allowing the TRI and PRI effects to be compared across energy, financials, industrials, and technology sectors within each G7 country. A second extension would be to apply the same framework to emerging market equity indices, testing whether physical risk, insignificant in G7 markets, is more meaningfully priced in more climate-vulnerable economies, as the work of Jan et al. (2026) suggests.

Climate risk is no longer a peripheral concern for financial markets. The results of this dissertation show that transition risk is already embedded in equity market pricing across the G7, that it is also reflected in bond yield movements, and that its market impact shifts meaningfully in response to major global events. Physical risk, by contrast, remains largely invisible to markets at monthly frequency, a gap that represents both a potential source of mispricing and an opportunity for more forward looking climate risk integration.

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