Climate Risks and Green Stocks in Vietnam

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Abstract[3]

Purpose

Vietnam is among the countries most vulnerable to tropical cyclone risks, and its carbon-intensive production model influences its climate change trajectory. Nevertheless, various initiatives have been undertaken to tap into the country's green economy potential, and I advance the related literature by exploring the connection between climate risks and green assets in Vietnam.

Design/methodology/approach

Firstly, by employing the predictive models, I examine the predictive power of climate risks for the returns of green (green) assets in Vietnam between 2010 and 2023 using monthly data. Secondly, to address endogeneity and heteroscedasticity, I employ the feasible quasi-generalized least squares estimator, evaluating both in-sample and out-of-sample connections between climate risks and green assets in Vietnam.

Findings

My findings include the following: (1) Green stocks in Vietnam do effectively hedge against climate risk in recent samples that coincide with commitments to international climate agreements, suggesting the importance of data frames and the government's commitment to modelling climatic outcomes. (2) Classification of assets based on the Vietnam Sustainability Index (VNSI) provides more theoretically compelling results, highlighting the need for robust measures of sustainability. (3) Controlling for key fundamentals, such as oil prices and exchange rate fluctuations, is essential to avoid model misspecification and potential overestimation of climate risk effects on green investment returns. (4) My findings show that incorporating climate risk into the predictive model for green asset returns significantly enhances forecast accuracy of the asset returns compared to benchmark models, such as the historical average and random walk, which overlook this risk factor.

Originality/value

I provide two major contributions to the literature. (1) I investigate the predictive power of climate risks for the returns of green (green) assets in Vietnam. (2) I conduct both the in-sample and out-of-sample predictability of the connections, as significant in-sample predictability outcomes do not necessarily translate into improved out-of-sample forecasts.

Keywords: Climate risks, Green asset returns, Hedging, Forecast evaluation

JEL Codes: C53; G11; Q54

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1. Introduction

The social and economic losses caused by climate-related changes are increasing at an alarming rate. Specifically, the global economic losses were estimated at 232 billion dollars and have continued to rise steadily since (see Aon, 2020). In particular, the depth of Vietnam's vulnerability to climate-related losses, as recently evidenced across various regions, has rekindled the urgency for mitigation strategies, including increased investment in green assets. Vietnam has a longstanding history of dealing with natural disasters, many of which are driven by climate change (Chaudhry & Ruysschaert, 2008; Huynh, 2024). To put this into context, Vietnam ranks among the countries most exposed to tropical cyclone risks due to its 3,444-kilometre coastline, its tropical location along the Eastern Sea, and an economy heavily reliant on agriculture, especially in the vulnerable Mekong and Red River Delta regions (Rana *et al*., 2022). The implementation of various mitigation strategies, including physical and financial adaptation mechanisms (see Lindegaard, 2020; Rana *et al*., 2022), highlights the country's vulnerability to climate-related risks.

Despite its potential for a green economy (see Ngoc & Anh, 2016), the influence of Vietnam's carbon-intensive economic model plays a significant role in shaping its climate change trajectory. The country's development remains anchored on a 'brown growth' pattern – marked by heavy reliance on raw material extraction, excessive consumption of fossil fuels and natural resources, and escalating environmental degradation. Indeed, the economy is largely dominated by unsustainable, energy-intensive industries centred on raw-material processing, starkly contrasting with green and low-emission technologies (Ngoc & Anh, 2016; Miraz & Soo, 2024). As such, policies such as environmental sanctions and stakeholder pressure in Vietnam (see Malesky & Nguyen, 2024) are expected to encourage compliance among high-emission companies. In reaction, many businesses are making significant investments in the green sector (International Finance Corporation, 2024). This is expected to impact all facets of the industry in Vietnam due to rapid industrialization, which is highly dependent on materials and energy (Economic Research Institute for ASEAN and East Asia, 2023; World Bank, 2024). On a broader note, regional efforts to mitigate climate change and improve firm sustainability by strengthening attention to the environmental, social, and governance (ESG) framework remain limited, despite its favourable impact on firms' returns (Handoyo & Anas, 2024; Le, 2024). This has revived the importance of market frictions in sustainable finance and how external climate policies, such as the US climate policy uncertainty, shape financial flows, green investment, and stock performance in emerging economies like Vietnam (Hong et al., 2024).

Akin to the above, this study uses a predictability approach to investigate the nexus between climate risks and returns on green stocks. The motivation stems from examining whether higher returns on these assets in the context of climate risk could attract investors to the green market and, in turn, support the broader transition from a brown to a green economy.

Strands of literature have shown that climate risks disrupt market activities, trigger market volatility and lower asset returns (Adediran *et al*., 2024; Salisu *et al*., 2023). This has led to the attractiveness of green assets as a hedge against risks relative to conventional stocks (see Tumala *et al*., 2023; Nguyen *et al*., 2025; Penzin *et al*., 2025). In the context of the Vietnamese economy, prior studies have only explored the effect of climate risks on sectoral stocks (see Thai *et al*., 2024); pieces of evidence are still required on the hedging properties of precious metals, exchange-traded, more importantly, green assets, which is the motivation of the current study. Thus, this study contributes to this strand of literature by evaluating the hedging ability of green assets in Vietnam against climate-related risks. In addition, the study examines the out-of-sample predictive power of climate policy uncertainty relative to the benchmark model (including a random walk and a historical average) that excludes this uncertainty measure. Furthermore, to avoid overstating the relationship between climate risk and green stocks due to potential model misspecification, the study controls for oil prices and exchange rates. Prior studies have shown that these variables play a critical role in enhancing the forecasting performance of key macroeconomic fundamentals, such as inflation (see, for example, Tule *et al*., 2020), as well as asset returns (see Adekunle *et al*., 2020). This study extends this literature strand to include emerging risks, such as climate-related threats.

Theoretically, the Capital Asset Pricing Model (CAPM) remains a foundational framework among various asset-pricing models used by investors to assess the profitability of investment in an asset. Introduced by Sharpe (1964) and Lintner (1975), the CAPM provides a method for constructing portfolios that aim to maximize expected returns while minimizing risk. The model distinguishes between systematic and unsystematic risk: systematic risk is market-wide and can only be mitigated, while unsystematic risk (such as climate risk) is asset-specific and can be managed through strategies such as hedging and portfolio diversification. Empirical notes on ESG-augmented capital asset pricing model also posit that climate risks, transition uncertainties, and sustainability preferences favour returns on green assets, given investors' concern for environmental and social outcomes (Pástor et al., 2021). Given this, I propose a predictive model to forecast the returns of green assets in Vietnam. To assess the broader impact of the green transition, I also conduct a comparative analysis using conventional asset returns.

As a prelude to my analysis, the main findings reveal that green stocks are effective in hedging climate risk in Vietnam in recent times however a long range of data may suggest other wise, indicating that the Vietnamese government's transition strategy in recent times is yielding positive results, as investors and businesses continue to view these assets as viable investment options compared to the conventional ones in recent times. Also, asset classification based on the Vietnam Sustainability Index (NVSI) yields results that are more theoretically compelling, highlighting the need for robust sustainability measures that accurately capture both private and public commitments towards a sustainable future in Vietnam.

Following this introduction, the remainder of the study is structured as follows: Section 2 presents stylized facts and summary statistics for relevant variables. Section 3 outlines the methodological approach that underpins my analyses. In Section 4, the study's findings are offered and discussed, while Section 5 concludes the study.

2. Stylized facts and preliminary results

2.1 Some stylized facts

Vietnam is one of the countries most vulnerable to the adverse effects of climate change (Chaudhry & Ruysschaert, 2008), with impacts evident across markets and human settlements (Lindegaard, 2020; Malesky & Nguyen, 2024). In response, the government has implemented a range of policy measures, including planned relocation, penalties for environmental violators, and green policy initiatives (Nogoc & Anh, 2016; Lindegaard, 2020; IFC, 2024; Quang *et al.*, 2025). Nevertheless, persistent developmental challenges remain an albatross (Economic Research Institute for ASEAN and East Asia, 2023). Monthly data from multiple sources on climate change indicators, Vietnam's stock and foreign exchange markets, and the oil market also lend credence to this literature (see Figures 1 – 6). In particular, Vietnam's stock markets, encompassing both green and conventional assets, have been vulnerable to various shocks, including climate-related risks, the COVID-19 pandemic, oil price volatility, and foreign exchange fluctuations. These conclusions are based on monthly data covering green and conventional assets within the country. The data scope for the study, as defined by the green asset prices, ranges from 2010-2023.

More specifically, I adopt a list of sustainable firms in Vietnam as provided by the Vietnam Chamber of Commerce and Industry (VCCI)[4]. Following that, I curate a list of sustainability-oriented or green stocks listed on the Ho Chi Minh City Stock Exchange (HOSE) or the Hanoi Stock Exchange (HSE). The stock price data for 26 firms that meet the VCCI criteria are thereafter aggregated. For conventional firms, I selected 30 listed firms that did not make the VCCI's list of sustainable firms, choosing 15 firms each from the top-lose[5] and the top-gainer categories to ensure a balanced representation. The data for these firms were subsequently aggregated. A list of both green and conventional firms is provided in the supplementary Tables 1 and 2, respectively. All stock price data were sourced from Investing.com. On the other hand, I examine two classes of climate risks: one related to policy and transition, and the other to physical risks. For each class, I adopt two proxies. The first proxy for climate risk relating to policy and transition is the monthly US climate policy uncertainty (CPU) by Gavriilidis (2021)[6]. While the other is the global transition risk index (TRI), both measures use a text-based approach that relies on a specific "climate risk vocabulary" designed to capture terms associated with policy and transition risk. A positive CPU or TRI value signify heightened policy and transition concerns.

To gain further insights into the nexus, I use the mean monthly variation in air temperature as a proxy for natural climate risk. I further include rainfall volume for additional analyses and robustness. These measures are sourced from the Vietnam General Statistics Office (GSO). The analysis also explores the role of oil prices and exchange rate dynamics in the nexus, with data

[4] Please see https://vbcsd.vn/en/ for extensive information.
[5] Top losers and gainers as of 25th March, 2025; it is critical to note that this categorization can be unstable; my approach is mainly to ensure that high- and low-performing firms are well represented.
[6] See https://www.policyuncertainty.com/climate_uncertainty.html

sourced from the US Energy Administration Information[7] and investing.com, respectively. The data are used to evaluate the nature of the green economic transition in Vietnam.

I provide a graph of both green and conventional stocks in Figure 1. The green stocks outperformed conventional stocks between mid-2010 and 2020, trading at higher prices but with noticeable breaks and recoveries during the sampled period. The highest difference between the stocks was recorded between 2015 and 2019. Interestingly, both stocks reached their highest levels during the COVID-19 period (2020-2022), suggesting their resilience to the pandemic. While both stocks fell during the pandemic (2020), green stocks experienced a milder crash and bounced back more strongly (see trend for 2023). Overall, Vietnamese stock values improved over the sampled period, while green assets performed better, suggesting they offered greater resilience to economic shocks and perhaps to climate risks.

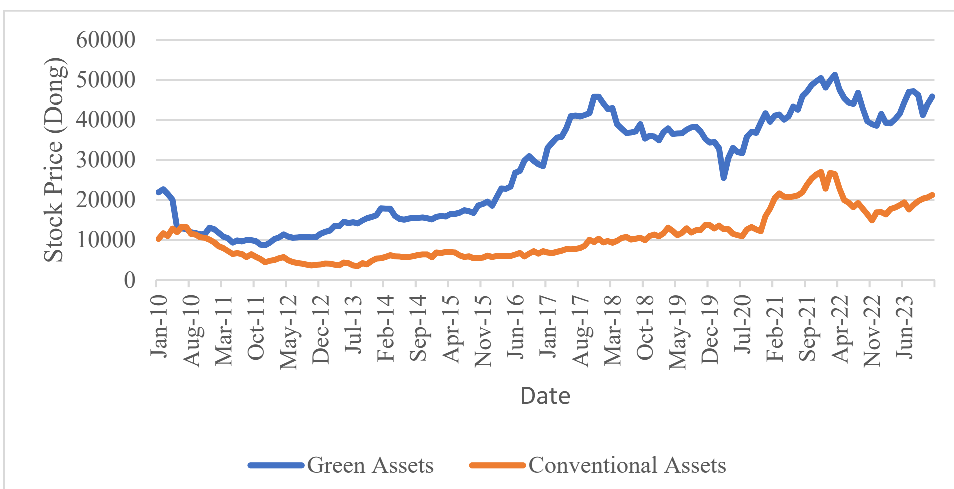
The relationship between stocks and climate policy uncertainty (CPU) is illustrated in Figure 2. Amid heightened CPU, green assets are more susceptible to climate risks compared to conventional assets. There are numerous instances where increased climate uncertainty leads to a decline in green asset returns, while conventional asset returns remain relatively stable. In addition to the CPU, I also examine the behaviour of climate transition risks relative to both stocks. Figure 3 shows that climate transition has received significant attention in the global policy space, given its unstable pattern over the sampled period. In line with the CPU, I also note that green stocks achieved better growth under TRI variability than conventional stocks in two distinct phases (Oct 2016 - Oct 2019, Jul. 2020 - Jan. 2022). However, higher climate transition risks can also negatively impact the growth of green stocks (see Jan. 2010- Oct. 2010 and Jul. 2014), suggesting that the impact of TRI on stock performance is mixed.

Figure 4 provides more intriguing perspectives on the behaviour of stock returns in relation to global oil returns. Prior to the 2014 oil price shock, green and oil returns were negatively correlated, suggesting potential diversification benefits between the two asset classes. However, this negative co-movement ceased following the shock, only becoming noticeable again in 2023 and beyond. Throughout these observations, the relative stability of conventional stock returns is consistently

[7] www.eia.gov/international/data

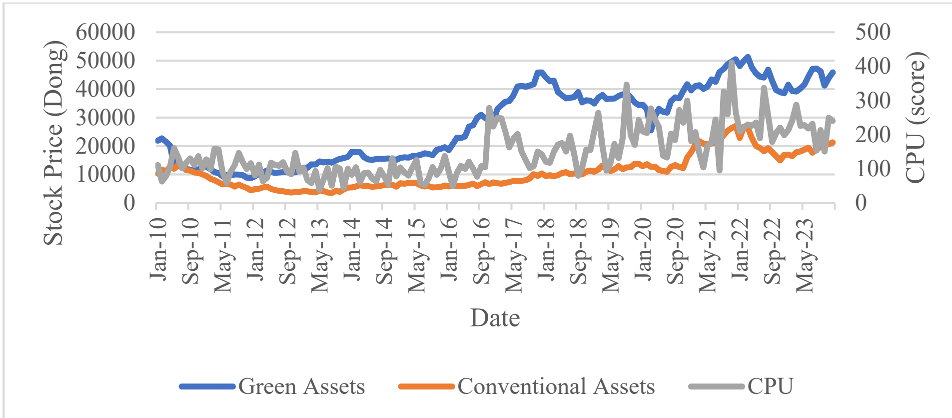
evident. In other words, while green stock returns fluctuate in response to climate uncertainty and oil price changes, conventional stock returns remain comparatively steady (see Figures 2, 3 and 4). A similar pattern is observed when temperature and rainfall variations are considered (see Figures 6 and 7). Expectedly, the temperature and rainfall patterns exhibit significant changes, with large positive values indicating a noticeable rise in climate over the years. Therefore, efforts to transition to a green economy have not yielded the intended results, as brown investments seem more attractive to investors than green alternatives. This could be attributed to various barriers, including access to green financing and inadequate infrastructure for renewable energy (see Quang *et al*., 2025). Furthermore, Figure 5 shows the behaviour of green and conventional assets to the exchange rate. Periods of higher exchange rates (implying rising depreciation) (e.g., 2022) correspond with lower asset prices, suggesting possible negative correlations. However, over time, the variables tend to co-move, suggesting possible hedging possibilities between the two asset classes (stocks and foreign exchange). Notwithstanding all these observations, no meaningful conclusion can be inferred from these without proper empirical analysis. This is done elaborately in Section 4 of the paper.

Figure 1: Green and Conventional Assets in Vietnam (2010-2023)



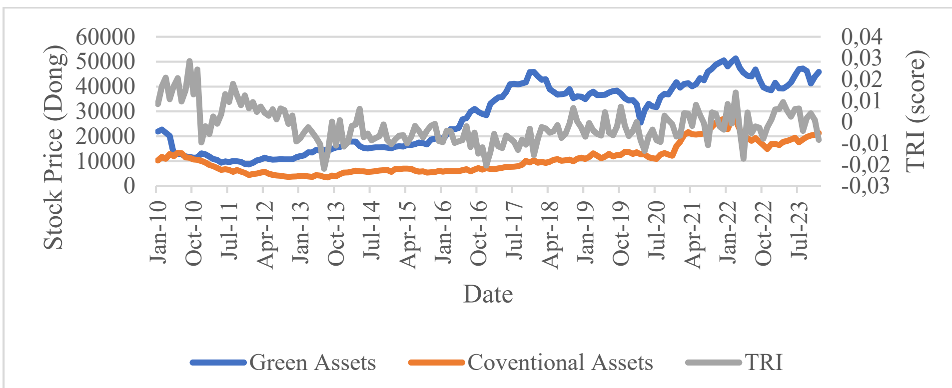
Source: Author's own work

Figure 2: Green and Conventional Assets in Vietnam, and US Climate Policy Uncertainty (CPU) (2010-2023)



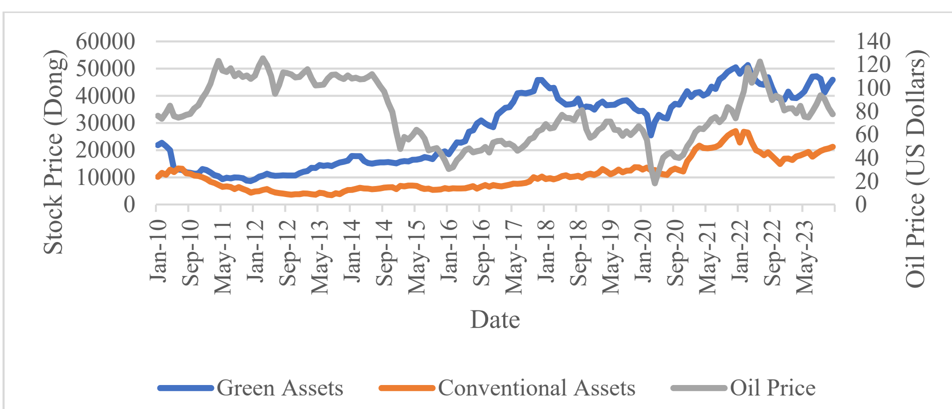
Source: Author's own work

Figure 3: Green and Conventional Assets in Vietnam, and Transition Risk Index (TRI) (2010-2023).



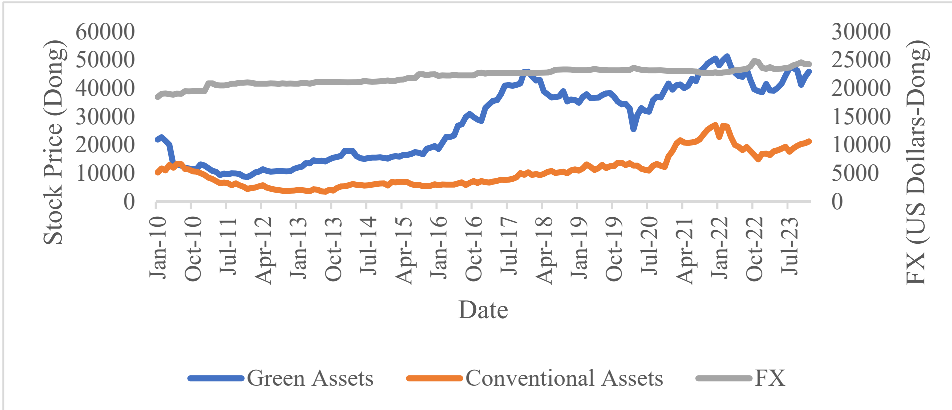
Source: Author's own work

Figure 4: Green and Conventional Assets in Vietnam, and Global Oil Prices (2010-2023)



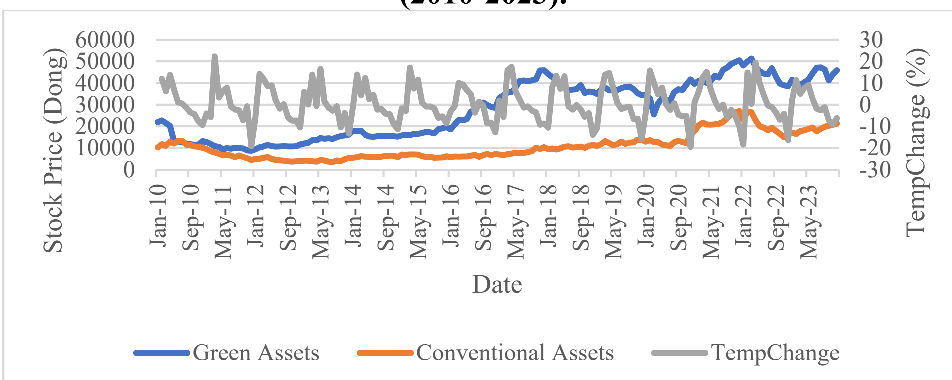
Source: Author's own work

Figure 5: Green and Conventional Assets in Vietnam, and Exchange Rate (2010-2023)



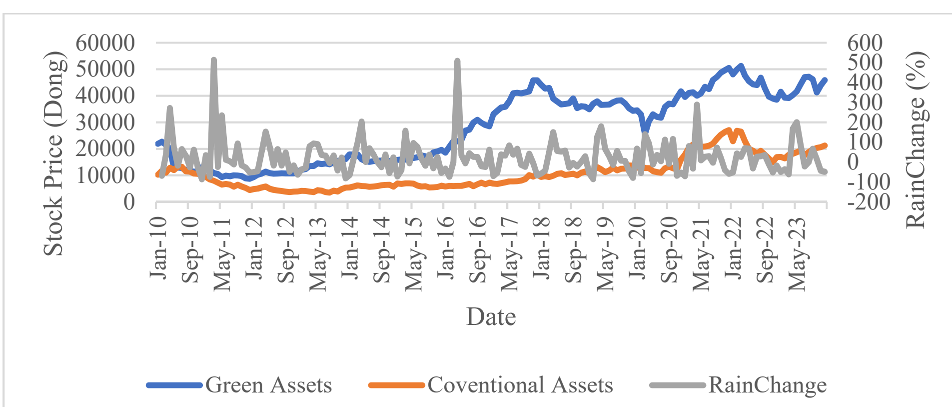
Source: Author's own work

Figure 6: Green and Conventional Assets in Vietnam, and (Temperature fluctuations) (2010-2023).



Source: Author's own work

Figure 7: Green and Conventional Assets in Vietnam, and Rainfall fluctuations (2010-2023).



Source: Author's own work

2.2 Some Preliminary Results

Further to the salient facts illustrated above, the statistical properties of the data used for this study are examined. This is done for proper guidance on the choice of methodological approach. These preliminary results are contained in Table 1. Comparing the returns of green and conventional (brown[8]) stock returns, the result in Table 1 shows that on average, brown assets yield a slightly higher return than their green counterparts. However, the latter is less volatile than the former, as measured by the coefficient of variation or the standard deviation. A comparison of their risk-adjusted returns indicates that the green assets offer significantly higher returns than the brown assets.

Table 1: Preliminary analyses

Panel A: Sum Stat and residual-based test

Statistics/Variables	**Green return**	**Brown return**	**CPU**	**temperature change**
Mean	0.6483	0.7608	149.0694	0.3895
Std. Dev.	6.2346	8.1927	70.3775	8.2300
CoV	961.6222	1076.8598	47.2112	2113.0371
Risk-adjusted return	0.001	0.0009	-	-
Observations	167	167	167	167

Panel B: Heteroscedasticity and Serial Correlation Tests

Hetero	**arch=5**	3.1861^{a}	1.6913	2.0876^{c}	2.8414^{b}
	arch=10	2.3936^{b}	1.0969	2.1385^{b}	2.4194^{b}
	arch=20	1.3850	1.1978	1.4297	2.0285^{b}
Auto	**Q=5**	1.9111	2.0295	290.67^{a}	23.1080^{a}
	Q=10	9.5923	9.3270	528.55^{a}	44.4360^{a}
	Q=20	10.6700	20.4470	892.01^{a}	155.7300^{a}

Panel C: Persistence and Endogeneity tests

	Endogeneity test		**Persistence test**	
	Green	**Brown**	**CPU**	**Temp change**
CPU	-0.0000^{c}	0.0000	0.0055^{a}	0.4420^{a}
Temp change	0.0242	0.1166		

Source: Author's own work

Note: 'CoV' is the coefficient of variation computed as the ratio of standard deviation (Std. Dev.) as a percentage of the mean. 'Hetero' stands for heteroscedasticity, and 'Auto' means autocorrelation. The ARCH-LM test is used to test for heteroscedasticity, and the associated F-statistic is reported. On the other hand, the Ljung-Box test Q-statistic is used to assess autocorrelation. To ensure robustness, three lag lengths (k = 5, 10, and 20) are used. The null hypothesis for the ARCH-LM test is that there is no conditional heteroscedasticity, while the null hypothesis for the autocorrelation test is that there is no serial correlation. Also, the null hypotheses for the endogeneity and persistence tests indicate that there is no evidence of endogeneity bias and persistence effect. Superscripts "a" and "b" indicate rejection of these null hypotheses at the 1 per cent and 5 per cent significance levels, respectively. The sample covers 2010M01-2023M12.

[8] The firms categorized as conventional assets primarily have high carbon emissions; therefore, the analysis section frequently uses the term "brown assets" synonymously with "conventional assets."

In addition, the hypotheses of no serial correlation, no conditional heteroscedasticity, and no endogeneity and persistence biases are also tested. These tests are essential for informed methodology choice. The results, as shown in Panels B and C of Table 1, reveal heteroscedasticity, serial correlation, and endogeneity biases in both green stock returns and climate risk proxies, as well as a persistence bias specifically in the climate risk measures. These biases necessitate the choice of a feasible quasi-generalized least squares technique, which is well known for addressing them. The biases are also presented in additional proxies, such as rainfall volume and the transition risk index (TRI) (see supplementary Table 3).

3. Methodology

There is no doubt that the growing havoc of climate change has prompted calls to adopt clean energy technologies and implement various policy measures to mitigate its effects. These developments can significantly influence investors' decisions to allocate capital to climate-friendly assets, such as green stocks. In this context, and based on the Capital Asset Pricing Model (CAPM), which provides a framework for constructing portfolios that maximize expected returns while minimizing risk (climate-related risks in this case), this study aims to empirically investigate the relationship between climate-related risk and investment in green assets in Vietnam. To achieve this, I specify a bivariate predictive model for the response of green asset returns to the measure of climate risks, temperature anomaly and CPU, as thus:

$$Ret_t = \alpha + \psi Ret_{t-1} + \beta ClimR_{t-1} + \gamma (ClimR_t - \rho ClimR_{t-1}) + \varepsilon_t \qquad (1)$$

In the above equation, Ret_t and Ret_{t-1} denote, respectively, the return on green investment and its first lag[9], while α is the intercept. $ClimR$, on the other hand, represents the measure of climate

[9] It is based on the intuition behind the Asynchronous Trading that stocks are not traded simultaneously; a lag in the price discovery process can emerge, leading to apparent correlation between a stock's current return and a lagged return from a related index or stock. Notwithstanding, I also find statistical evidence for the first lag of the dependent variable, as it is significant in all specifications in which it appears. These results, however, are suppressed for brevity, since the focus is on the climate risk factors. In addition, this form of predictability extends the forecast evaluation to the Random Walk as a benchmark in a nested form. This will enable the use of the same forecast measure for both the historical average and the random walk. In other words, if both the historical average and the random walk are nested within the proposed predictive model, I can employ the Clark and West (2007) method, which makes the forecast comparison between the proposed model and two benchmark models more realistic.

risk[10], and ε_t is a zero-mean idiosyncratic error term. The slope associated with the risk measure, β, indicates the response of green investment returns to climate risk and serves as a measure of the hedging potential of green assets. Accordingly, four possible responses are: no hedging, partial hedging, full hedging, and superlative hedging. The green assets provide no hedging potential if $\beta < 0$; weak hedging if $\beta = 0$; partial hedging if $0 < \beta < 1$; and full and superlative hedging if $\beta = 1$ and $\beta > 1$ (see Salisu *et al*., 2020). Nonetheless, with the exception of weak hedging, these outcomes are only evident if the associated coefficients are significant, at least at the 10% level.

To mitigate potential biases that could compromise my findings (see Table 1), I implement several corrections. Specifically, endogeneity – arising from the correlation between the predictor and the error term – is addressed by including the term $\gamma(ClimR_t - \rho ClimR_{t-1})$, where ρ adjusts for persistence bias (see Lewellen, 2004) (see the technical details in the supplementary material (Supplementary B) on how this term is derived). In addition, the issue of conditional heteroscedasticity is resolved by pre-weighting the data using the inverse of the standard deviation of the residual term. The resulting equation is estimated using OLS (see the technical details of the weighting procedure in Westerlund & Narayan, 2012, 2015), and the resulting estimator is technically described as the feasible quasi-generalized least squares estimator, as introduced by Westerlund and Narayan (2012, 2015).

Furthermore, to guard against possible misspecification and/or overestimation of the climate risk effects on green investment returns, I account for the roles of oil prices and exchange rate dynamics. These two fundamentals are critical for modelling stock performance (see also Inci & Lee, 2014; Bahmani-Oskooee & Saha, 2015; Salisu & Isah, 2017). Thus, Equation (1) is re-specified as:

$$\begin{aligned} Ret_t = \alpha + \psi Ret_{t-1} + \beta ClimR_{t-1} + \gamma(ClimR_t - \rho ClimR_{t-1}) \\ + \vartheta CV_{t-1} + \sigma(CV_t - \rho CV_{t-1}) + \varepsilon_t \end{aligned} \tag{2}$$

[10] I use climate policy uncertainty (CPU), temperature change, the Global Transition Risk Index (TRI), and rainfall and rainfall change as climate risk measures. The CPU, TRI, and rainfall are expressed in natural logarithms, while temperature change and rainfall are expressed as first differences.

where CV_t denotes the control variable(s) (i.e., oil price and Vietnamese Dong – US Dollar exchange rate dynamics, both of which are expressed in natural logarithms). For completeness and to allow comparison with green stock returns, I also conduct a separate analysis of the predictability of climate risks for conventional (brown) stock returns.

Finally, I evaluate the forecasting performance of the predictive models by comparing them to benchmark models –specifically, the historical average and random walk models. To achieve this, I employ both the Root Mean Square Error (RMSE) and the Clark & West (2007) test. A lower RMSE relative to the benchmark indicates superior performance of the predictive model, while a positive and statistically significant Clark & West (2007) test statistic supports the predictive model's dominance over the benchmark. For emphasis, the hypothesis of a zero coefficient will be rejected if the t-statistic exceeds +1.282 for 0.10; +1.645 for 0.05; or +2.00 for 0.01, all for a one-sided test (see Clark & West, 2007). There is no universally accepted method for splitting data for forecast evaluation, as different researchers and forecasters have adopted different splits. However, I prefer a 90:10 split between in-sample and out-of-sample data, as the data span January 2010 to December 2024, which leaves very limited options for robust analyses. Therefore, the forecast split provides sufficient observations for in-sample predictability, yielding robust estimates for out-of-sample forecasts. The out-of-sample forecast evaluation is conducted across multiple forecast horizons, including 3, 6, and 12 months ahead. This is also required to robustly evaluate out-of-sample forecasts.

4. Results and Discussion

This section presents and discusses the findings emanating from my empirical analyses. It is organized into several sub-sections. The first focuses on the main result: the hedging ability of green asset returns against climate risks. The analysis is then extended to consider the influence of key macroeconomic fundamentals, such as oil prices and exchange rates, which are known to shape financial markets. This extension helps to examine whether the impact of climate risk on green assets is overstated. Subsequently, I evaluate the forecast accuracy of the climate-based model vis-à-vis the benchmark models, including the historical average and the random walk. Additionally, I conduct a similar analysis for the conventional assets and finally, I consider several robustness checks to strengthen the quality of results.

4.1. Main findings: Climate risks and Green stock returns

As previously discussed, Vietnam is among the most vulnerable countries to the risks associated with climate change. This is due to its geographical characteristics, such as its proximity to the coastline and its tropical location along the Eastern Sea, as well as its heavy reliance on carbon-intensive energy sources for economic activities. In recent years, efforts have been intensified to unlock the country's green economic potential. With this information set, one would expect investors to be less inclined to allocate capital to carbon-intensive assets and instead to favour cleaner, greener alternatives when making investment decisions. If this is true, increased demand for green investments would drive up their prices and, consequently, their returns. I therefore hypothesize a positive relationship between climate risk and green asset returns. In other words, green assets may serve as a hedge against heightened climate-related risks. But does this also hold for Vietnam?

Contrary to this hypothesis, I find a negative, statistically insignificant relationship between CPU and green asset returns in Vietnam. However, TRI significantly and negatively impacts green asset returns, indicating a lack of hedging potential of the green assets (see Table 2 and supplementary Table 6). Measures of physical risks, such as changes in temperature and rainfall, also provide credence to this relationship. My results contrast with several established findings in the literature (for example, Adediran *et al*., 2024; Salisu *et al*., 2025; Tanveer *et al*., 2025). This contrasting evidence may be due to differences in the scope of the samples. For instance, Salisu *et al*. (2025) explore the hedging potential of various energy-related financial innovations (a global analysis given the stride in climate risk mitigation) for climate risks and find that these assets offer protection against physical risk (such as natural disaster) and transition risk (US climate policy). My study only focuses on Vietnam, where sustainability efforts are still evolving (Biu & Vu, 2025). Also, alternative measures of climate transition risks, such as Vietnam's climate policy attention and ESG scores for ASEAN economies, positively impact overall firm performance, suggesting that national and regional climate change policies are favourable to business developments (Hong et al., 2024). However, firms in Vietnam remain vulnerable to natural climate shocks and global climate uncertainties due to a lagging national response and limited alignment with international ESG accountability standards, which hinder sustainable finance and renewable energy investments (Handoyo & Anas, 2024).

In addition, I incorporate oil prices as a control variable in my analysis to develop a more representative model in line with the asset pricing models. Empirical evidence on the influence of oil prices on stock market dynamics is mixed. A strand of this evidence, grounded in the cash-flow hypothesis, documents a negative relationship. It is opined that an increase in oil prices raises production costs, reduces output, and consequently lowers dividends/share to investors. On the other hand is the literature that views rising oil prices as an indicator of expansion, which, in turn, can lead to higher stock prices and returns (see Smyth & Narayan, 2018, for a detailed review). My results lend credence to the former view (see supplementary Table 4[11] as well as supplementary Table 8).

Building on these facts, I control for oil prices in my bivariate model of climate risks and green asset returns. These results, labelled as 'With control', are presented in Table 2 and supplementary Table 6. Two key findings are discernible from these results. One, the lack of hedging capabilities of green assets becomes more evident particularly for CPU. This outcome highlights the significance of controlling for oil prices when modelling the relationship between climate risks and green asset returns, particularly for Vietnam.

Table 2: Nexus between climate risks and green asset returns

Without control		**With control**	
CPU	**Temp change**	**CPU**	**Temp change**
-0.2523	-0.1205[a]	-0.7025[b]	-0.0990[a]
(0.2082)	(0.0158)	(0.2682)	(0.0133)
[-1.2120]	[-7.6009]	[-2.6190]	[-7.4487]
{-0.5988 0.0941}	{-0.1468 -0.0941}	{-0.2561 -1.2364}	{-0.1211 -0.0769}

Source: Author's own work

Note: The model without controls examines only the nexus between green asset returns and climate risks. On the other hand, the model with 'control' accounts for the role of oil price in the nexus. Two climate risk proxies are used, including climate policy uncertainty (CPU) and temperature anomaly (temp change). Superscripts 'a and 'b' indicate significance at $p < 0.01$ and $p < 0.05$, respectively, signifying rejection of the no predictability hypothesis. Standard errors are shown in parentheses ( ), while t-statistics are presented in square brackets [ ]. 90% confidence interval in {}. The sample covers 2010M01-2023M12.

Furthermore, this influence of oil prices suggests that Vietnam's green transition efforts are still evolving, as businesses rely heavily on carbon-intensive energy sources for production. This would be confirmed by conducting a distinct analysis for the conventional (brown) and climate risk nexus.

[11] The table reports the relationship between oil price and green (and brown) returns in both climate policy uncertainty (CPU) and temperature anomaly (temp change) models.

Before then, I conclude my green asset analysis by comparing the forecast accuracy of the two models (with and without control) for predicting green returns.

4.2. Forecast Analysis

The out-of-sample forecast performance of the predictive models (with and without controlling for oil prices) is evaluated against two benchmark models: the historical average and the random walk. These two benchmarks are used to assess robustness. While the historical average model forecasts green returns using only a constant term, the random walk model assumes an AR (1) process. In all, both benchmarks overlook the significance of climate risks in modelling or forecasting green asset returns.

Table 3 reports results for both model specifications (with and without control variables) using the climate-adjusted model (Model 1) and the benchmark model (Model 2). A model with lower RMSE is considered to have superior accuracy. Moreover, since determining the statistical significance of forecast errors in the RMSE test is not possible, the Clark & West (C-W) (2007) test is employed. In other words, the (C-W) formally assesses whether the observed differences in forecast errors are statistically meaningful. Thus, a positive, significant constant parameter in the C-W test indicates that the climate-adjusted model, which includes an adjusted mean squared error (MSE), significantly outperforms the benchmark model. Otherwise, the benchmark is considered superior.

Results presented in Table 3 show that the forecast performance of the models without control variables is sensitive to the specific measure of climate risk used. Nonetheless, consistent evidence emerges that the climate-adjusted model outperforms the benchmark once oil prices are included as a control. My findings are robust to additional measures of climate risks (see supplementary Tables 9 and 10). These findings highlight the importance of incorporating multiple proxies for climate risks and controlling for key fundamentals when modelling stock returns, green asset returns inclusive (see also Salisu & Isah, 2017; Adekunle *et al*., 2020; Salisu *et al*., 2025). I have visualized forecast performance by plotting actual values against fitted values for the alternative specifications (see supplementary Figures 1 and 2). My findings indicate a relatively close movement between the two, reinforcing the impact of climate risks on the return predictability of both asset classes.

Table 3: Out-of-Sample Forecast Evaluation

	Panel A: Without Control						Panel B: With Control					
	RMSE: Historical Average						RMSE: Historical Average					
	h=3		h=6		h=12		h=3		h=6		h=12	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
CPU	6.5779	6.5609	6.5351	6.5247	6.5265	6.5104	6.3459	6.5609	6.3191	6.5247	6.3289	6.5104
Temp change	6.4774	6.5609	6.4482	6.5247	6.4341	6.5104	6.2925	6.5609	6.2764	6.5247	6.2630	6.5104
	RMSE: Random Walk						RMSE: Random Walk					
	h=3		h=6		h=12		h=3		h=6		h=12	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
CPU	6.5779	6.5794	6.5351	6.5431	6.5265	6.5281	6.3459	6.5794	6.3191	6.5431	6.3289	6.5281
Temp change	6.4774	6.5794	6.4482	6.5431	6.4341	6.5281	6.2925	6.5794	6.2764	6.5431	6.2630	6.5281
	C-W: Historical Average			C-W: Random Walk			C-W: Historical Average			C-W: Random Walk		
		CPU	**Temp change**	**CPU**	**Temp change**			**CPU**	**Temp change**	**CPU**	**Temp change**	
	h=3	0.4921	2.9420^{a}	0.5522	3.0045^{a}		**h=3**	6.5027^{a}	7.5481^{a}	6.5497^{a}	7.5999^{a}	
		(0.6267)	(1.4144)	(0.6455)	(1.4158)			(2.0278)	(2.6900)	(2.0262)	(2.6837)	
		[0.7852]	[2.0800]	[0.8553]	[2.1222]			[3.2068]	[2.8060]	[3.2325]	[2.8319]	
	h=6	0.5717	2.8116^{a}	0.6346	2.8761^{a}		**h=6**	6.3074^{a}	7.2304^{a}	6.3565^{a}	7.2837^{a}	
		(0.6170)	(1.3904)	(0.6355)	(1.3917)			(1.9931)	(2.6464)	(1.9916)	(2.6402)	
		[0.9266]	[2.0221]	[0.9986]	[2.0667]			[3.1645]	[2.7321]	[3.1917]	[2.7588]	
	h=12	0.4840	2.7834^{a}	0.5460	2.8475^{a}		**h=12**	5.9195^{a}	7.0764^{a}	5.9659^{a}	7.1287^{a}	
		(0.6096)	(1.3495)	(0.6279)	(1.3512)			(1.9360)	(2.5521)	(1.9343)	(2.5460)	
		[0.7941]	[2.0625]	[0.8696]	[2.1074]			[3.0576]	[2.7728]	[3.0843]	[2.7999]	

Source: Author's own work

Note: The out-of-sample forecast evaluation results are presented for Root Mean Square Error (RMSE) and Clark and West (C-W). Model 1 and Model 2 for RMSE represent the climate-based and benchmark models, respectively, with the model with the lower RMSE preferred. Since C-W is a nested model, superscript 'a' against its values indicates the rejection of the equal forecast accuracy (between climate-based and benchmark model) hypothesis at the 1 per cent. Values in parentheses – ( ) – denote standard errors, while those reported in square brackets – [ ] – are t-statistics. For emphasis, the hypothesis of a zero coefficient will be rejected if the t-statistic exceeds +1.282 for 0.10; +1.645 for 0.05; or +2.00 for 0.01, all for a one-sided test (see Clark & West, 2007). The sample covers 2010M01-2023M12.

4.3 Comparing the green asset returns behaviour to the browns'

As I previously did for the green asset returns without control variables, I also examine whether modelling conventional assets vis-à-vis climate risk alone is enough. From this exercise, I once again find contrasting evidence for the two classes of climate risk proxies. While the result is positive and significant for CPU, implying effective hedging of brown assets against this risk, the opposite is true for TRI and the measures of physical risks (temperature and rain anomalies), suggesting no hedging potential (see Table 4 and supplementary Table 7). However, when the role of oil is accounted for, the strong hedging potential of brown assets against CPU weakens, while the losses associated with TRI, rainfall, and temperature anomalies intensify. The foregoing confirms the tendency of models that exclude oil prices to overestimate hedging capabilities, and also reiterates that brown assets are equally prone to climate risks.

Table 4: Nexus between climate risks and brown asset returns

Without control		With control	
CPU	**Temp change**	**CPU**	**Temp change**
0.9180[a]	-0.1087[a]	-0.0280	-0.1549[a]
(0.2675)	(0.0167)	(0.2452)	(0.0258)
[3.4316]	[-6.5175]	[-0.1143]	[-5.9935]
{0.4730 1.3630}	{-0.13655 -0.0810}	{-0.4361 0.3800}	{-0.1979 -0.1119}

Source: Author's own work

Note: The model without controls examines only the nexus between conventional (brown) asset returns and climate risks. On the other hand, the model with 'control' accounts for the role of oil dynamics in the nexus. Two climate risk proxies are used, including climate policy uncertainty (CPU) and temperature anomaly (temp change). Superscript 'a' indicates significance at $p < 0.01$, signifying rejection of the no predictability hypothesis. Standard errors are shown in parentheses ( ), while t-statistics are presented in square brackets [ ]. 90% confidence interval in {}. The sample covers 2010M01-2023M12.

Comparing the behaviour of green and brown asset returns in the face of climate risks further confirms my earlier concerns about Vietnam's carbon-intensive economy and the mild attractiveness of brown assets to investors. Specifically, both assets do not seem to consistently offer significant hedging potential against climate risks. Similarly, the losses associated with temperature anomalies (as well as rainfall changes) are less severe for brown assets compared to green assets, suggesting greater resilience (of brown assets) to this risk type. This conclusion holds across the models that do not control for oil and the one that does (except for temperature anomalies in the latter). Moreover, my out-of-sample forecast accuracy results also lend additional support to the superiority of the climate risk-based model in forecasting brown asset returns, compared to its predictions for green asset returns (see Tables 3 and 5). Thus, for Vietnam to realize its green economy potential (see Ngoc & Anh, 2016), efforts to mitigate existing sustainability barriers (see Biu & Vu, 2025; Quang *et al.*, 2025) must be accelerated.

Table 5: Out-of-Sample Forecast Evaluation

	Panel A: Without Control						Panel B: With Control					
	RMSE: Historical Average						RMSE: Historical Average					
	h=3		h=6		h=12		h=3		h=6		h=12	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
CPU	8.1143	8.1552	8.0451	8.0872	7.9617	8.0040	8.0485	8.1552	7.9816	8.0872	7.9061	8.0040
Temp change	8.0205	8.1552	7.9546	8.0872	7.8636	8.0040	8.1195	8.1552	8.0501	8.0872	7.9583	8.0040
	RMSE: Random Walk						**RMSE: Random Walk**					
	h=3		**h=6**		**h=12**		**h=3**		**h=6**		**h=12**	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
CPU	8.1143	8.1171	8.0451	8.0496	7.9617	7.9674	8.0485	8.1171	7.9816	8.0496	7.9061	7.9674
Temp change	8.0205	8.1171	7.9546	8.0496	7.8636	7.9674	8.1195	8.1171	8.0501	8.0496	7.9583	7.9674
	C-W: Historical Average			**C-W: Random Walk**			**C-W: Historical Average**			**C-W: Random Walk**		
		CPU	**Temp change**	**CPU**	**Temp change**			**CPU**	**Temp change**	**CPU**	**Temp change**	
	h=3	0.1240	4.9558[b]	0.0952	5.0497[b]		**h=3**	3.2827[b]	7.3772[b]	3.3226[b]	7.6210[b]	
		(0.2912)	(2.6075)	(0.2920)	(2.6655)			(1.8616)	(3.7772)	(1.8794)	(3.8515)	
		[0.4257]	[1.9006]	[0.3261]	[1.8945]			[1.7634]	[1.9531]	[1.7679]	[1.9787]	
	h=6	0.1426	4.8519[b]	0.1234	4.9523[b]		**h=6**	3.2161[b]	7.2841[b]	3.2634[b]	7.5337[b]	
		(0.2859)	(2.5594)	(0.2869)	(2.6162)			(1.8270)	(3.7068)	(1.8444)	(3.7796)	
		[0.4988]	[1.8957]	[0.4301]	[1.8930]			[1.7603]	[1.9651]	[1.7693]	[1.9932]	
	h=12	0.1508	4.9004[b]	0.1406	5.0108[b]		**h=12**	3.0188[b]	7.2873[a]	3.0705[b]	7.5454[a]	
		(0.2770)	(2.4680)	(0.2794)	(2.5231)			(1.7626)	(3.5792)	(1.7794)	(3.6501)	
		[(0.5443]	[1.9856]	[0.5033]	[1.9859]			[1.7127]	[2.0360]	[1.7255]	[2.0671]	

Source: Author's own work

Note: The out-of-sample forecast evaluation results are presented for Root Mean Square Error (RMSE) and Clark and West (C-W). Model 1 and Model 2 for RMSE represent the climate-based and benchmark models, respectively, with the model with the lower RMSE preferred. Since C-W is a nested model, superscript 'a' against its values indicates the rejection of the equal forecast accuracy (between climate-based and benchmark model) hypothesis at the 1 per cent. Values in parentheses – ( ) – denote standard errors, while those reported in square brackets – [ ] – are t-statistics. For emphasis, the hypothesis of a zero coefficient will be rejected if the t-statistic exceeds +1.282 for 0.10; +1.645 for 0.05; or +2.00 for 0.01, all for a one-sided test (see Clark & West, 2007). The sample covers 2010M01-2023M12.

4.4. Additional Analysis that accounts for the exchange rate

Additional analysis that incorporates the exchange rate in place of oil prices yields similar findings, particularly for the out-of-sample forecast performance of the predictive model (see Table 7 and supplementary Table 11). The only notable difference lies in the in-sample predictability outcome. While the outcome is somewhat mixed in terms of significance when the oil price is used, both assets consistently exhibit vulnerability to climate risk when the exchange rate is used as a control variable (see Table 6). The results are also consistent across the four climate risk proxies. This is plausible as exchange rate dynamics tend to impact financial markets uniformly.

In addition, following the Dornbusch and Fisher (1980) model, a positive relationship is generally expected between the exchange rate and stock prices, and by extension, stock returns. Exchange rate depreciation makes exports cheaper and may lead to increased foreign demand and, consequently, higher sales, resulting in increased stock prices and returns, regardless of whether the assets are brown or green. My results for the impact of the exchange rate on both asset classes also validate this expectation (see supplementary Tables 5 and 8).

Finally, the out-of-sample significance of the proposed models compared to the benchmark models is further confirmed. This aligns with the importance of considering climate risks and macroeconomic fundamentals when forecasting stock returns. Additionally, in-sample predictability is illustrated in supplementary Figures 3 and 4, which demonstrate how the predictive models align with the actual data and show a relative co-movement between the two series. This further supports the outcomes of the out-of-sample forecasts.

Table 6: Nexus between climate risks and green and brown asset returns

Green asset returns		Brown asset returns	
CPU	**Temp change**	**CPU**	**Temp change**
-2.6798[a]	-0.1104[a]	-1.5967[a]	-0.0590[a]
(0.3069)	(0.0095)	(0.3230)	(0.0050)
[-8.7309]	[-11.5892]	[-4.9425]	[-11.9104]
{-3.1909 -2.1687}	{-0.1263 -0.0946}	{-2.1345 -1.0588}	{-0.0673 -0.0508}

Source: Author’s own work

Note: Two climate risk proxies are used, including climate policy uncertainty (CPU) and temperature anomaly (temp change). Superscript ‘a’ indicates significance at $p < 0.01$, signifying rejection of the no predictability hypothesis. Standard errors are shown in parentheses ( ), while t-statistics are presented in square brackets [ ]. 90% confidence interval in {}. The sample covers 2010M01-2023M12.

Table 7: Out-of-Sample Forecast Evaluation

	Panel A: Green Assets						Panel B: Brown Assets					
	RMSE: Historical Average						**RMSE: Historical Average**					
	h=3		**h=6**		**h=12**		**h=3**		**h=6**		**h=12**	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
CPU	6.3151	6.5609	6.2748	6.5247	6.2706	6.5104	7.8997	8.1552	7.8312	8.0872	7.7648	8.0040
Temp change	6.2765	6.5609	6.2446	6.5247	6.2231	6.5104	7.7661	8.1552	7.7030	8.0872	7.6381	8.0040
	RMSE: Random Walk						**RMSE: Random Walk**					
	h=3		**h=6**		**h=12**		**h=3**		**h=6**		**h=12**	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
CPU	6.3151	6.5794	6.2748	6.5431	6.2706	6.5281	7.8997	8.1171	7.8312	8.0496	7.7648	7.9674
Temp change	6.2765	6.5794	6.2446	6.5431	6.2231	6.5281	7.7661	8.1171	7.7030	8.0496	7.6381	7.9674

	C-W: Historical Average		**C-W: Random Walk**			**C-W: Historical Average**		**C-W: Random Walk**	
	CPU	**Temp change**	**CPU**	**Temp change**		**CPU**	**Temp change**	**CPU**	**Temp change**
h=3	7.0679^{a}	7.0396^{a}	7.1486^{a}	7.1008^{a}	**h=3**	7.8431^{a}	12.5225^{a}	7.8447^{a}	12.5506^{a}
	(2.1109)	(2.1878)	(2.1095)	(2.1840)		(3.2597)	(3.7625)	(3.2546)	(3.7780)
	[3.3483]	[3.2176]	[3.3888]	[3.2514]		[2.4060]	[3.3282]	[2.4103]	[3.3220]
h=6	7.0384^{a}	6.9041^{a}	7.1218^{a}	6.9678^{a}	**h=6**	7.7436^{a}	12.2838^{a}	7.7551^{a}	12.3201^{a}
	(2.0713)	(2.1484)	(2.0699)	(2.1446)		(3.1989)	(3.6946)	(3.1938)	(3.7096)
	[3.3980]	[3.2136]	[3.4406]	[3.2490]		[2.4207]	[3.3248]	[2.4281]	[3.3211]
h=12	6.8374^{a}	7.0128^{a}	6.9202^{a}	7.0769^{a}	**h=12**	7.4375^{a}	11.9260^{a}	7.4606^{a}	11.9745^{a}
	(2.0203)	(2.0903)	(2.0196)	(2.0872)		(3.0881)	(3.5669)	(3.0832)	(3.5812)
	[3.3843]	[3.3549]	[3.4265]	[3.3906]		[2.4084]	[3.3436]	[2.4198]	[3.3437]

Source: Author’s own work

Note: The out-of-sample forecast evaluation results are presented for Root Mean Square Error (RMSE) and Clark and West (C-W). Model 1 and Model 2 for RMSE represent the climate-based and benchmark models, respectively, with the model with the lower RMSE preferred. Since C-W is a nested model, superscript 'a' against its values indicates the rejection of the equal forecast accuracy (between climate-based and benchmark model) hypothesis at the 1 per cent. Values in parentheses – ( ) – denote standard errors, while those reported in square brackets – [ ] – are t-statistics. For emphasis, the hypothesis of a zero coefficient will be rejected if the t-statistic exceeds +1.282 for 0.10; +1.645 for 0.05; or +2.00 for 0.01, all for a one-sided test (see Clark & West, 2007). The sample covers 2010M01-2023M12.

4.5 Additional analysis: an alternative measure of green assets using the Vietnam Sustainability Index

The Vietnam Sustainability Index (VNSI), launched in 2017, was created by the Ho Chi Minh Stock Exchange (HOSE) and serves as a benchmark for companies that meet strict environmental, social, and governance (ESG) standards. It is a market capitalization-weighted index with free-float adjustments, featuring firms with the highest sustainability scores. Selection starts with the VN100, comprising the 100 largest companies listed on HOSE, which undergo a structured ESG assessment to qualify for inclusion. Due to limited and non-public historical data for the official VNSI, I computed the index using the full list of qualified firms. To do so, I first listed all 20 firms included in the VNSI (see supplementary Table 12), then created a market-capitalization-weighted index based on data from investing.com. The index starts at a base value of 100, with each firm’s free-float market cap combined and divided by a constant divisor to determine the index level over time.

I therefore replicate all the analyses for the original green assets for the VSI as well. However, since the data scope is short, I limit the analysis to in-sample predictability starting in 2017. Notwithstanding, I consider alternative measures of climate risk involving CPU and temperature change, with and without the control variable, using the global oil price as previously done for the original group of green assets. The results are presented in Table 8, and one striking outcome, contrary to the previous analysis, is that recent datasets after the Paris Agreement of 2015 appear to suggest a reasonable level of improvement in the behaviour of the green assets, as this class of assets offers a good hedge against climate risk regardless of the climate risk measure. This is an indication of a conscious commitment by the country in question to promoting sustainable investment, which appears to offer a higher return for bearing additional (climate-oriented) risks.

Table 8: Climate risk and the Vietnam Sustainability Index [VSI]

Without control		With control	
CPU	**Temp change**	**CPU**	**Temp change**
7.8962[b]	0.2204[a]	9.2102[b]	0.5332[a]
(3.5162)	(0.0587)	(4.5364)	(0.1385)
[2.2456]	[3.7551]	[2.0303]	[3.8504]
{1.9505 13.8419}	{0.1213 0.3195}	{1.5108 16.9097}	{0.2982 0.7682}

Source: Author's own work

Note: As in the previous analyses, I used the VSI's log returns as the dependent variable. The model without controls examines only the nexus between green asset returns and climate risks. On the other hand, the model with 'control' accounts for the role of oil price in the nexus. Two climate risk proxies are used, including climate policy uncertainty (CPU) and temperature anomaly (temp change). Superscripts 'a and 'b' indicate significance at $p < 0.01$ and $p < 0.05$, respectively, signifying rejection of the no predictability hypothesis. Standard errors are shown in parentheses ( ), while t-statistics are presented in square brackets [ ]. 90% confidence interval in {}. The sample covers 2010M01-2023M12.

Motivated by the latter results and the need to adjust for sample frames that coincide with periods of high climate awareness, I reestimate the relationship between climate risks and asset classes using the VCCI sustainability index, based on a sample similar to VNSI (2017-2023) (see Table 9). I find that green assets now hedge climate risks significantly based on the CPU measure, whereas the same cannot be inferred for temperature changes. Thus, it is imperative to conclude that the VNSI provides a better measure of sustainability, given its ability to explain differences in green and brown assets with respect to climatic risks and in line with theoretical expectations.

Table 9: Climate risk and the Vietnam Chamber of Commerce and Industry (VCCI) Sustainability Index for Reduced Sample (2017-2023)

Green Assets		Brown Assets	
Without control		Without control	
CPU	Temp change	CPU	Temp change
4.1594[a]	-0.0906[b]	2.9704[a]	-0.1699[a]
(0.6120)	(0.0425)	(1.0379)	(0.0388)
[6.7962]	[-2.1329]	[2.8619]	[-4.3802]
{3.1217 5.1971}	{-0.1626 -0.0186}	{1.2181 4.7227}	{0.2354 -0.1044}

Source: Author's own work

Note: Superscripts 'a and 'b' indicate significance at $p < 0.01$ and $p < 0.05$, respectively, signifying rejection of the no predictability hypothesis. Standard errors are shown in parentheses ( ), while t-statistics are presented in square brackets [ ]. 90% confidence interval in {}. The sample covers 2010M01-2023M12.

5. Conclusion

This study examines the predictive content of climate-related risks, such as climate policy uncertainty and temperature anomalies, for the returns of green assets in Vietnam. Vietnam has a longstanding history of exposure to natural disasters, many of which are exacerbated by climate change. In recent years, efforts have intensified to unlock the country's green economic potential. The contribution of this study is premised on three main objectives. First, it examines whether green stocks in Vietnam can hedge against climate-related risks. Second, it evaluates whether a bivariate model sufficiently captures the relationship between climate-related risk and green stock returns. As such, I incorporate oil prices and exchange rates as control variables. These two fundamentals are reputable for influencing stock market dynamics. Third, I assess the forecasting accuracy of models that incorporate climate risk factors, comparing them with benchmark models that overlook such risks, including the historical average and a random walk. For robustness, similar analyses are conducted for conventional (brown) stock returns.

The findings from my analysis indicate that green stocks in Vietnam effectively hedge against climate risk in recent datasets covering periods after the Paris Agreement of 2015, suggesting a reasonable level of improvement in the behaviour of green assets in line with international commitments and the government's green transition efforts. Also, classification by assets using the Vietnam Sustainability Index (VNSI) yields results that are more theoretically compelling, highlighting the need for robust sustainability measures to understand the climate risk-investment nexus in Vietnam. Interestingly, the climate–brown model results reveal a statistically positive but inconsistent relationship between climate policy uncertainty and brown stock returns, implying that investors and businesses still consider conventional assets viable. Additionally, I find evidence that models that omit key fundamentals, such as oil prices and exchange rate fluctuations, tend to overestimate the impact of climate risk on green (and brown) investment returns. Meanwhile, accounting for these macro fundamentals greatly improves the out-of-sample forecast performance. This established predictive value of the proposed model offers useful insights into how climate risks can be incorporated into forecast models for asset returns, on the one hand, and how this information can be exploited to improve decision-making by policymakers and practitioners, on the other hand.

These findings have important implications for policymakers in Vietnam. To ensure a smooth transition to a green economy, it is essential to implement policies that will further enhance the attractiveness of green asset investments. Thus, in line with existing findings, policymakers should develop the country's green bond markets as a means of improving capital flow and operational efficiency of companies undergoing sustainable transition; also, ESG disclosures should be made more mandatory and appealing through tax incentives and other policy mix to improve green financing, and assist complying firms. While this study acknowledges Vietnam's ongoing transition efforts, a dedicated investigation into these strategies, supported by various simulations and scenario analyses, would be worthwhile. This could provide a framework for making informed decisions effectively and open the door to future research.

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