MSQE Project Proposal

Project Title (Tentative) - *When Carbon Spikes, Do Green Stocks Shine? The Effect of EU-ETS Carbon-Price Shocks on Green-Energy Equity Performance and Volatility*

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1. Project Mentor

Professor Hamed Ghoddusi has informally agreed to serve as our project advisor. We will meet with him during week 6 to discuss further details. Additionally, we will consult with Shashwat Pandey, an ML Engineering Manager at a leading unicorn tech startup, to refine our machine learning framework and implementation strategy.

2. Motivation

Climate policy is becoming increasingly significant for global financial markets, particularly as carbon pricing mechanisms like the European Union Emissions Trading System (EU-ETS) exhibit dramatic price fluctuations. Recent literature, including Bolton and Kacperczyk (2021) and Chun et al. (2022), demonstrates that rising carbon prices materially impact company valuations—raising costs for high-emission firms and potentially benefiting renewable-energy-focused companies. However, existing studies frequently use low-frequency data (monthly or quarterly), leaving gaps in understanding short-term market responses and volatility implications of sudden carbon-price shifts. Moreover, endogeneity issues such as reverse causality and omitted variable bias often remain unaddressed. This knowledge gap is critical for investors, policymakers, and financial analysts who aim to manage climate-related financial risks and identify sustainable investment opportunities effectively.

3. Research Questions and Hypotheses

Part A: Market-Impact Analysis

Research Question: When there's a sudden, unexpected jump in EU carbon prices, how does this impact the stock market performance and risk profiles (realized and option-implied volatility) of renewable-energy ("green") companies compared to high-emission ("brown") companies?

Null Hypothesis (H_0-A): Unexpected carbon-price shocks have no differential effect on the returns or volatility of green versus brown energy stocks.

Alternative Hypothesis (H_1-A): When carbon prices suddenly rise, green-energy companies experience larger gains and increased volatility compared to brown-energy companies, which see smaller gains or losses. The magnitude of these effects correlates with the firm's level of green intensity.

Part B: Forecasting and Stress-Test Analysis

Research Question: Can an advanced machine-learning method (a Transformer model) predict carbon-price volatility—and consequently, green-energy stock volatility—more accurately than traditional forecasting models (ARIMA/GARCH)? Would this improvement assist investors and policymakers in developing more precise climate stress-test scenarios?

Null Hypothesis (H_0-B): Transformer models provide no significant improvement over traditional ARIMA/GARCH models in forecasting carbon-price volatility or in predicting subsequent green-energy stock volatility for climate scenarios.

Alternative Hypothesis (H_1-B): Transformer models significantly outperform ARIMA/GARCH models in forecasting carbon-price volatility and extreme market movements. Enhanced accuracy from Transformer models provides more reliable estimates of green-energy stock volatility under realistic climate-policy scenarios, such as sudden €50 or €200 per ton increases in carbon prices.

4. Conceptual Model

Our conceptual framework leverages asset-pricing theory, which ties equity valuations to expected future cash flows and discount rates. Increased carbon prices could elevate expected cash flows for renewable-energy firms by boosting their competitive advantage, thus enhancing returns. However, policy uncertainty and energy market disruptions could also elevate risk premiums, resulting in higher volatility. This tension between improved profitability and increased uncertainty motivates our expectation that greener firms will experience more pronounced returns and volatility following carbon-price shocks.

5. Methodological Approach and Data

We will test our hypotheses through a combination of econometric analysis and machine-learning techniques:

Sample Period and Data Sources

- **Sample Period:** January 2018 to December 2024, encompassing recent carbon market volatility including COVID-19 disruptions and post-pandemic recovery.
- **Data Sources:**
    o Daily EU-ETS allowance prices (ICE and Sandbag)
    o Daily returns from green (ICLN ETF) and brown (XLE or STOXX 600 Oil & Gas) equities
    o Option-implied volatility data (EOD Historical Data)
    o Macroeconomic controls (VIX, Brent oil prices) from FRED
    o Firm-level data on 150+ European energy companies from Refinitiv Eikon

Green Intensity Measurement

We will construct a comprehensive green intensity metric using:

- Carbon intensity ratios (Scope 1 & 2 emissions/revenue)
- Percentage of revenue from renewable sources
- Capital expenditure allocated to green projects
- Third-party ESG ratings (MSCI, Sustainalytics) as validation measures

Identification Strategy

To address endogeneity issues, we will:

- **Primary Strategy:** Identify carbon-price shocks using ARIMA residuals that exceed 1.5 standard deviations.
- **Policy Event Identification:** Incorporate dummy variables for specific events:
    o ETS Phase IV implementation announcements
    o Major EU climate policy votes
    o Market Stability Reserve adjustments
    o Brexit-related carbon market disruptions
- **Instrumental Variables:** Weather anomalies affecting renewable generation and fossil fuel demand.
- **Fixed-Effects Approach:** Firm and time fixed effects to control for unobservables.
- **Panel Structure:** Implement panel-robust standard errors and dynamic panel estimators where appropriate.
- **Event Study Framework:** Supplement Local Projection methods with traditional event study methodology as robustness check.

Causal Inference

- **Causal Forest Algorithm:** Estimate heterogeneous treatment effects across firms
- **Pre-specified Subgroups:** Analyze differential impacts based on:
    o Industry classification (utilities vs. pure-play renewables)
    o Geographic exposure (countries with varying renewable subsidies)
    o Size (market capitalization quartiles)
    o Pre-existing carbon intensity
- **Limitations:** We acknowledge the inherent challenges of establishing true causality in financial markets due to confounding factors and will carefully interpret results accordingly

Machine Learning Implementation

- **Model Selection:** Compare models using BIC, AIC, and out-of-sample performance metrics
- **Computational Resources:** High-performance computing resources from University Computing Center (confirmed access) for Transformer model implementation
- **Volatility Forecasting:** Transformer and GARCH-MIDAS models with cross-validation

6. Literature Review

Understanding how carbon pricing policies ripple through financial markets—particularly equity markets—is increasingly urgent in the age of climate risk and energy transition. The European Union Emissions Trading System (EU-ETS), the world's most developed carbon market, plays a central role in this policy landscape. As carbon prices swing—sometimes sharply—what happens to firms aligned with green energy versus those rooted in fossil fuels? This literature review explores how researchers have approached this question, the tools they've used, where they disagree, and most importantly, where our research can make a unique contribution.

Green vs. Brown Stocks in the Age of Carbon Pricing

A central thread in the literature is the differential performance of green and brown stocks in response to climate policy and carbon pricing. Bauer et al. (2023) and Albanese et al. (2025) find robust evidence that green stocks, especially those tied to renewable energy, outperform their brown counterparts over the long run, particularly when carbon prices rise. These studies support the idea of a "carbon premium"—a compensation investors earn for holding climate-resilient assets.

However, this positive association isn't universally consistent. Fang et al. (2021), using quantile regression, show that the relationship between carbon prices and green stock returns is asymmetric and varies with market conditions. Green equities don't always behave like textbook hedges. At times, they exhibit heightened sensitivity and volatility, especially during policy uncertainty or commodity price shocks.

Endogeneity Concerns: A critical methodological challenge in this literature is addressing endogeneity. Most studies rely on simple OLS or VAR frameworks that struggle to establish causality between carbon prices and stock returns. As highlighted in "Carbon Policy and Stock Returns" (IMF, 2023), regulatory events affecting carbon prices may simultaneously impact broader market sentiment, creating omitted variable bias. Similarly, "International Stock Markets' Reactions to EU Climate Policy Shocks" (2024) notes that reverse causality can occur when market anticipation of policy changes drives both carbon prices and stock movements. These endogeneity issues are particularly acute in high-frequency settings, where market microstructure and liquidity dynamics further complicate identification.

What's missing in most of these studies is the granularity to capture how short-term, unexpected spikes in carbon prices—like sudden jumps after an EU policy announcement—impact returns and risk. Much of the literature relies on monthly or quarterly data, which tends to smooth over volatility episodes that are precisely what investors care about.

Modeling Volatility: Traditional Econometrics vs. Machine Learning

Forecasting how carbon-price volatility translates into financial market volatility is another key concern. Here, the literature splits into two camps. One sticks to the classic econometric toolkit. Zhang et al. (2021), for instance, use GARCH-MIDAS models to show that economic policy uncertainty increases the volatility of carbon futures. These models offer interpretability and are well-established in finance literature. But they often struggle with capturing non-linearities or reacting quickly to rare, high-impact events.

The second camp explores deep learning models. Sun et al. (2023) introduce a hybrid Transformer-LSTM architecture and show it significantly outperforms ARIMA and traditional GARCH in predicting carbon futures volatility. Chen et al. (2024) go further, showing that Transformer-based models can learn latent market structure and anticipate volatility spikes with impressive accuracy—even in chaotic price environments.

Policy Relevance: These volatility forecasting advances have substantial implications for regulatory frameworks. The European Central Bank's climate stress testing framework (2022) and the Network for Greening the Financial System (NGFS) scenarios rely heavily on carbon price path assumptions that currently fail to capture realistic volatility dynamics. More accurate volatility forecasts could significantly enhance the realism of these stress tests, helping financial institutions better prepare for climate transition risks. Similarly, as the EU's Sustainable Finance Disclosure

Regulation (SFDR) and green taxonomy evolve, better volatility models could inform risk disclosures and sustainability ratings. Our research directly addresses these policy needs by evaluating which modeling approaches provide the most reliable inputs for regulatory stress-testing frameworks.

What's exciting (and still underexplored) is the potential to link these volatility forecasts with the performance of green equities, especially under simulated carbon-stress scenarios. Our project will directly contribute to this space by comparing these modeling approaches and testing their value in practical climate risk assessment.

Accounting for Heterogeneity: Not All Green Is the Same

It's tempting to think of "green stocks" as a monolith, but that assumption is increasingly challenged. Athey et al. (2019) introduce causal forests as a way to uncover heterogeneity in treatment effects—in this case, how different firms respond to shocks like carbon-price increases. This method doesn't impose a linear structure and allows for complex interactions, such as between a firm's emissions intensity and its exposure to fossil fuel supply chains.

Building on this, Kattenberg et al. (2023) show how causal forests can be adapted for panel data and difference-in-differences frameworks, helping disentangle firm-specific effects from broader market dynamics. Yet, these methods have been applied far more in policy evaluation or labor economics than in environmental finance—a gap we aim to fill. By applying causal forests to a large panel of firms with varying "green intensity," we can move beyond average treatment effects and identify which firms truly benefit from carbon price shocks, and which do not.

Where the Literature Falls Short

Despite the surge in research on green finance and carbon markets, major blind spots remain. First, the vast majority of studies focus on average outcomes and long-term correlations, leaving us in the dark about how markets react to high-frequency carbon-price shocks. Second, while deep learning models show promise, few papers connect their forecasts to real financial decisions, like stress-testing green portfolios. Third, heterogeneity in firm responses is often acknowledged but rarely modeled rigorously. In essence, we know a lot about whether carbon pricing matters—but far less about how, when, and for whom it matters most.

Interdisciplinary Context: Our research bridges critical divides between traditionally separated domains. While climate economics (e.g., Nordhaus's DICE/RICE models) has long modeled carbon prices as gradual, predictable trajectories, financial market research suggests they may be volatile and unpredictable. Similarly, while climate science establishes physical risk parameters, translating these into financial market impacts requires sophisticated asset pricing frameworks. By connecting carbon market dynamics to equity performance through advanced econometric and machine learning techniques, our work creates an integrated approach that spans climate science, financial economics, and computational modeling—a perspective increasingly necessary as financial markets grapple with the complexities of climate transition.

Our Contribution

Our project directly engages with these gaps. First, by using local projection methods (Jordà, 2005), we estimate the short-run impulse responses of green and brown stocks to carbon-price shocks, overcoming the limitations of low-frequency or static regression approaches. Second, we compare volatility forecasting models—both traditional (GARCH-MIDAS) and cutting-edge (Transformers)—to evaluate their predictive power under different market conditions. Finally, we leverage causal forests to capture heterogeneity in firm-level responses based on green-intensity scores, moving beyond simplistic green/brown binaries.

In doing so, we bridge finance, econometrics, and machine learning—producing insights that are timely, methodologically novel, and useful to investors and policymakers grappling with climate transition risk.

7. Step-By-Step Plan/Timeline

- **Literature Review:** Review and summarize 10 peer-reviewed articles from journals like Energy Economics, Journal of Financial Economics, and Review of Financial Studies, emphasizing endogeneity concerns. (10 hours)
- **Data Acquisition and Cleaning:** Collect and process EU-ETS prices, equity returns, and volatility data. (10 hours)
- **Shock Identification:** Identify carbon-price shocks using AR(5) residual analysis. (5 hours)
- **Descriptive Statistics:** Compute summary statistics, preliminary figures, and visual analyses. (5 hours)
- **Local Projection IRFs:** Estimate dynamic response functions for equity returns post-carbon shocks, including endogeneity checks. (7 hours)
- **Instrumental Variable and Fixed-Effects Models:** Conduct IV regressions and fixed-effects analyses for robustness. (6 hours)
- **Causal-Forest Analysis:** Analyze heterogeneity in firm responses based on green-intensity. (10 hours)
- **Volatility Modeling:** Develop and evaluate Transformer and GARCH-MIDAS models. (10 hours)
- **Robustness Checks:** Conduct placebo tests, sensitivity analyses, and subsample verifications. (5 hours)
- **Draft Paper and Visualizations:** Compose a comprehensive 25-page research paper with supporting figures, tables, and presentation materials. (15 hours)
- **Final Review and Submission:** Ensure reproducibility, validate findings, finalize documentation, and submit project. (5 hours)

Total Estimated Hours: 88 (22 hours per member in a four-person team).

8. References

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