Breaking news…or was it? Understanding stock market response to the Inflation Reduction Act

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Abstract: This study examines the renewable energy financial market response to the U.S. Inflation Reduction Act (IRA), a landmark climate policy aimed at accelerating clean energy transition. Using a multi-method empirical approach, this research analyzes both immediate and intertemporal market reactions of renewable energy firms to the policy's announcement and implementation. To capture informational dynamics, Natural Language Processing (NLP) tools are employed, including Latent Dirichlet Allocation (LDA) for topic modeling and the ClimateBERT model for sentiment scoring of climate-related news occurring between 2021 and 2023. Immediate response event study demonstrates statistically significant cumulative abnormal returns (CARs) of up to 17% following the IRA's announcement, with media narratives playing a critical role in amplifying investor sentiments. Extended term dynamics from a Difference-in-Differences study, however, reveal that these effects were not uniformly sustained. There was a gradual reversion in both cumulative abnormal returns and trading volumes in the year following the associated IRA policy announcement, suggesting investor reassessment as implementation frictions and policy uncertainties emerged. These patterns are indicative of adaptive market behavior, wherein initial optimism is tempered by evolving information and institutional bottlenecks. By integrating financial econometrics with behavioral finance and climate news analytics, this study contributes novel insights into the equity market pricing dynamics of transition risk.

JEL Codes: Q54, Q58, G12, G14, C21

Keywords: Inflation Reduction Act, climate finance, U.S. climate policy, green policy, transition risk, climate risk, renewable energy, asset-pricing, Dynamic difference-in-differences, news sentiment analysis, Latent Dirichlet Allocation, Natural Language Processing

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Introduction

The Inflation Reduction Act of 2022 (IRA) remains the largest climate policy action ever undertaken in U.S. history (Bauer et al., n.d.). Contingent on political stability, the IRA was designed to offer significant financial support for the renewable energy industry through tax credits and direct government spending (Bistline et al., 2023a). It also proposed incentives aimed at encouraging U.S. households and businesses to invest in the necessary equipment and capital to lower their carbon emissions. Measured in terms of total fiscal cost, the cumulative budgetary requirement of the climate bill was estimated to reach around $1.2 trillion over the next 10 years (Bistline et al., 2023b). Although, subsequent legislative changes under the Trump administration have impacted its implementation[2], the IRA still represents a major realization of climate transition risk and can therefore provide valuable insights into investor behavior to a significant climate policy action.

Given the relatively recent enactment of the IRA, few studies have thus far examined its impact on the U.S. financial markets (Bauer et al., n.d.; Fedorova & Iasakova, 2024; Pham et al., 2023). These studies uniformly report a positive and significant immediate effect on the performance of 'green' or environmentally friendly stocks. However, their analyses are concerned with short time horizons following legislative actions pertaining to the IRA's passage. Additionally, they do not distinguish between renewable energy stocks and the broader category of green stocks[3]. Evidence indicates that the pricing of the former follows a markedly different trajectory and is driven by distinct factors compared to the latter (Li et al., 2024). This divergence has not yet been fully explored in the context of the IRA. In this study, I pose the following questions: What was the immediate investor reaction to the IRA climate act as reflected in renewable energy stock price movements in the U.S.? By extension, how did climate narratives during the high transition risk period of the Biden administration influence the financial market performance of the renewable energy sector? And finally, after accounting for other climate-related impulses, macroeconomic factors, and firm-specific characteristics, was there a significant prolonged impact of the act on renewable energy stock prices?

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[2] Report by Thomson Reuters, February 27, 2022, "IRA's uncertain future: How the Trump administration's approach could impact corporate tax functions". Retrieved from https://www.thomsonreuters.com/en-us/posts/corporates/ira-uncertain-future/

[3] A note on the difference between *green* and strictly renewable energy firms is in order here. Environmentally friendly companies which also include those transitioning to low-carbon technologies, or what S&P Global terms as climate transition stocks (retrieved from S&P Dow Jones Indices. https://www.spglobal.com/spdji/en/indexfamily/sustainability/climate/#overview. Last access: November 10, 2024) are conventionally included in the broad category of green firms. This study is restricted to firms whose principal business activity concerns the production and dissipation of renewable energy (see Section 1.1.1). While there is a rapidly growing literature on the pricing of climate risks in green and brown (fossil fuel heavy) stocks (Ardia et al., 2023; Bauer et al., n.d.; Bolton et al., 2023; Carattini & Sen, 2019; Cassidy, 2023; Hsu et al., 2021; Kacperczyk et al., n.d.; Monasterolo & de Angelis, 2020; Pastor et al., 2021; Pham et al., 2023), literature on renewable energy stocks is limited (Cao et al., 2020; Fahmy, 2022; Guinea et al., 2024; Liu et al., 2021; Yildiz & Karan, 2020).

A broad range of behavioral and economic literature sheds light on the importance of narrative sentiment in driving financial systems, and that how and why "similar thinking among large groups of people" commands market sentiment in the form of shared group narratives evoking either excitement or anxiety (Shiller, 2015). For example, evidence suggests that irrational exuberance among investors before the global financial crisis dictated the magnitude of the market crash in 2007 (Shiller, 2015) . Similarly, there has been a recent proliferation of literature that studies the role of narratives and biases in financing climate mitigation through determination of asset prices of climate sensitive firms (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2023; Nyman et al., 2021; Santi, 2023).

Any possibility of climate action is accompanied by beliefs about anticipated or abrupt financial and operational shifts in businesses arising out of government intervention. This is termed as "transition risk" (Ardia et al., 2023). Political signaling that affirms (denies) climate beliefs like rejoining of (withdrawal from) the Paris Agreement by President Biden (Trump) in 2020 (2016) indicates a high (low) transition risk period. These periods often signal potential disruptions for pollution-heavy industries (Stroebel & Wurgler, 2021) but may foster positive or even volatile sentiments towards clean-energy sectors (Ramelli et al., 2021). For example, Antoniuk & Leirvik, (2024) found that the Paris Agreement raised public awareness of global warming and support towards climate change legislation benefiting the overall U.S. renewable energy sector. In case of IRA, Bauer et al., (n.d.) performed an event study analysis to show that clean energy indices reacted positively to major news that improved the likelihood of the passage of IRA. This suggested that equity markets had expected clean energy companies to benefit by its policies. IRA however, is a unique case of both realized transition risk upon the passage of the policy action (Bauer et al., n.d.) and perceived transition risk concerning its future implementation. It could therefore be construed that the whole effect of the IRA passage on the renewable energy stock market took longer than a few days to play out.

Another reason to investigate this trajectory is to inform the *ex-ante* and *ex-post* reaction of renewable energy firms to an *anticipated* policy action. While price effects of unanticipated climate shocks can be fairly accurately isolated, effects of anticipated changes are confounded by pricing in of both current and the present value of future path of policy (Gürkaynak et al., 2004). This is because over time, investor sentiments are susceptible to belief updating driven by news coverage and social interaction (Ardia et al., 2023; Faccini et al., 2023; Fedorova & Iasakova, 2024; Santi, 2023; Yazici & Gültekin, 2023). Santi, (2023) shows that when investors have positive sentiments about climate change originating from high news coverage about natural disasters and carbon policies during times of high social interaction, it leads to shift towards green investment. But since part of the belief updating is irrational and more emotionally charged than fact- or knowledge-based (Bang et al., 2000; Lo, 2004), the spike in prices goes back to zero

in the longer term. This phenomenon, based on adaptive market hypothesis (Lo, 2004) is illustrated in Figure 1 for the case of IRA.

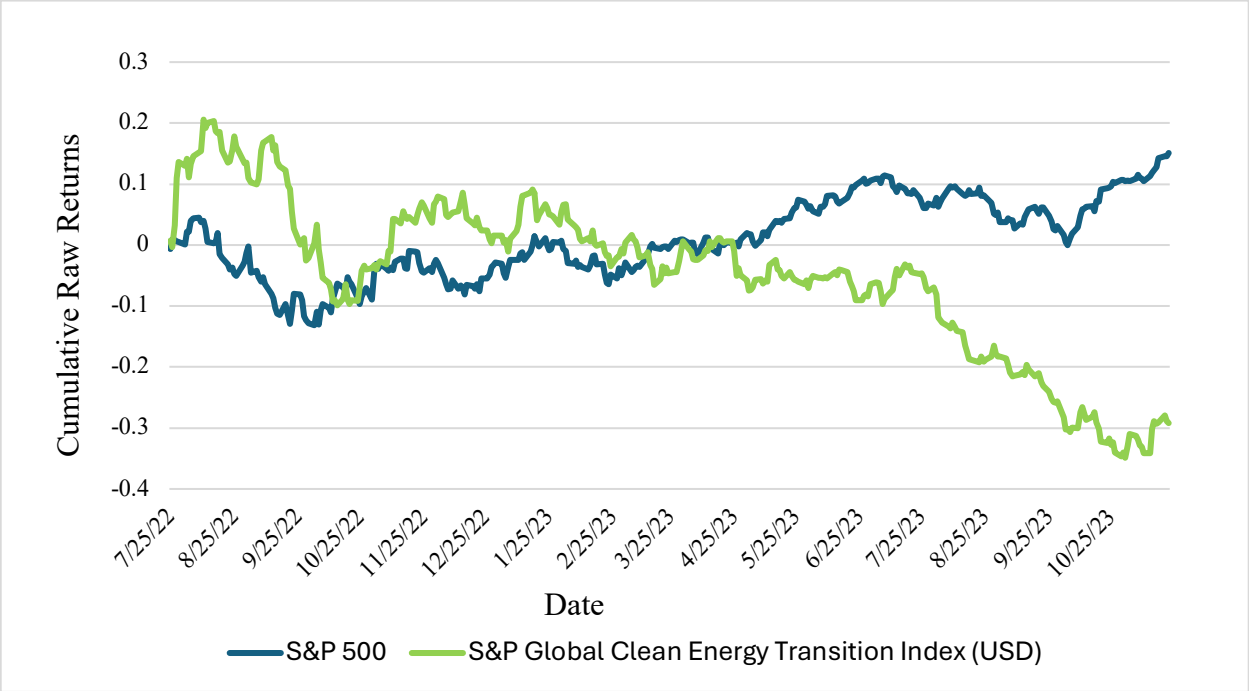


Figure 1: Cumulative raw returns of S&P Global Clean Energy Transition Index (green), which constitutes 100 largest renewable energy firms in the world, and S&P 500 Index (blue), a U.S. stock market representative of largest firms. Returns are illustrated from July 27, 2022, when the Inflation Reduction Act (IRA) was announced in the Senate up till November 2023.

Figure 1 shows the cumulative raw returns of the U.S. stock market representative S&P 500 index and the S&P Global Clean Energy Transition Index. Constituents of the latter include 100 large-cap renewable energy firms in the world. The graph begins on July 27, 2022, when the Inflation Reduction Act (IRA) was announced in the Senate and goes up till November 2023. Evidence suggests that July 27 experienced the bulk of the market shock resulting from the IRA passage (see Section 1.4). The initial outperformance followed by a steady and sharp decline of the clean energy index signifies possible overcorrection and then price reversal by the market. However, is it not clear whether the observed divergence reflects policy-driven overvaluation or broader macroeconomic headwinds.

Accordingly, I use two timeframes to examine how the renewable energy financial market initially interprets and subsequently adjusts to an uncertain policy intervention like the IRA. I assess the immediate effect using the Fama-French 3-factor (FF3) asset pricing model, grounded in the Efficient Market Hypothesis (Fama & French, 2007). It posits a linear relationship between expected returns and systematic risk and allows for the identification of immediate, risk-adjusted pricing reactions under the assumption of rational investor behavior and rapid information assimilation (Fama, 1970). Subsequently, I

analyze the extended period response through the lens of the adaptive market hypothesis to capture gradual market adjustments and behavioral responses to evolving policy signals (Lo, 2004).

While there is a well-established short-horizon asset pricing analysis methodology in financial literature, approaches to longer term horizons vary. One of the traditional easy-to-apply models is the Buy-and-Hold-Abnormal-Returns (BHAR). It computes cumulative abnormal returns over extended periods but suffers from cross-sectional and time-series interdependencies, leading to confounding results (Dionysiou, 2015). Studies have also used structural Vector Autoregressive Models (Engle et al., 2020), panel-data fixed effects model (Santi, 2023) as well as generalized method of moments to study long-run variations in stock prices. However, such methods do not consider ex-ante effects of policy.

Therefore, I employ the Difference-in-Differences (DiD) framework to isolate the extended term causal impact of IRA on renewable energy stock prices. DiD is an improvement on BHAR in that it circumvents its biases by introducing control variables and a counterfactual period prior to the event under analysis[4]. Since this is an individual-firm study, I am able to use various specifications of DiD to investigate firm-size heterogeneity. Additionally, I perform a dynamic DiD analysis to assess the intertemporal variations in renewable energy sector cumulative returns.

Literature shows that media narratives and communicated social norms play a significant role in forming investor beliefs (Botzen et al., 2021; Howlett & Rawat, n.d.). Therefore, apart from macroeconomic and firm-specific controls, I use news sentiment measures in my model to control for narrative biases. To build the controls, I implement textual and sentiment analysis of climate news coverage over the period of 2021-2023 using natural language processing (NLP) methods on full-text articles from major financial news sources. The methods are consistent with the burgeoning literature on application of machine learning to identify the relation between media attention and climate sentiments (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2023; Fedorova & Iasakova, 2024; Jiang et al., 2017; Noailly et al., 2021; Patronella, 2021; Santi, 2023).

[4]Short-term market models like the Fama-French 3-factor model used in Section 1.4 are grounded in the Efficient Market Hypothesis (EMH), which posits that asset prices fully reflect all available information, thus suggesting that any observed abnormal returns are short-lived anomalies that should quickly vanish (Fama, 1998). With this assumption, they fulfil the causal inference tenets, namely covariation between stock and event, temporal precedence (event happens before stock disruption), no confounding variables (due to very small timeframe considerations) and counterfactual modeling (beta calculations capture normal stock returns prior to the event) (Stone, 1993). BHAR also depicts association between event under analysis and stock price compared to a reference group, but its design does not isolate causal impacts due to non-fulfilment of the 'no confounding variables' and 'counterfactual' clause. The biases discussed by Barber & Lyon, (1997) that BHAR suffers from relate broadly to the choice of benchmark which can be partially rectified by matching portfolios of similar size and book-to-market ratios. The intertemporal bias, however, cannot be resolved without a counterfactual that considers a prior period with no event impact. The model suffers from issues of cross-sectional as well (Bolton & Kacperczyk, 2021) due to long time frames and omission of control variables. In this context, DiD incorporates the tenets of causal inference much like the short-term asset pricing method. A well-established method for policy evaluation (Pearl, 2010), it includes a pre-treatment counterfactual measure as well as controls for other confounding variables to isolate the impact of specific events or policies.

After collecting news on climate change from ProQuest, I first employ the Latent Dirichlet Allocation (LDA) to identify underlying textual themes in climate news reporting. Next, I perform a sentiment analysis of the text using the transformer-based ClimateBERT model (see Section 1.3). Both measures provide daily and monthly time-series scores of average thematic weightage and sentiment score which are then used as controls in the DiD model. Further, I process the news scores to identify windows of high media coverage pertaining to the four identified themes of climate policy, extreme weather phenomena, geopolitics and energy transition. I use these to gain insight into the immediate effect of thematic events on renewable energy stocks during high transition risk periods.

In order to limit the analysis to a comprehensive set of U.S. based renewable energy firms, I combine the Bloomberg Industry Classification (BIC) and North American Industry Classification (NAICS) codes for identification of relevant firms. The final list consists of 263 renewable energy firms, with most of them being small- to mid- cap. A control group is then built from the subsample of S&P500, S&P 600 and S&P400 index constituents following the guidelines prescribed by Barber & Lyon (1997a), that suggests matching on size, book-to-market ratio and geography while excluding energy firms that might directly be impacted by the IRA (see Section 1.1.2). Daily and monthly data for stock and firm characteristics are obtained from Center for Research in Security Prices (CRSP) and Compustat via the Wharton Research Data Services (WRDS).

This study reveals sharp, short-horizon stock market responses of renewable energy firms to the passage of the Inflation Reduction Act (IRA) and to high-salience news events related to climate policy, physical risk, and geopolitical developments. Results from the FF3 model show that renewable stocks experienced the strongest abnormal returns (up to +13%) following the surprise July 27, 2022, IRA announcement, while earlier policy reversals and legislative uncertainty—such as the failure of the Build Back Better bill—led to sharp market declines. Notably, there was no significant market reaction to the final passage of the IRA on August 16, 2022, indicating that the policy had already been priced in. Extreme weather events generated consistently negative abnormal returns prior to the IRA, suggesting investors perceived renewable infrastructure as vulnerable to physical risks. In contrast, news surrounding the Ukraine war and geopolitical summits yielded modest positive returns, likely reflecting renewed attention to energy security and clean energy transition. These patterns underscore how investor sentiment, news narratives, and behavioral biases interact with policy signals, producing swift but varied short-term market responses.

Extended term study results indicated strong sustained market response to the IRA driven largely by medium and large sized renewable energy firms—cumulative abnormal returns rose by 12.5% within ±30

days and 13.4% within ±4 months of the announcement—followed by a gradual price dissipation over the subsequent year. Importantly, cumulative trading volumes surged significantly during this period, reflecting elevated price correction. Thematic news interactions revealed that geopolitical developments reinforced market optimism, whereas weather-related events consistently dampened returns. Other climate policy news had negligible effects, underscoring the unique signaling power of the IRA. These findings underscore that large-scale climate policies like the IRA can significantly influence clean energy financial markets and investor expectations. However, the eventual price correction suggests that implementation faced economic bottlenecks—such as high interest rates, inflation, and supply chain disruptions—that diluted initial investor optimism for future profitability. Policymakers should align climate action with broader macroeconomic conditions and ensure clear, timely communication to reinforce credibility and investor confidence, particularly when public discourse is fragmented or politically polarized.

This study contributes to the literature in several ways. It is the first to analyze extended term causal effect of IRA on the renewable energy financial market. It is also one of the few studies to take the complete sample of U.S. -based renewable energy firms into consideration. This research adds to the financial event study methodology by proposing a model to combine the best practices of BHAR with the event study framework applied in economic literature. Using a dynamic framework, it adds to the understanding of market adaptation to a huge climate policy event. Lastly, textual and sentiment news analysis in a period of high transition risk provides insights into the impact of media attention on clean energy stocks. Overall, the study adds to narrative on the impacts of decarbonization pathways on investor sentiments towards shift to clean energy.

The rest of the paper is divided in following sections: Section 0 provides a review of literature, Section 0 describes the data and news analysis, Section 0 outlines the method and present the results for short-term asset pricing analysis, Section 0 describes the method for long-term event study, Section 0 discusses its results and implications, and Section 0 concludes.

Review of Literature

This study is related to and expands on three strands of the literature: renewable energy financial market response to climate policy; impact of physical on renewable energy stock price dynamics; and investor behavior towards climate risk communicated through media attention and narratives.

Within the first strand of literature, no study has yet examined the effect of IRA specifically on renewable energy stocks. Bauer et al., (n.d.) uses asset pricing and a fixed-effects model to examine the stock market effect of IRA on green and brown stocks. They find that although financial market response to the act was economically important, it did not lead to industry instability in the short run, suggesting that transition risks posed by climate policies even as ambitious as the IRA may be manageable. Pham et al. (2023) uses asset-pricing to investigate the effect of IRA among other climate policies and finds that reactions vary between the tightening and loosening of climate policy and across subgroups of the green stock markets.

In the extant literature on other significant climate policy events, Barnett (2023) identifies several climate policy events and shows that industries with a larger exposure to changes in oil prices exhibit a more negative stock market response to events that increase the likelihood of future climate policy action. Cassidy (2023) constructs a dataset of climate policy announcements and documents that brown stocks perform better than green stocks around events with a large amount of climate policy news. Monasterolo and De Angelis (2020) documents shifts in the risk characteristics of green and brown stock indices before and after the announcement of the 2015 Paris Agreement.

Few studies have examined the renewable energy sector in relation to other climate policies. An early study by Sadorsky, (2012) shows that for the renewable company sales growth has a negative impact on company risk while oil price increases have a positive impact on company risk. On the other hand, Cao et al. (2020) uses Generalized Method of Moments (GMM) to finds that oil price uncertainty has negative impact on renewable energy firms in China, especially on the more volatile small size firms. (Antoniuk & Leirvik, 2024) find that clean energy firms benefitted from the Paris Agreement, Climategate, and Fukushima since these events increased climate change awareness and favor toward policies related to reducing the impact of climate change.

With regard to dynamics between physical risk and renewable energy prices, Liu et al., (2021) investigates the largest clean energy stock performance in the U.S to most notorious, economically damaging hurricanes in the North Atlantic Ocean using the structural VAR model and finds the most positive and statistically significant impact for renewable energy. Fahmy (2022) uses portfolio choice model to examine investor's adaptation to climate change. They find that investors who believe that climate hazards are rising over time tend to be skeptical of investments in clean energy and/or mitigation or adaptation projects. (Faccini et al., 2023) does not find any significant result in the pricing of natural disasters or physical climate risk. Survey results from (Krueger et al., 2020; Stroebel & Wurgler, 2021) show that different kinds of risks are priced differently, and that physical risk in general is underpriced by Environmental-Social-Governance (ESG) stocks. (Alehile et al., 2025) use the GARCH-MIDAS model to

compare the resilience of renewable and non-renewable energy stocks to climate-related risks. Results suggest that investors may perceive renewable stocks as more resilient and stable considering climate-induced shocks.

There has been a recent proliferation of literature on news sentiment analysis. Specifically in case of renewable energy stocks, (Santi, 2023) document investors overreaction to clean stocks during climate change risk and reversal in longer horizons. They show that report on climate change and abnormal weather events, facilitate the investor learning process and correction of the mispricing. Guinea et al., (2024) shows that combination of news shocks captured in renewable energy stock prices significantly affect economic volatility. Noailly et al., (2021) finds that salience of environmental policy in newspapers is associated with a greater probability of cleantech startups receiving venture capital funding and reduced stock returns for high-emissions firms. Yildiz & Karan (2020) investigate the effect of country-level environmental performance and national culture on the stock price crash risk of the renewable energy sector, using 626 firms across 31 countries, and find them to strong but nonlinear predictors, which is not the case for fossil fuel firms. Yazici & Gültekin (2023) discusses the news framing effects of media on renewable energy firms, which in turn is driven by the current socio-economic situation, eco-political agenda and even international relations. Baker & Wurgler (2007) show that stocks which are hard to value are more affected by investor sentiments, which is the case with renewable energy firms.

In other contexts, seminal research by Engle et al.(2020) and Ardia et al. (2023) shows that unexpected increases in a news-based index of climate change concerns benefit green stocks over brown stocks. Faccini et al. (2023) finds that transition risk is priced in the stock market, while physical risk is not. Ramiah et al. (2015) examines the interplay between environmental regulations, capital markets, and political leadership in Barack Obama's administration that advocates for the adoption of green initiatives. Based on industry level analyses, they find that polluters have negative abnormal returns, while climate-responsible firms see non-significant responses indicating that these regulations may not be effective enough. Ramelli et al. (2021) shows that Biden’s 2020 election shifted climate policy sentiments dramatically upward. However, firms with climate-responsible strategies gained during Trump’s tenure as well. (Misev & Balles, n.d.) examine green and brown ETF to show that media attention devoted to climate change concerns drives shifts in investor behavior towards green investments.

Outside of the U.S, (Teutrine et al., 2024) investigates the Stoxx Europe 600 constituents response to the sixth Intergovernmental Panel on Climate Change report published between 2018 and 2023, and find greater volatility for climate-sensitive stocks than emission-graded. Hengge et al. (2023) study carbon

policy news related to the European Union Emission Trading System. They examine events with exogenous changes in the price of emission permits following Känzig (2023) and show that a surprise increase in the carbon price leads to negative abnormal returns of brown stocks compared with green stocks, measured using emission intensities.

Hence, prior research underscores that market responses to climate policy announcements vary significantly by firm characteristics and event context, highlighting both the opportunities and challenges faced by renewable energy firms. Additionally, physical climate risks have shown mixed influence on stock valuations, with broader investor uncertainty regarding long-term climate risks. Lastly, literature on media narratives emphasizes the significant role news sentiment and salience play in shaping investor sentiment and market outcomes for renewable energy investments, both in short- and longer-term horizon.

Data and Natural Language Processing

1.1. Stock market and firm-level data

1.1.1. Renewable energy firms

Most market response studies take either one or a combination of stock market indices that are commonly used to represent the sectors under consideration (Monasterolo et al., 2022; Morina et al., 2021; Pham et al., 2023). Individual firm studies, however, can inform the extent to which the policy is affecting the expected financial performance of a comprehensive sector. It allows for a more granular investigation of the policy's variable impact on heterogenous firm characteristics, especially in the longer term (Faccini et al., 2023; Pastor et al., 2021; Pham et al., 2023). In this study, I construct a universe of renewable energy companies incorporated on the U.S. by following the definition provided by WilderHill Clean Energy Index (ECO), one of the major global trackers of clean energy sectors. It defines renewable energy companies as those that "contribute to advancement of clean energy, including those developing and selling energy technologies and energy management services[5]." This includes primary businesses that fall into the following broad categories: (i) Renewable Energy Harvesting (ii) Energy Storage (iii) Power Delivery and Conservation (iv) Energy Conversion (v) Greener Utilities and (vi) Cleaner Fuels.

I first obtain information on the 209 renewable energy firms listed under the Bloomberg Industry Classification (BICS) classification for "Renewable Energy"[6]. I then identify primary NAICS codes for

[5] Retrieved from WilderHill Clean Energy Index ECO. https://wildershares.com/about.php. Last access: November 10, 2024

[6] No other widely used industry classifications, including the Global industry Classification (GICS), the North American Industry Classification (NAICS) or the Fama-French Industry portfolio have an explicitly stated renewable energy firm category. In fact, Bauer et al., (n.d.) find that in case of Fama-French Industry portfolio, the industry's level of greenness is a poor predictor of its stock market reactions.

Electric Power Generation from clean energy sources (221111 and 221114-7), and other relevant codes pertaining to renewable energy supplies, energy storage, and semiconductors using the Mergent database[7]. Out of these, I manually select firms by scrutinizing primary business details of listings under each code and choosing those that match the specifications provided by ECO. This delivers a final list of 263 renewable energy firms, out of which 216 have stock price data and firm-level data. 67.32% of the firms are small to micro-cap, that is their market capitalization is less than $2 billion, 15.45% are medium-cap (market capitalization between $2 billion to $10 billion) and 17.23% are large-cap (market capitalization above $10 billion).

1.1.2. Benchmark group and other controls

A benchmark portfolio is required for detecting abnormal stock returns of renewable energy firms. For the causal investigation of policy impact, this benchmark serves as a control group. Since S&P 600, 400 and 500 indices are U.S. stock market benchmarks for small-, medium- and large- cap firms, I construct a control group out of their combination by following a matching procedure similar to Barber & Lyon, (1997). In this method, the sample or treatment firms (here, renewable energy firms) are matched to control firms of similar sizes (market capitalization) and book-to-market (book value of equity divided by market value of equity) ratios, excluding firms exposed to specific events. Treatment and fossil-fuel firms are therefore excluded from the control portfolio, and the size-factor is controlled for in the empirical design (see Section 1.5). Firm-distribution by market-cap for both groups is presented in Table 1.

Table 1: Firm-size distribution across renewable energy (treatment) and benchmark (control) group.

	Control		**Renewables**	
Mkt. Cap	**Frequency**	**Percent**	**Frequency**	**Percent**
Small	11,999	36.10%	3,090	67.32%
Medium	6,938	20.87%	709	15.45%
Large	14,305	43.03%	791	17.23%
Total	33,242	100%	4,590	100%

Finally, for the cross-section of all firms, I obtain data for daily and monthly stock prices, trading volumes, and monthly financial ratios from the Center for Research in Security Prices (CRSP) and Compustat via the Wharton Research Data Services (WRDS). Firm-level financial variables include firm size measured by market capitalization, profitability measured by return on asset, leverage measured by total debt divided by earnings before interest, taxes, depreciation, and amortization (EBITDA), company valuation measured by book-to-market ratio and cash effective tax rate (total income taxes paid divided

[7] See Appendix Table A 1 for a list of NAICS codes used.

by pretax income). Chicago Board Options Exchange (CBOE) Volatility index (VIX) to represent market expectations and monthly Gross Domestic Product (GDP), are downloaded from the Federal Reserve Bank of St. Louis website (FRED), monthly inflation rate is extracted from the Bureau of Labor Statistics (BLS) and the Dow Jones Commodity Index Crude Oil from S&P Global. The dataset ranges from January 1, 2021, to December 31, 2023. Summary statistics are presented in Table 2.

1.2. News articles from ProQuest

Building on the methods used by numerous studies to quantify climate risk portrayed in news reports and media sentiments (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2023; Fedorova & Iasakova, 2024), I collect all news articles related to the subject of climate change from major financial newspapers based in the U.S. between 2021-2023. Next, I implement the natural language processing (NLP) models for textual and sentiment analysis for two purposes: (i) to identify windows of high-impact news to test their effect on short-term renewable energy asset prices (ii) to construct a time-series score of daily thematic and sentiment weights to be used as proxies for climate risk perception variability in the causal panel-data analysis.

I first extract an initial collection of news articles using the ProQuest US New stream based on a single query "*climate change*" for full-text articles between January 1, 2021, and December 31, 2023, without any duplicates. This collection consists of 64,072 articles published across the digital and print versions of major financial news sources including *The New York Times, Boston Globe, USA Today, Washington Post, Wall Street Journal, The Barron's, Los Angeles Times, and Chicago Tribune*. Each source is a national key player in delivery of financial information, and this makes them likely to affect stock market prices by means of dissemination of news and communication of related narratives.

Next, I apply further filters to discard entries that are irrelevant summaries, article corrections, or simply company and stock market reports. The remaining sample, however, includes a diverse set of subjects such as healthcare, technology, politics, finance, agriculture among others. While they contain at least one appearance of the bigram "*climate change*", the topics are largely extraneous to climate risk, which is the focus of this study. There is also the concern of omission of articles related to subjects of renewable energy and transition risk which might not contain the query. I therefore expand the algorithm to the following series of bi- and trigrams with the connecting operator "OR": *Inflation Reduction Act, global warming, climate bill, climate change Biden, green jobs, renewable energy, solar energy, electric vehicles, clean energy, wind energy, fossil fuel, gas price, oil energy, coal energy, carbon tax.* This yields the final sample for analysis consisting of 6,726 articles.

Since the period under consideration is a high transition risk, the textual corpus extracted comprises a very eclectic set of climate-related news reflecting rapidly fluctuating sentiments. Entries describe climate change policies, views expressed in domestic and national political debates, scientific research, investment and deployment of renewable energy, corporate views and marketing initiatives, the aftermath of pandemic, energy repercussions of the Ukraine war, reports on extreme meteorological events, and a few regionally confined climate events. To group the heterogenous news into comprehensible subcategories and optimally extract news with high-media attention, I conduct textual and sentiment analysis using natural language processing methods described in the following sections.

1.3. Natural Language Processing: Concepts and Estimation

NLP is a burgeoning field of artificial intelligence focused on enabling machines to understand, interpret, and generate human language in a manner that is meaningful and contextually appropriate. To prepare the news articles, the standard procedure is to preprocess the articles using the Natural Language Tool Kit (Bird et al., 2009). As a first step, I combine all full-text articles into a single document which will form the text data or textual corpus for analysis. Punctuation marks, newlines and tabs are then removed, and all letters are converted to lower case. Next, I remove stop words (for example: the, is, are) and reduce words to their respective word stems to limit textual variability through the process of lemmatization. Finally, I tokenize the textual corpus (the corpus is trimmed such that the words or '*tokens*' that appear less than 5 times and in more than 90% of the documents are removed to filter tokens that are either very rare or common). I then execute textual and sentiment analysis over this prepared text corpus.

1.3.1. Textual analysis: Latent Dirichlet Allocation

The first method I use is the Latent Dirichlet Allocation (LDA) to extract underlying thematic structures in the extensive textual data that will help infer systemic risk factors. LDA is a statistical method used to detect hidden themes or *topics* within a large collection of documents by grouping words that frequently appear together (Blei et al., 2003). It is one of the most commonly used topic modeling methods employed in notable climate risk studies (Faccini et al., 2023; Zhao et al., 2015). LDA is essentially an unsupervised machine learning method, i.e., it is the method, rather than the user, which dissects textual heterogeneity in topics. It lets the user predefine the number of topics they want the whole text to be divided into, but not specific themes like in dictionary-based methods (Apel et al., 2023; Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020). Once LDA delivers the topics in the form of a list of words

weighted by probability of appearance, the user can interpret and label them based on defining characteristics of words[8].

Results from LDA deliver two metrics: a categorical variable of a single highest probability topic for each article, and a continuous variable of each topic's probability-weights in each article, with each topic's share indicating its relative intensity within the article. Summing up the topic shares in the second metric across all daily articles generates a measure of daily topic intensity. This delivers a time-series of news coverage by climate topic based on the articles' timestamps. An increase in a news topic can reflect either an increase in the number of articles published, and/or an increase in the media's attention to a particular topic, for a given number of articles published. Both can therefore lead to short-term but significant investor sentiment and stock market disruptions.

Through trial and error, I choose the corpus to be divided into 5 topics as any larger division reveals idiosyncratic themes. A word cloud of 4 major topics resulting from the final LDA iteration is presented in Figure 2. *Topic 1* is about events related to U.S. climate policy developments and therefore highlights policy transition risk. *Topic 2* elucidates events pertaining to extreme weather events or physical risk. *Topic 3* collects news on climate geopolitics and international climate summits with underlying transition risk. *Topic 4* is about news reported from the lenses of energy transition from fossil fuels to renewable energy. While it may not largely contain news events different from other topics, the narrative's direct focus is on domestic transition risk. *Topic 5*, which mainly contains news about Rhode Island and Providence is discarded for its regional nature that does not affect majority of the treatment group firms.

[8] Essentially, LDA is a Bayesian factor model for discrete data. In a model with K topics, each topic is a probability vector β^k over the V unique words in the textual corpus (k=1…K). Each article is modeled as a distribution over topics, with articles being independently but not identically distributed. Analogous to Principal Component Analysis, a topic being a probability distribution over the unique words, reduces the dimensionality of thematic patterns. For this study, the LDA model is implemented using the scikit-learn library. This implementation uses variational Bayes approximation for estimating the posterior distributions, similar to the approach originally introduced by Blei et al. (2003).

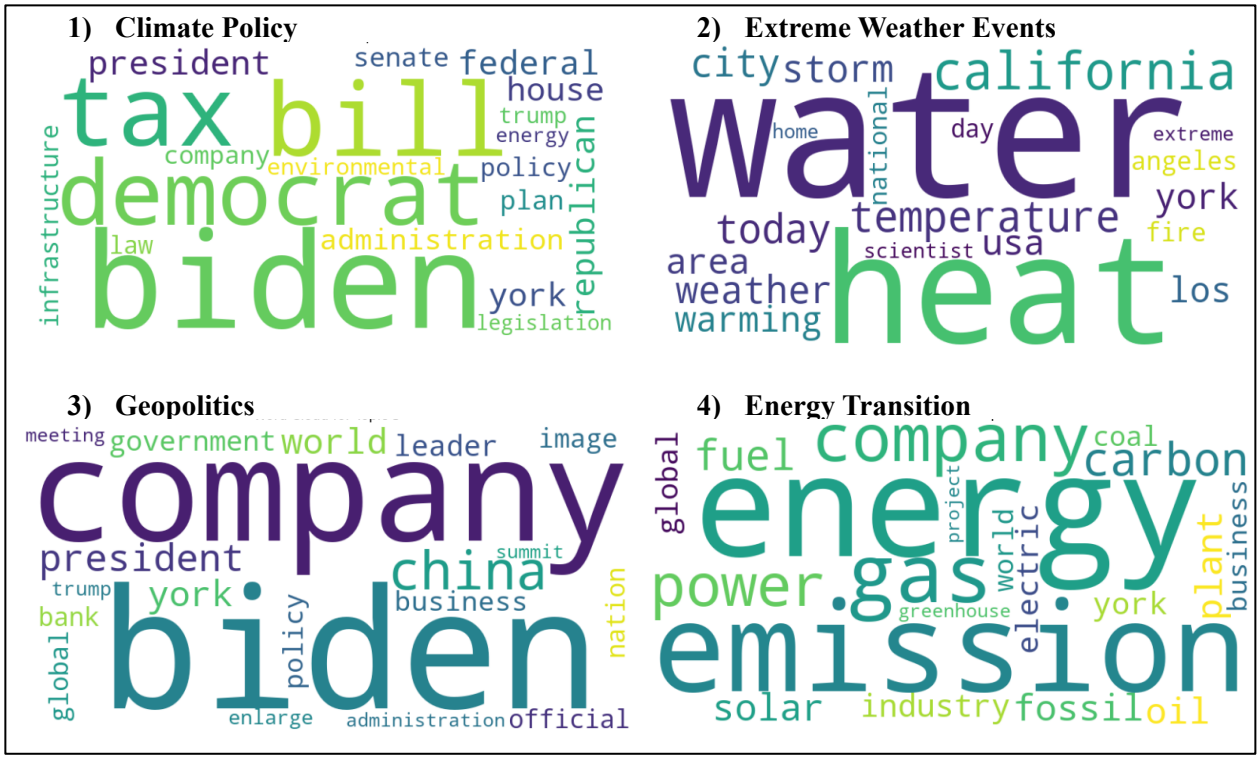


Figure 2: Word clouds for 4 climate news textual factors. Word clouds are delivered by the Latent Dirichlet Allocation (LDA) method. Words in bigger fonts occur more frequently in the articles. The title for each word cloud characterizes its broad theme.

Figure 3 illustrates the time-series evolution with marked news events of very high media-attention[9] for each topic separately. It is assumed that intensive news coverage depicts sources of concern (Engle et al., 2020; Faccini et al., 2023) or of high importance to the economy. For example, note that the trajectory of Figure 3(i) indicates concentrated news weights during 2021 and 2022, but they are significantly subdued in 2023. The trend is corroborated by Biden administrations' term activity which starts with the U.S. rejoining the Paris Agreement in January 2021[10], but ends with Biden's approval of a major Alaskan oil drilling project[11] and forgoing of climate summits[12] in 2023 within the study period. Holding radically different views about climate change from his predecessor, Joe Biden called for a bold set of climate measures concerning green investment and jobs immediately after he took office in 2021. This encompassed announcement of the Build Back Better (BBB) program in March 2021, the even more sweeping and ambitious $3.5 trillion Infrastructure Investment and Jobs Act (IIJA) through the Bipartisan

[9] The threshold for very high media-attention is taken as 3 standard deviations above the mean for each topic, illustrated by dotted lines in each graph in Figure 3. Event on the dates that have topic weightage higher than the threshold are described and tested in Section 1.4.
[10] Report by USA Today, January 20, 2021, "*Joe Biden rejoins Paris Agreement, requires masks on federal property in swift Day 1 directives".* Retrieved from ProQuest.
[11] While the government later in the year took steps to control and stop the drilling project, the reversal was not as frequently or intensely reported. Report by Boston Globe, March 16, 2023, "*The Willow Project: What to know about the massive Alaska oil-drilling venture Biden approved this week*". Retrieved from ProQuest.
[12] Report by New York Times, November 29, 2023, "*Biden's Absence at Climate Conference Highlights His Fossil Fuel Conundrum*". Retrieved from ProQuest.

Infrastructure Bill in April 2021, as well as the capstone IRA bill. Each program was passed after considerable debates and deliberations in both the House and the Senate. A turn in the likelihood of each legislation being passed was dictated by statements of key politicians, especially Senators Machin and Schumer, and it reflected prominently in policy news weights as well as asset prices (see Section 1.4).

Figure 3(ii) illustrates news weight trend of catastrophic natural disasters, extreme weather events, as well as the Ukraine War[13] through the study period. As a depiction of physical risk, it followed a steady trajectory in contrast to policy news. While concerns of global warming got amplified with the seasonal regularity of extreme temperatures, hurricanes were most prominently featured in the news. Chief events included Hurricane Ida, Ian and Idalia in August 2021, 2022, and 2023 respectively, winter storms in January, tornado outbreaks in February, and heat waves, droughts and floods during the summer months of each year. News about the Ukraine war expressed concerns about gas supplies and advised strategic shift towards renewable energy, unlike the narratives about natural phenomena which highlighted institutional and infrastructural vulnerability[14].

The time-series weights for news topic on geopolitics and international climate summits is presented in Figure 3(iii). There was a surprisingly high coverage of the annual Conference of the Parties (COP) summits, with the daily frequency of articles ranging between 15 (for COP28) and 34 (for COP26) which were some of the highest news volumes for any event. Earth Day summits that involved clean energy negotiations with other countries were also featured in the theme. Narratives on COP26, COP27 and other global climate negotiations might have signaled economic concern stemming from possible increase in global tax on pollutants, climate contributions and reduction in emissions (Faccini et al., 2023). A tightening of carbon policy can lead to escalation in energy prices, reducing risk and increasing immediate investments in renewable energy companies (Morão, 2024; Sadorsky, 2012). Ambiguous geopolitical relation and climate stance can however communicate mixed signals and volatility. Note that the trend here mimics that of climate policy in that the summits in 2023 are not weighted above threshold. This can be explained by waning international climate policy stronghold of the U.S. democrats due to their unclear fossil fuel stance[15].

[13] While the Ukraine War is not a natural disaster, it is nevertheless a "physical risk" and appears prominently in Topic 3 of the LDA analysis.

[14] For example, report by Boston Globe, September 20, 2022, "*Energy officials warn that winter could bring blackouts here: Natural gas shortages driven by Ukraine war pose threat.*" Report by USA Today, September 18, 2021, "*Rising seas, sinking land: Life on this Hurricane Ida-battered Louisiana barrier island may never be the same*". Retrieved from ProQuest.

[15] For example, report by Los Angeles Times, April 13, 2021, "*Biden Wants Leaders to Make Climate Commitments for Earth Day*". Report by New York Times, November 27, 2023, "*Could Biden's Clean Energy Push Be a Victim of Its Success?*" Retrieved from ProQuest.

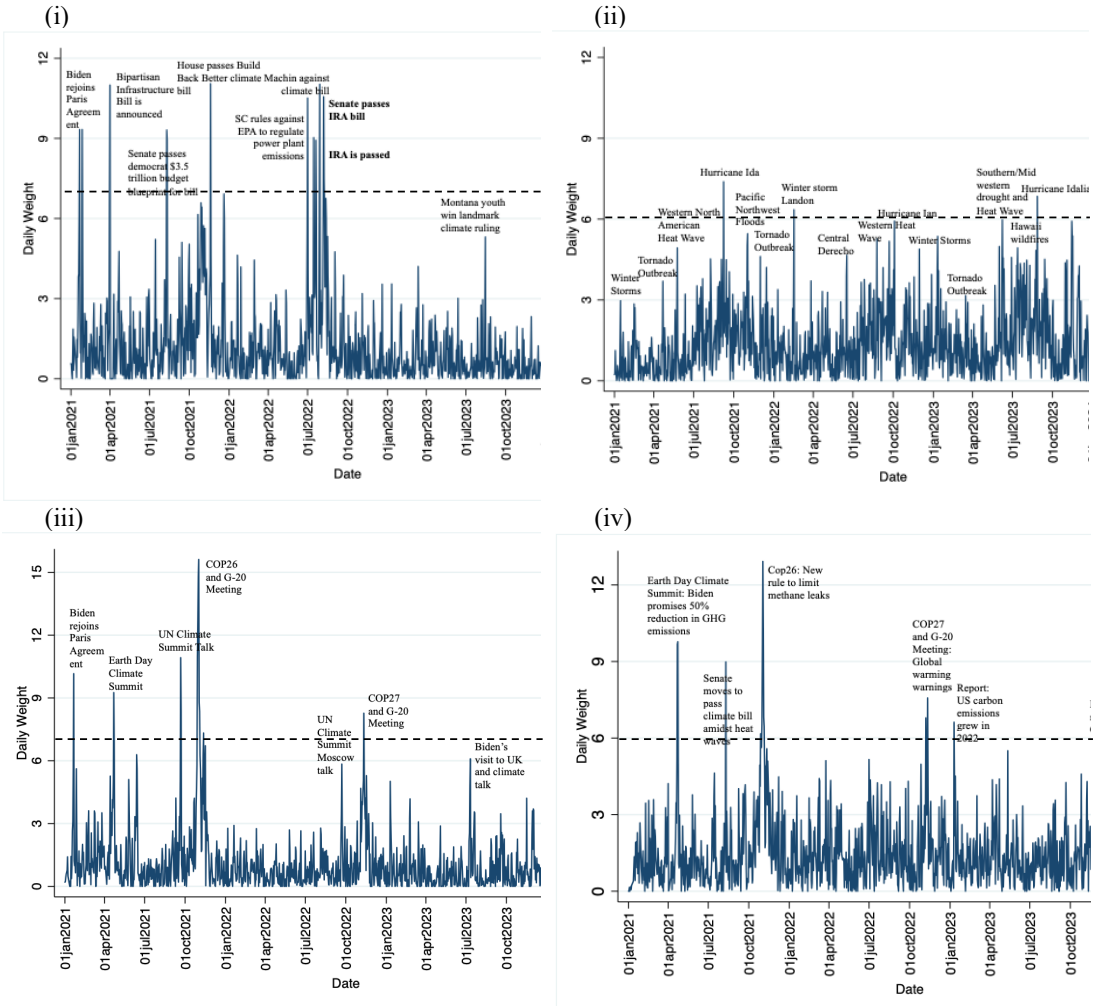


Figure 3: Climate news textual factors over January 1, 2021- December 31, 2023, and their associated with news releases. The vertical axis measures the topic shares for each factor, i.e. the percentage of words in each article associated with a given factor. To obtain the daily topic share associated with a given factor, the topic shares of all articles published on that day are added up. Dotted lines show thresholds placed for values 3 standard deviations above mean.

Figure 3(iv) demonstrates the news weights trend for the energy transition textual factor. The theme collected domestic news on solar and wind energy infrastructure projects, electricity grid and storage, gas price inflation, tax incentives for electric vehicles, solar project in new-income households, and Environmental Protection Agency (EPA) proposed rules on Methane emissions. It also featured international statistics on fossil fuel usage, carbon emissions and cost of energy transition. However, news with the most rigorous coverage are events spilt over from other themes. The focal point of the content of such articles is the impact of those events on renewable energy or fossil fuels. For example, Biden's promise on the Earth Day climate summit to reduce greenhouse gas emissions by half during his term garnered substantial media attention. Solar and wind investment and tax provisions under the IRA bill received their separate share of spotlight. Media scrutiny of negative data insights on rising global

emissions as well as oil and gas usage towards the second half of 2023 may have led to the dampening of democrat's climate efforts, among other factors. While asset price impact evaluation of the energy transition theme can add to a multi-dimensional understanding of energy market reactions, it is difficult to isolate any such news event for the purpose of analysis, at least through current event study methods.

1.3.2. Sentiment Analysis: Pretrained ClimateBERT model

News stories are usually written from a biased perspective depending on publications and can drive the market in different directions based on the angle of reporting (Jiang et al., 2017). While LDA facilitates bifurcation of systemic risk, sentiment analysis of articles can provide insight into whether climate news reflects positive or concerning signals for the economy i.e. it indicates behavioral risk patterns. Many studies use different methods to generate sentiment-marked factors. Engle et al., (2020), Ardia et al., (2023) and Jiang et al., (2017) use "bag of words" based dictionary[16] methods to classify articles, whereas Faccini et al., (2023) marks the contents manually.

Similar to Fedorova & Iasakova, (2024), I use ClimateBERT (Bidirectional Encoder Representations from Transformers), a pre-trained transformer neural network designed to understand contextual relationship in climate text data designed by Webersinke et al., (2022)[17]. ClimateBERT classifies climate-related paragraphs into one of the three sentiment classes: a positive *opportunity*, a *neutral*, or a negative *risk*. A notable advantage of this model therefore is that it considers communicated narratives between words and sentences in climate-related text.

[16] In most dictionary methods, the tone of textual data is estimated by using a lexicon and calculating the frequency of word occurrence in the text. The meaning of separate words is considered, but the context and semantics of the text are ignored.

[17] Webersinke et al. (2022) uses the state-of-art DistilROBERTA model and 135,391 news articles on climate change topics such as climate politics, climate actions, floods and droughts to train the model, reducing the margin of error by 3.58% in comparison to similar Language models. This study uses package from the Hugging Face open-source library updated by the authors to run the model on the collected corpus of full-texts (Retrieved from the Hugging Face transformers library. https://huggingface.co/climatebert/distilroberta-base-climate-detector. Last access: November 10, 2024).

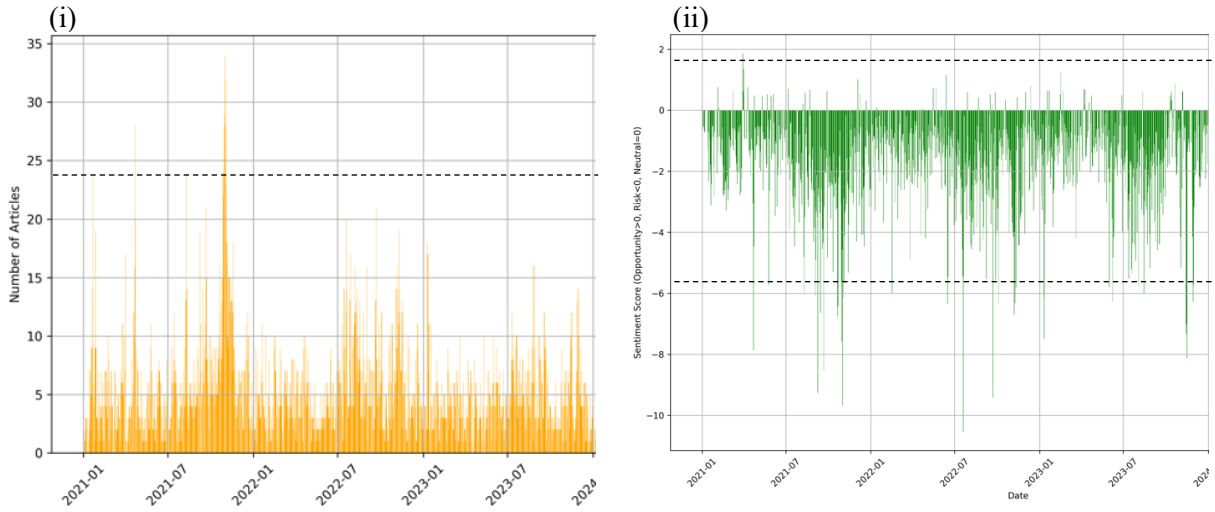


Figure 4: Daily climate sentiment scores and article volumes over January 1, 2021- December 31, 2023. The vertical axis for sentiment analysis measures the sentiment score. Risky news is assigned a value below -1, neutral is assigned 0 while opportunity is assigned above 1 by the ClimateBert sentiment analysis model. To obtain the daily scores, all scores for each article published on that day are added up. Dotted lines show thresholds placed for values 3 standard deviations above mean.

Like in the case of LDA, results generate a categorical series of sentiment-class-annotated news articles and a continuous series of sentiment scores for each article. I then sum up the scores across all daily articles forming a time-series of news sentiment scores and average them for monthly measures. The largest share is of articles communicating risky climate sentiments, with the class forming 47.8% of the corpus. Neutral articles that do not lean towards any bias also hold a substantial 47.4% share. The smallest share is of articles conveying opportunity sentiments, which form only 4.8% of the articles. Figure 4(ii) illustrates the daily sentiment weight trend over the 2021-2023 period. The event with the largest negative sentiment score of -11 was on July 20, 2022, days after Senator Machin's withdrawal of support from the IRA bill. Amidst public reaction to deadly heat waves, senatorial obstacles to passing of the climate bill, and republican's criticism to Biden's plans to convert an out-of-operation coal mine in Massachusetts to a wind energy production facility, the President was urged by democrats to declare a climate emergency[18]. Other adverse sentiment days included narratives of and reactions to extreme weather events and climate summit talks. While in most cases of textual analysis high frequency news days were earmarked to specific events, sentiment analysis outliers highlighted oppositional stories of overlapping events, such as Moscow summit talk amidst rising smog and asthma cases among black and Hispanic children in September 2022.

[18] Report by Wall Street Journal, July 20, 2022, "*Biden Is Pressed to Declare Emergencies After Climate, Abortion Setbacks; Some Democrats and activists want president to use executive powers to unlock more authority and funding; declarations would face criticism and legal challenges."* Retrieved from ProQuest.

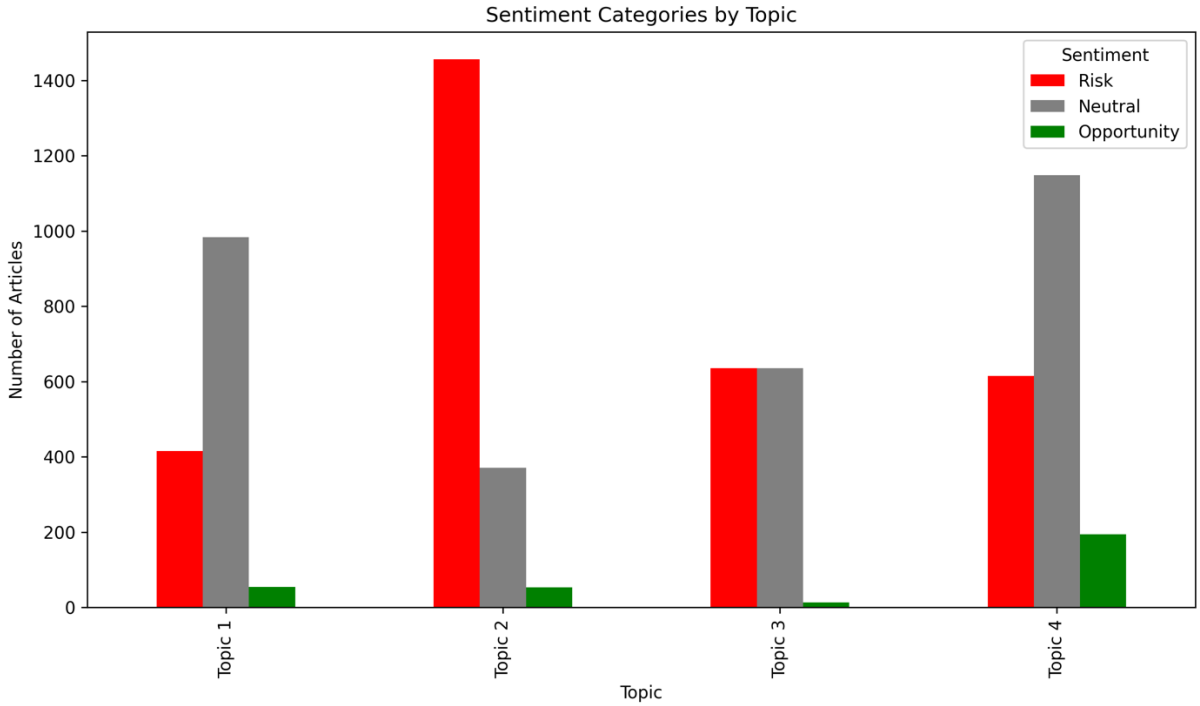


Figure 5: Relationship between news topic, volume and sentiment. The vertical axis shows number of articles per day. The four topics bifurcate news about U.S. climate policy (topic 1), extreme weather events (topic 2), global climate politics and international summits (topic 3) and energy transition (topic 4). Each bar for each topic shows division of sentiments across categories.

A visualization of number of articles per day is also presented in Figure 4(i). Although not necessarily indicative of a specific theme or sentiment, the sheer volume of news articles published within a single day can exert a considerable influence on market sentiment (Hsu et al., 2021). The day with the highest volume of news coverage (34 articles) is November 1, 2021, featuring Biden's visit to COP26 Glasgow summit. Other high frequency media days include the IRA climate bill passage on July 27, 2022 (16 articles), the BBB passage on April 1, 2022 (18 articles) and the Earth Day Summit on April 22, 2022 (20 articles).

Figure 5 is a perceptive depiction of correlations between textual and sentiment analysis for all articles. Associated sentiments serve as a possible measure of degree of riskiness for each theme. For example, note that the markers show a significant overlap of risky sentiments with textual topic on extreme weather events reinforcing their broadly concerning narrative of increased physical risk. Most news coverage for *Topic 1* (U.S. climate policy) have a neutral tone suggesting that the related article corpus might be elucidating on both positives and negatives of policy initiatives. *Topic 4* (energy transition) has the largest share of optimistic as well as neutral articles, mostly pertaining to solar and wind energy infrastructure

development, deployment and planning. A concise summary of monthly time-series news sentiment measures in presented in Table 2.

Table 2: Monthly summary statistics for renewable energy (treatment) and benchmark (control) group.

Stock Variables						
Variable	**Group**	**Observations**	**Mean**	**SD**	**Min**	**Max**
Stock Price	Control	33,242	115.883	257.3539	0.0001	7000.45
	Renewables	4,590	25.5916	50.64082	0.0001	498.56
Cumulative Returns	Control	33,242	0.10548	0.447214	-0.999	5.633272
	Renewables	4,590	-0.2081	1.367305	-1.000	37.08164
Trading Volume	Control	33,214	49200000	135000000	6	2900000000
	Renewables	4,539	35900000	135000000	100	4140000000
Firm Characteristics						
Book to Market	Control	27,287	0.5182	0.4961	0.0002	8.7762
	Renewables	1,978	0.6362	0.8679	0.0002	10.8001
Return on Asset	Control	28,552	0.1215	0.1082	-0.7021	1.9887
	Renewables	2,012	-0.0932	0.6540	-12.5548	0.3163
Effective Tax Rate	Control	24,234	0.1970	0.5722	-6.6417	9.0000
	Renewables	970	0.1537	0.6681	-0.6481	6.1367
Total Debt to EBITDA	Control	28,493	3.5060	103.2776	-2288.1670	9237.2420
	Renewables	2,061	4.0570	61.3998	-529.0426	1183.5870
Macroeconomic Variables						
Variable	**Observations**	**Mean**	**SD**	**Min**	**Max**	
CBOE Volatility Index (VIX)	37,832	20.60	4.5200	12.72	30.01	
Crude Oil Index	37,832	41.65245	7.8841	28.16	67.5	
Gross Domestic Product	37,832	0.0320	0.0308	-0.0434	0.1262	
Inflation Rate	37,832	0.4537	0.4054	-0.30	1.40	
News Sentiment Measures						
Variable	**Observations**	**Mean**	**SD**	**Min**	**Max**	
Climate Policy Factor	37,832	1.169148	.7528101	.3016624	3.378952	
Extreme Weather Events Factor	37,832	1.398581	.5319905	.5300457	2.495405	
Geopolitics Factor	37,832	1.087603	.7548139	.3628842	3.789615	
Energy Transition Factor	37,832	1.522645	.5785140	.8219599	3.871828	
Article Sentiment	37,832	-1.710179	0.693577	-3.417571	-0.698384	
Article Volume	37,832	5.336885	1.962505	2.866667	12.36667	

Short Horizon Event Study: Immediate Stock Market Responses

This section illustrates the immediate market reaction of renewable energy stocks to (i) the passage of IRA and (ii) highly publicized news shocks pre- and post- IRA. To establish a threshold for each news measure, an average for all time-series factors built in Section 1.3 is computed and only those dates are chosen for analysis which display higher (or lower) values than 3 standard deviations above (or below) the mean. Specifically, all dates with a news volume of 20 stories per day, with a sentiment score less than - -6.61 or more than 1.25, and with a weightage of more than 6.89 for *topic 1*, 5.25 for *topic 2*, 6.66 for

topic 3 and 5.95 for *topic 4* are chosen. These thresholds are marked by a dashed black horizontal line in respective time-series figures.[19]

To conduct this study, I employ an asset-pricing model from the well-established financial literature on event studies to calculate abnormal returns for each event. Abnormal returns are derived from the difference between the observed raw returns and the expected returns predicted by a multifactor framework, following the Fama and French, (1993) methodology. Specifically, I estimate the Fama-French three-factor model (FF3) by regressing daily, equal-weighted raw returns of renewable energy stocks on expected returns of the market portfolio, the size factor (Small-Minus-Big or SMB) and the value factor (High-Minus-Low or HML) obtained from the Kenneth R. French Data Library[2021]. By incorporating the size and value factors, the model provides an unbiased measure of abnormal returns, allowing for an improved understanding of the risk-adjusted performance in response to news events. I use the '*estudy*' package in STATA to perform the event study analysis on cumulative stocks of all renewable energy firms. For each event, I report the 1-day, 3-day and 5-day cumulative average abnormal returns (CAARs). Returns are accumulated over each window for multiple days and averaged over multiple stocks.

1.4. FF3 Results

The CAARs for all renewable energy firms around climate policy, extreme weather and geopolitical news events as identified through extensive media coverage during January 2021 to December 2023 are shown in Figure 6[2223]. Note that the dates analyzed do not constitute an exhaustive list of *all* events affecting renewable energy stocks. This section primarily addresses the short-term, immediate responses to very high transition and physical risk periods. Particularly, I examine the swift and pronounced market reactions to abrupt legislative changes preceding the IRA's enactment, assuming that the market, under the Efficient Market Hypothesis, quickly assimilates such impacts. The observed market disturbances offer insights into investor risk perceptions and the magnitude of events, potentially highlighting deviations influenced by behavioral biases and herding behaviors. (Botzen et al., 2021; Bua et al., 2022;

[19] In most news analysis studies, variations of structural vector autoregressive models are used to identify news shocks or innovations (Engle et al., 2020; Hsu et al., 2021; Liu et al., 2021; Morão, 2024). While SVARs are robust models to identify few precise and unanticipated shocks over extended periods, this study seeks to capture a broader range of influential events by identifying multiple windows of heightened media coverage across 2021-2023 to gain insight into various news themes. Rather than focusing solely on shocks, the threshold approach targets periods of elevated significance in public discourse, as reflected in media attention.

[20] Data on market risk-free rate, size factor (Small-Minus-Big or SMB) and value factor (High-Minus-Low or HML) from October 1, 2020, to December 31, 2023, is obtained from the Kenneth R. French Data Library. See Fama/French 3 factor, Kenneth R. French Data Library. https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Last access: November 10, 2024.

[21] See Appendix A1 for detailed asset pricing method.

[22] High intensity energy transition news as well as extreme sentiment events overlap with other topics, and they are discussed in the results but not illustrated separately. However, it must be noted that as time-series measures, they still represent different dimensions of climate risk.

[23] For more detailed results, see Appendix Table A 2. Table A 2: Results from FF3 model for different news textual factors.

Pham et al., 2023; Ramiah et al., 2015). The insight can help policymakers respond rapidly and efficiently to discourse shifts (Stede & Patz, 2021).

I first start with looking at the impact of climate policy (*Topic 1*) events. Results for the passage of IRA are consistent with (Bauer et al., n.d.; Pham et al., 2023). The first legislative step towards the policy initiative was arguably the house passing the highly debated Build Back Better (BBB) program. The program was in many ways a more ambitious economic and social policy bill with similar aims as the IRA[24] and was ultimately stalled by the Senate. Figure 6 shows that returns from the portfolio of renewable energy firms significantly outperformed the expected market return by 4-6% over a period of 5 days on November 19, 2021, when the BBB was passed by the House. A month later the returns dropped below market expectations by as much as -8% when Senator Machin, the key holdout in an evenly divided senate announced his decision to vote against the bill.

This led to months of negotiations to redesign the bill to a more economically workable Inflation Reduction Bill. However, returns plunged to abnormally low (-3%) when press reported Senator Schumer's and Machin's dissention to the IRA. The market showed rapid recovery by day 5, signaling anticipated pessimistic investor expectation. This also explains their sizeable jump on July 27, when the IRA was announced by Schumer and Machin as a new climate legislation. Renewable energy stocks outperformed expected market returns by 13% over 5 days, highest among all events examined in this study. The increasing trend in abnormal returns over days 1, 3 and 5 indicate a considerably unanticipated shock. In fact, subsequent legislative changes including passage of the act by the Senate and the House on August 7 and 12 respectively, and even the final signing of the bill into an act by Biden on August 16 did not experience significantly abnormal renewable energy market returns[25]. Bauer et al., (n.d.), who examines the clean energy indices like the Wilderhill and S&P Global clean energy index finds similar results.

Prior policy announcement questioned the ability of the democrats to convert their claims into actionable policies with significant Senate backlash. Announcement of the BBB as well as passage of IIJA by the Senate had a progressively negative impact on the market returns driven probably by sentiments and narratives. While the total sentiment score for April 1, 2021, was 1 (optimistic) resulting in slightly higher returns on day 1, subsequently featured debates in the Senate dampened the market. On the other hand,

[24] Report by Joint Economic Committee Democrats, "11 Ways the Build Back Better Act Would Reduce Inflationary Pressure and Bring Down Costs for Families." Retrieved from https://www.jec.senate.gov/public/_cache/files/f9a6f7a3-9a50-4530-bc43-c7215abc8d27/bbb-and-inflation-fact-sheet.pdf

[25] Dampened renewable energy stock returns can also be explained by heterogeneity and subjectivity in media coverage to fully anticipated news. Most news reports on August 7, 12 and 16 bear a neutral stance. Some examples of headlines on August 16 include report by News York Times, "*Biden Signs Climate, Health Bill into Law as Other Economic Goals Remain*" and report by Los Angeles Times, "*Climate bill is big deal, but drama persists; Inflation Reduction Act has $370 billion for clean energy, but scientists say much more must be done*". Retrieved from ProQuest.

sentiment score for August 10, 2021, was -6 as news articles continued to elucidate on the challenges facing the Democrats after passing a $3.5 trillion bill[26]. Other studies reveal a large increase in green stock returns on Biden's election and rejoining of Paris Agreement (Pham et al., 2023). However, I do not test for news before April 1, 2021, in this study to allow a beta calculation period of at least 120 days before all events.

Analyses of *Topic 2* events reveals interesting patterns and forms another significant contribution of this study. Overall, market performance shows that the depressing effect of physical risk arising out of natural disasters and extreme weather phenomena was not neutralized by renewable energy stocks. News on winter storms, Hurricane Ida and tornado outbreaks in 2021 lead to underperformance of renewable energy stock returns by -6 to -10%. Other highly publicized natural disturbances also produced negative abnormal returns. But note that their magnitude was somewhat reduced after the year 2021. Only the Ukraine war resulted in significantly positive abnormal returns.

These results fit well with the tenets of climate policy uncertainty, limited attention hypothesis and behavioral myopia among investors (Botzen et al., 2021; Horváth et al., 2025; Song & Dong, 2024). The limited number of studies on the relationship between natural disasters and energy stocks reveal heterogenous and complex dynamics (Misev & Balles, n.d.)[27]. Climate shocks, especially hurricanes, are invariably related to incurred costs of infrastructural disruption and energy availability (Mukherjee et al., 2018). Although growing in quality, renewable energy infrastructure is still more vulnerable than that of fossil fuels. In such a case, restricted cognitive abilities prohibit investors from processing an overload of information. Their attention is limited to media portrayal of the event, leading to myopia or heavy discounting of future risk reduction benefits and over-weighting of upfront costs (Botzen et al., 2021) (see Section 1.3.1). With reduced climate policy uncertainty however, rebuilding funds after disasters and prospects of clean energy availability increased (Song & Dong, 2024), leading to neutralizing of renewable energy stock prices to climate shocks.

Conversely, articles on the Ukraine war highlighted the sudden supply chain disruption of gas[28]. The portrayal of the war bears similarity with the Covid-19 pandemic as an external, non-climate-related

[26] Report by Wall Street Journal, August 10, 2021, "*Senate Moves to Pass Democrats' $3.5 Trillion Budget Blueprint; Democrats will face difficult choices, as they work to transform the budget framework into detailed antipoverty and climate legislation.*" Retrieved from ProQuest.
[27] There is considerable evidence to suggest that fossil-fuel stocks are more vulnerable to climate shocks that renewable energy stocks (Alehile et al., 2025; Liu et al., 2021; Misev & Balles, n.d.). But here, the comparison is between renewable energy stock movements and a neutral benchmark.
[28] Report by The Washington Post, February 26, 2022, "How the Ukraine invasion scrambles American energy politics." Retrieved from ProQuest.

disruption which exposed the vulnerability of dependence on oil (Albuquerque et al., 2020; Garel & Romec, 2020).

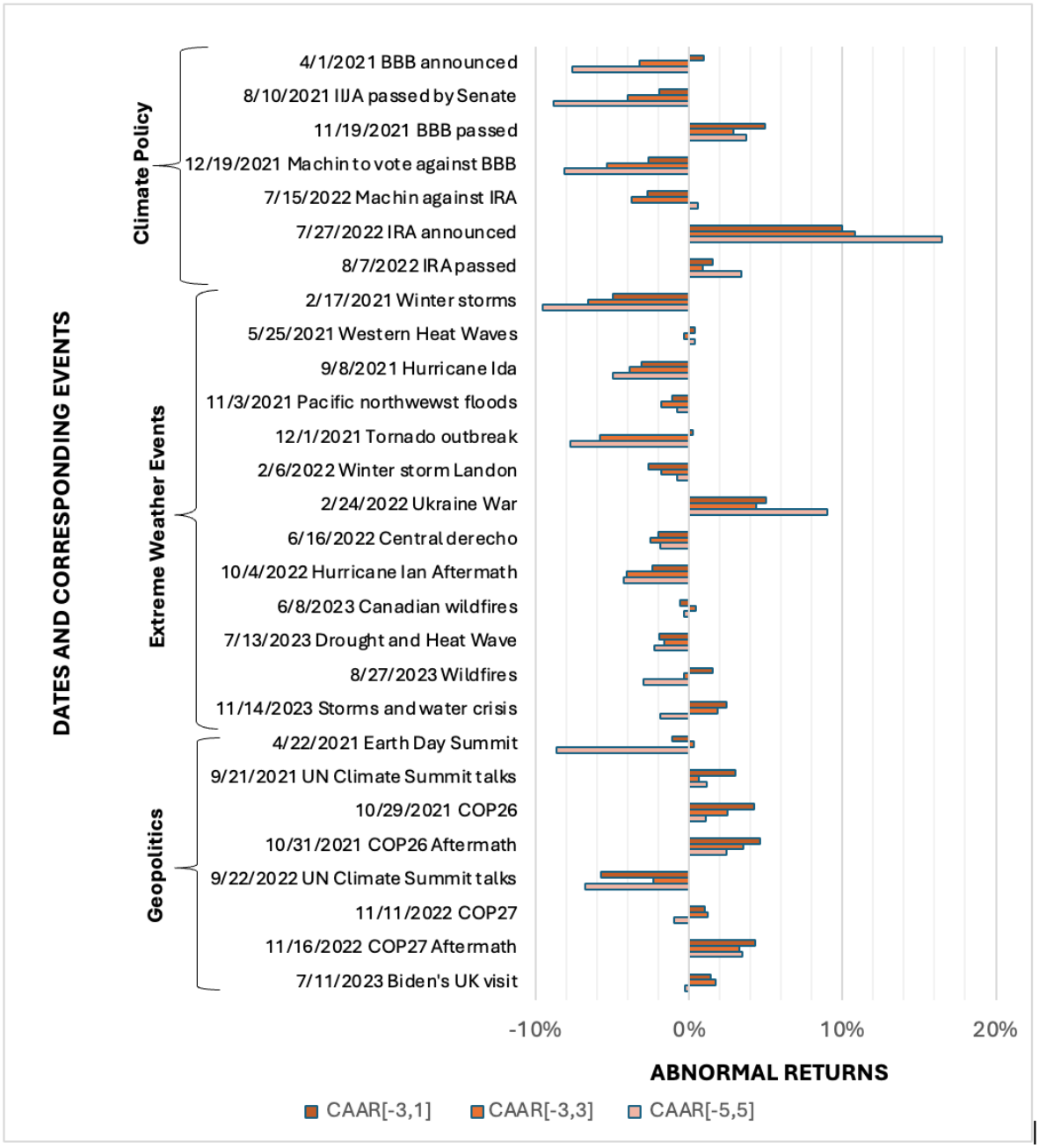


Figure 6: Cumulative Average Abnormal Returns (CAARs) for renewable energy firms over multiple windows calculated using the Fama-French 3 factor model. Results are presented for various high attention news events segregated by thematic textual analysis using the Latent Dirichlet Allocation (LDA).

Stock price responses to geopolitical summits generally exhibited positive trends following President Biden's commitments to lead international clean energy transitions. Exceptions were observed at the 2021 Earth Day Summit and the September 2022 U.N. climate talks, which recorded lower abnormal returns. These were attributed to market uncertainties stemming from the announcement of the Build Back Better (BBB) plan and the resignation of World Bank President David Malpass due to his climate-related stances, respectively. Results are consistent with the study by (Antoniuk & Leirvik, 2024) that show that clean energy indices benefited from Paris Agreement, Climategate, and Fukushima events.

Extended Horizon Event Study: The design

In this section, I extend the stock market impact evaluation of the IRA over a relatively longer period up to the point where the abnormal returns are discernable. For this, I employ the DiD framework for extended term asset price analysis[29]. I assign daily stock-returns for renewable energy firms to the treatment group and use the control group for benchmark formed by daily stock-returns of S&P 500, 400 and 600 constituents as described in Section 1.1.2. I weigh the daily cumulative returns by market capitalization to facilitate comparison across heterogenous firm sizes.

An explanation of event-date choice is in order here. I select July 27, 2022, (rather than the official date of August 16, 2022, when IRA was passed into law) to mark the passage of IRA as event under analysis, This is for three key reasons: (i) based on insight from the study's short-term asset pricing test, the immediate market impact of the IRA was observed on July 27; by August 16 the effect had been largely anticipated and priced in (see Section 1.4); (ii) Bauer et al. (n.d.) corroborates this by showing that it was July 27, marking the announcement of IRA by Manchin and Schumer, that saw the highest gains in clean energy stock indices; and (iii) the parallel trends analysis depicted in Figure 7 demonstrates a similar noticeable trend shift beginning on July 27 rather than August 16. For these reasons, July 27, 2022[30], is assumed to represent the event date for the passage of IRA for extended term stock price analysis.

The subsections below outline the econometric method followed for each model.

1.5. Difference-in-Differences (DiD) Model

The primary goal of the DiD model is to identify the average causal impact of IRA on daily/monthly cumulative returns and daily/monthly volume of traded shares of renewable energy firms. The primary identifying assumption is that in the absence of IRA, the treated (renewable energy) firms would have

[29] To facilitate comparison of results, I also run Buy and Hold Abnormal Returns (BHAR) model for similar specifications. See Appendix **Error! Reference source not found.** for model and results.
[30] Placebo test with other dates do not reveal significant trends. See Table A 5.

experienced the same trends in outcomes as the control group firms after controlling for confounding factors. This "parallel trends" assumption is illustrated in Figure 7. For a baseline model, a 2 × 2 (two groups, two periods) panel fixed effects DiD approach is employed, with errors clustered on state. A daily frequency regression specification is as follows:

$$\mathrm{Y_{it}} = \alpha + \beta_1 \mathrm{Post_t} + \beta_2 \mathrm{Treat_i} + \delta(\mathrm{Post_t} \times \mathrm{Treat_i}) + \beta_3 \mathrm{X}_{it} + \epsilon_{\mathrm{it}}$$

Where Y_{it} are the daily value-weighted cumulative returns of each stock *i* on closing day *t*, Post_t is the post-IRA period indicator or post-July 27, 2022, and $Treat_i$ is the treatment group indicator (here, renewable energy firm sample). X_{it} is the vector of control variables—daily volume of shares traded to capture liquidity, daily weightage for each of the four news topics and daily news sentiment score to control for media influence and public sentiment dynamics, and the CBOE VIX index to account for expected market volatility. Firm characteristics are only available in monthly frequency and are therefore included in a modified low frequency specification. Specifications are also run with log of volume traded as the dependent variable and for different firm-size groups.

$(Post_t \times Treat_i)$ is the primary variable of interest and equals one if an observation is in the intervention (renewable energy) group and from the post-treatment (IRA) period. δ measures the average treatment effect of the intervention. If δ>0 and significant, it suggests extended term average positive abnormal returns for renewable energy firms after the passing of the IRA, in comparison that of the control group. It reflects lower risk perception of clean energy stock prices, probability of future profits and expected growth leading to higher actual returns today. If δ=0, it indicates the dissipation of the effect of IRA on renewable energy firm prices, and therefore a complete market absorption of any benefits arising from the climate bill. This is also a semi-positive effect as it suggests no market disruption even after such an ambitious policy (Bauer et al., n.d.). A negative and significant δ, will however suggest extended term negative abnormal returns for renewable energy firms after the passing of the IRA, in comparison to the control group, indicating increased transition risk perceptions and reduced growth in future. Finally, ϵ_{it} is error term clustered around state of incorporation of the firm.

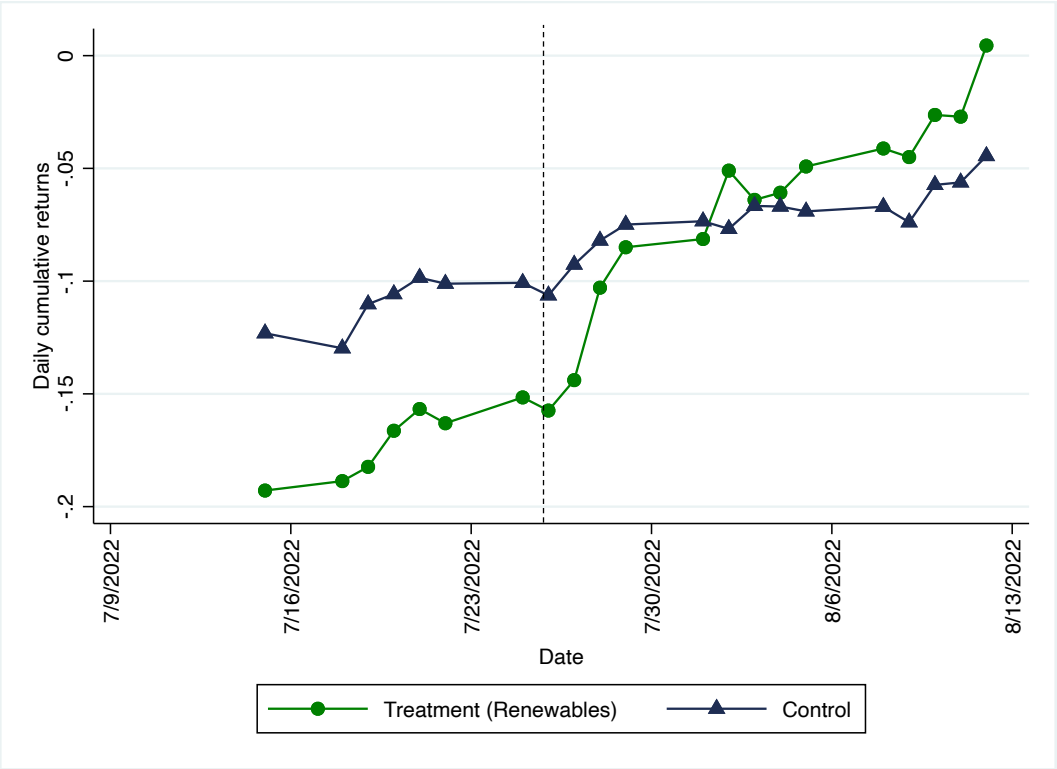


Figure 7: Parallel trends between treatment and control group. Diversion occurs on July 27, 2022, represented by the vertical dotted line.

The results for all specifications are presented in Section 1.7.

1.6. Dynamic DiD Model

Based on insights about high volatility of energy stock market returns in general (Işık et al., 2024), I utilize a dynamic DiD approach within an event-study framework to estimate the effects of the IRA intervention on monthly cumulative returns and volume traded of renewable energy stocks over the period. I slice the timeframes in monthly intervals, from 5 months before the event, that is January 2022 to 12 months after the event, that is July 2023 to measure intertemporal trends. The dynamic DiD has two chief advantages; first, the estimation of pre-treatment intervention effects makes it possible to statistically inspect the parallel trend assumption; second, the model is able to deal with treatment effect heterogeneity and captures the dynamic effects of the IRA over time. I use the STATA package *'eventstudyinteract'* developed by Sun and Abraham (2021)[31] to run the model. The equation is as follows:

[31] '*reghdfe',* which is a commonly used two-way fixed effects regressions that includes leads and lags of the treatment, might lead to coefficient contamination of related events.

$$Y_{it} = \alpha + \beta_1 Time_t + \beta_2 Treat_i + \sum_{k=-3}^{13} \delta_k (Time_{t+k} \times Treat_i) + \beta_3 X_{it} + \epsilon_{it} \quad (2.4.8)$$

Where Y_{it}, $Treat_i$, X_{it} and ϵ_{it} are the same as above, including firm characteristics. The variable $Time_t$ indicates the relative month of an observation from 3 months before to 13 months after the implementation of IRA. The parameter of interest, δ_k captures the temporal effects of the intervention by comparing the difference in cumulative returns between intervention and control groups to such a difference in the reference period (June 2022-a month prior to the event occurrence month). Results are provided in the next section.

Results and Discussion

1.7. DiD and dynamic effects

Table 3 and Table 4Table 4 summarize the findings from the DiD estimation examining cumulative abnormal returns (CARs) of renewable energy firms associated with the enactment of the IRA.

Table 3 reports the shorter-term daily CARs. The DiD estimator indicates that renewable energy firms exhibited statistically significant positive abnormal returns of 12.5% within ±30 days ($p<0.01$) and 13.4% within ±120 days ($p<0.05$) around the policy event. Disaggregating by firm size, the results demonstrate significant positive CARs for medium-cap (6.87%, $p<0.01$) and large-cap firms (10.9%, $p<0.1$), whereas small-cap firms exhibit statistically insignificant effects.

Table 4 extends this analysis to monthly CARs of renewable energy firms to facilitate incorporation of firm-level financial controls and macroeconomic indicators other than the VIX index. The DiD estimator highlights robust abnormal returns of 14.8% within ±6 months ($p<0.05$), although the longer-term (±12-month) effect becomes statistically indistinguishable from zero. Further size-specific analysis reveals statistically significant positive CARs among medium-cap (6.53%, $p<0.05$) and large-cap firms (18.7%, $p<0.05$). Additionally, incorporating climate-specific news factors indicates that geopolitical news significantly enhances CARs, whereas weather-related news exerts a negative impact. Effect of climate policy news (other than the passage of IRA) is not statistically significant[32].

Table 5 reports the Difference-in-Differences (DiD) analysis examining cumulative abnormal trading volumes (CATVs) of renewable energy firms surrounding the announcement of the Inflation Reduction Act (IRA). The findings indicate significant increases in trading activities of renewable energy firms

[32] Correlation test (see Appendix Table A 3Table A 3) reveals high factor correlation between sentiment measure and extreme weather phenomena news theme, as well as geopolitics and energy transition theme. Therefore, only topics 1,2 and 3 factors are included in the regression specification presented in Table 3, Table 4 and Table 5The results are robust if the topic factors are exchanged with the sentiment score factor. See Appendix Table A 5 for robustness checks.

within shorter-term windows, with CATVs rising by 30.7% (±3 months, p<0.05) and 26.1% (±6 months, p<0.05). For small-cap firms, the CATVs increase by 11.9% over the ±12-month window, although this result lacks statistical significance. Further decomposition reveals that climate-related news significantly influences trading activity. Geopolitical factors positively drive abnormal volumes at the 6-month (16.0%, p<0.01) and 12-month (8.07%, p<0.01) horizons. In contrast, weather and climate policy-related factors negatively affect abnormal trading volumes consistently across these windows.

All regression models incorporate comprehensive macroeconomic controls, and sentiment-based news variables, with standard errors clustered by state, while monthly frequency models also include firm-specific characteristics. The CARs reported are market-cap-weighted and have been winsorized at the 1st and 99th percentiles to address potential biases arising from extreme observations.

Table 3: Extended term event study results of daily average cumulative returns from DiD analysis.

	All firms	**All firms**	**Small cap**	**Medium cap**	**Large cap**
	CAR (-30, +30)	CAR (-120, +120)	CAR (-120, +120)	CAR (-120, +120)	CAR (-120, +120)
	(1)	(2)	(3)	(4)	(5)
Post × Treated (DiD Estimator)	0.125***	0.134**	0.0576	0.0687***	0.109*
	(0.0350)	(0.0506)	(0.0356)	(0.0211)	(0.0603)
Post (after IRA)	0.0105**	-0.0623***	-0.0283***	-0.0116	-0.0626***
	(0.00513)	(0.00844)	(0.00677)	(0.00895)	(0.00833)
Treated (Renewable Firms)	-0.0827**	-0.0684**	-0.0271	-0.0358***	-
	(0.0325)	(0.0300)	(0.0244)	(0.0130)	-
News sentiment controls	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No
Observations	46,560	193,514	96,039	32,455	65,020
R-squared	0.373	0.491	0.066	0.123	0.519

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Standard errors are clustered around state. Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal returns from X days before to X days after July 27, 2022.

Table 4: Extended term event study results of monthly average cumulative returns from DiD analysis.

	All firms	**All firms**	**Small cap**	**Medium cap**	**Large cap**
	CAR (-6, +6)	CAR (-12, +12)	CAR (-6, +6)	CAR (-6, +6)	CAR (-6, +6)
	(1)	(2)	(3)	(4)	(5)
Post × Treated (DiD Estimator)	0.148**	0.112	0.0390	0.0653**	0.187**
	(0.0734)	(0.0686)	(0.0627)	(0.0304)	(0.0852)
Post (after IRA)	-0.0163	-0.0725*	0.00441	-0.0199	-0.0968*
	(0.0188)	(0.0176)	(0.0123)	(0.0156)	(0.0245)
Treated (Renewable Firms)	-0.0866**	-0.0878**	-0.0502	-0.0290	-
	(0.0390)	(0.0345)	(0.0757)	(0.0402)	-
Climate policy factor x Treated	-0.00279	-0.00402	0.0214	0.0147	0.0174
	(0.00813)	(0.0100)	(0.0268)	(0.00888)	(0.00826)
Weather factor x Treated	-0.0807***	-0.0612***	-0.0244	-0.0948*	-0.0348***

	(0.0231)	(0.0195)	(0.0712)	(0.0507)	(0.00815)
Geopolitics factor x Treated	0.0651***	0.0296*	-0.0210	0.0661**	0.0344**
	(0.0205)	(0.0166)	(0.0374)	(0.0278)	(0.0127)
Firm controls	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No
Observations	8,666	16,792	2,827	1,854	7,564
R-squared	0.696	0.619	0.157	0.171	0.637

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal returns from X months before to X months after July 2022.

Table 5: Extended term event study results of average cumulative share volume traded from DiD analysis.

	All firms	**All firms**	**All firms**
	CATV (-3, +3)	CATV (-6, +6)	CATV (-12, +12)
	(1)	(2)	(3)
Post × Treated (DiD Estimator)	0.307**	0.261**	0.119
	(0.141)	(0.127)	(0.112)
Post (after IRA)	-0.105***	0.103	-0.00592
	(0.0162)	(0.0820)	(0.0415)
Treated (Renewable Firms)	-0.138	-0.153*	-0.165***
	(0.0832)	(0.0882)	(0.0611)
Climate policy factor x Treated	0.00284	-0.0382**	-0.0450***
	(0.00562)	(0.0178)	(0.0141)
Weather factor x Treated	-0.0247***	-0.178***	-0.104**
	(0.00736)	(0.0630)	(0.0397)
Geopolitics factor x Treated	0.0146	0.160***	0.0807***
	(0.0137)	(0.0468)	(0.0229)
Firm controls	No	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Time FE	No	No	No
Observations	193,514	8,666	16,792
R-squared	0.443	0.630	0.566

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Cumulative volumes are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal trading volumes from X months before to X months after July 2022.

While the immediate impact model results (see Section 1.4) are explained largely by investor sentiments driven by news portrayal of policy legislations within days of the event, the extended impact measured through the DiD entails behavioral updating over time (Bauer et al., n.d.; Santi, 2023). Santi, (2023) uses the adaptive market hypothesis (Lo, 2004) to explain observed time variation in market efficiency. Behavioral finance models predict that during policy changes subjective valuation of a firms' performance due to informational asymmetry along with the limits to arbitrage can lead to prolonged mispricing of asset (Shleifer & Vishny, 1997). A sudden upsurge in CAR followed by its gradual nullification implies that part of the investor reaction to climate sentiment was irrational. It could indicate that overtime renewable energy firm's response to phased policy implementation aided in rationalizing

beliefs about future firm profits. Bauer et al., (n.d.) suggests three channels though which IRA implementation could affect green stocks: *cost channel*, through which supply-side subsidies reduce the green firm's marginal costs; *demand channel* or demand-side subsidies which increase demand for clean energy; and the *cost of capital channel*, wherein transition uncertainty for emission-heavy firms raises the expected returns for green firms.

The apparent effectiveness of these channels became clearer over months after the passage of IRA. A 2024 MorningStar report[33] suggest that U.S. solar and wind energy sector recorded their highest growth in 2022 at the end of November and beginning of December, largely attributed to regulatory certainty and investment tax-credits. But clean energy projects were weighed down by interest rate hikes, high inflation supply chain bottlenecks, and increased development costs resulting in lower investor profits. An explanation of gradual reversion in equity prices could indicate that high cost of capital and excess supply to meet current demand diminished expected profitability channels and investor beliefs.

The adaptive behavior timeline can be further visualized through results from the dynamic DiD model, illustrated in Figure 8. The graph shows the temporal progression of cumulative abnormal returns (CARs) before and after the enactment of the Inflation Reduction Act (IRA). In this plot, the marked vertical line at time zero represents the policy event (July 2022), with cumulative abnormal returns measured from three months prior to thirteen months after the event.

Initially, there was a notable and statistically significant surge in CARs immediately following the policy announcement. This rapid increase in returns is consistent with investor optimism and a swift, yet partial, market reaction to new information—reflecting short-term mispricing opportunities. The progressive decline in abnormal returns in the following months suggests the market initially overestimated future firm performance, subsequently adjusting valuations downward toward equilibrium as the true economic impacts of the transition policy became clearer. The phenomenon is explained through the lens of market inefficiencies arising from bounded rationality and cognitive biases resulting in investor myopia. Such transient irrational exuberance could create arbitrage opportunities that persist until market participants gradually process the available information.

[33] Valerio Baselli, MorningStar, Aoril 18, 2024, "*Clean Energy is the Future. So Why Have Investors Struggled*?" Retrieved from https://www.morningstar.co.uk/uk/news/248370/clean-energy-is-the-future-so-why-have-investors-struggled.aspx

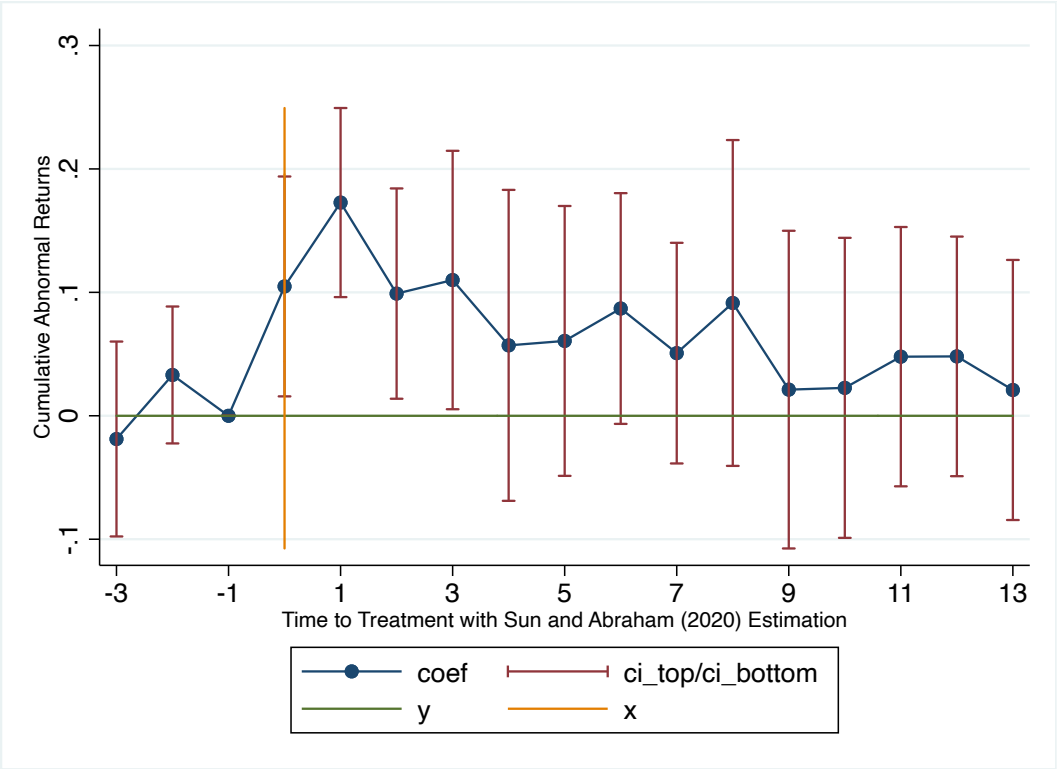


Figure 8: Dynamic Impact of the Inflation Reduction Act on average monthly cumulative returns of renewable energy stocks relative to the control group.

This hypothesis is corroborated further by the elevated levels of CATV for a prolonged period, suggesting persistent investor disagreement and ongoing arbitrage activity (Chordia et al., 2001). As investors adapted to new information, high trading activity from IRA policy implementation led to price reversal and final assimilation into the market by August 2023.

Additionally, the market volatility is found to be concentrated on mid- and large-cap renewable firms. This differential responsiveness based on market capitalization can be attributed to a combination of operational scale effects, policy compliance resources, and institutional investor base of large- and mid-cap firms which helps them navigate supply-chain bottlenecks more efficiently (Seetharam, 2017). Bauer et al., (n.d.) finds that industrial sectors- particularly electrical equipment manufacturers, utilities, and construction firms- exhibiting stronger positive equity response to IRA policy announcements were disproportionately represented by larger firms. However, the size-effect of climate policy impact on stock prices remains underexplored.

Positive CARs for geopolitical news interactions with renewable energy firms indicate that investors interpreted international summits and climate negotiations as beneficial to future profitability, possibly due to Biden's pro-climate stance (Ramelli et al., 2021). Higher CATV however indicates rapid price correction, suggesting the effects were short-lived. Conversely, a stable downward correction in prices

(negative CATV) in case of weather-related news denote investor caution regarding physical climate risks, reflecting heightened operational and profitability uncertainty during high-interest rate periods. The insignificant influence of climate policy news interactions might signal that the investors already anticipated such policy developments, resulting in muted incremental market reactions.

These findings provide critical insights for policymakers aiming to maximize the effectiveness and market acceptance of climate policies such as the IRA. Most importantly, they prove that such a large-scale transition policy effort did have a sustained positive impact on the renewable energy market. Additionally, the investigation underscores the practicability of aligning climate policy implementation, with broader economic conditions to enhance investor confidence and ensure optimal market outcomes. The observed prolonged market adjustment, persistent abnormal trading volumes, and investor sensitivity to external shocks like geopolitical and weather-related events suggest policymakers should carefully consider timing and macroeconomic context—including inflationary pressures, interest rate trends, and supply chain stability—when introducing major policy interventions. Clear, transparent, and consistent policy communication is also essential to minimize informational asymmetries, reduce prolonged price disturbances, and mitigate unnecessary volatility driven by arbitrage activity. Additionally, given the varied responses among firms based on market capitalization, tailored policy measures may be necessary to ensure broad-based effectiveness across the renewable energy sector.

Conclusion

Through this study, I investigate how renewable energy financial markets responded to the U.S. Inflation Reduction Act (IRA), a landmark climate policy aimed at accelerating the clean energy transition. Specifically, I examine the immediate- and extended-term effects of the IRA and related climate news on the stock prices and trading volumes of individual firms. While previous literature has explored the general impact of climate policy on financial markets, few have isolated the causal effect of the IRA on clean energy equities, nor accounted for the role of news sentiment and external shocks in shaping investor behavior.

To address this gap, I employ a two-pronged empirical strategy. A short-horizon event study, based on the Fama-French three-factor model, is used to capture immediate market reactions to high-salience policy and climate-related news events. For longer-term effects, a Difference-in-Differences (DiD) framework is implemented to estimate cumulative abnormal returns (CARs) and trading volumes (CATVs) around the IRA's announcement and passage. The analysis integrates firm-level financial controls, macroeconomic indicators, and sentiment-based news measures to isolate the policy's effect from broader market dynamics. News measures are built using natural language processing (NLP) techniques, specifically

Latent Dirichlet Allocation (LDA) for topic modeling and ClimateBERT for sentiment analysis, to dissect the role of media attention and investor sentiment in shaping market responses.

The findings reveal a strong and statistically significant positive response of renewable energy stocks to the IRA's announcement, with CARs reaching up to 17% over a 5-day window and remaining elevated for several months. However, this initial optimism gradually faded, suggesting that the market reassessed its expectations as implementation challenges—such as inflation, interest rate hikes, and supply chain disruptions—became more apparent. The initial investor euphoria followed by a phased price reversal is explained by the adaptive market hypothesis. Thematic news interactions further reveal that geopolitical developments amplified market responses, while weather-related news negatively affected returns and trading volumes.

These results underscore several important policy implications. First, the IRA had a meaningful and lasting effect on clean energy markets, reinforcing the influence of large-scale climate legislation on investor sentiment and capital allocation. However, the subsequent price correction highlights the need for policymakers to anticipate and mitigate implementation bottlenecks that may undermine long-term market confidence. Aligning climate policy with favorable macroeconomic conditions and ensuring transparent, credible communication are essential to sustaining investor engagement. Overall, this study contributes to the growing evidence base on how financial markets respond not only to the content of climate policy but also to its timing, communication, and real-world feasibility.

Future research could expand on these findings by examining the IRA's effects on fossil fuel and oil-price movements and performing comparative analysis over extended time-horizons. Studies can build on these findings through a more granular firm-level analysis to uncover heterogeneity in policy responsiveness based on factors such as technology type, geographic exposure, or ownership structure. It must be noted that while the results of the study can be explained by implementation bottlenecks, the direct impact of infrastructural vulnerability is not tested, which can significantly add to the understanding of climate policy design. Finally, comparative studies across different policy regimes—such as the EU Green Deal or Asia's renewable finance frameworks—could offer valuable insights into the global financial dynamics of the low-carbon transition.

Data Statement

The data that support the findings of this study are available from the Compustat Capital IQ, but restrictions under agreement with the data platform apply to the availability of these data, which were used under license for the current study, and so are not publicly available. Data for news analysis is available from ProQuest and for macroeconomic variables including GDP growth, CPI, VIX and crude oil index are available from the FRED platform.

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References

Albuquerque, R., Koskinen, Y., Yang, S., & Zhang, C. (2020). Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash. *The Review of Corporate Finance Studies*, *9*(3), 593–621. https://doi.org/10.1093/rcfs/cfaa011

Alehile, K. S., Mohammed, S. S., Musa, N., & Ali, M. (2025). Comparative Analysis of Climate Change Financing Potential of Renewable and Non-Renewable Energy Stocks: A Predictive Approach. *Energy RESEARCH LETTERS*, *6*(Early View). https://doi.org/10.46557/001c.125865

Antoniuk, Y., & Leirvik, T. (2024). Climate change events and stock market returns. *Journal of Sustainable Finance & Investment*. https://www.tandfonline.com/doi/abs/10.1080/20430795.2021.1929804

Apel, M., Betzer, A., & Scherer, B. (2023). Real-time transition risk. *Finance Research Letters*, *53*, 103600. https://doi.org/10.1016/j.frl.2022.103600

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2023). Climate Change Concerns and the Performance of Green vs. Brown Stocks. *Management Science*, *69*(12), 7607–7632. https://doi.org/10.1287/mnsc.2022.4636

Baker, M., & Wurgler, J. (2007). Investor Sentiment in the Stock Market. *Journal of Economic Perspectives*, *21*(2), 129–152. https://doi.org/10.1257/jep.21.2.129

Bang, H.-K., Ellinger, A. E., Hadjimarcou, J., & Traichal, P. A. (2000). Consumer concern, knowledge, belief, and attitude toward renewable energy: An application of the reasoned action theory. *Psychology & Marketing*, *17*(6), 449–468. https://doi.org/10.1002/(SICI)1520-6793(200006)17:6<449::AID-MAR2>3.0.CO;2-8

Barber, B. M., & Lyon, J. D. (1997). Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. *Journal of Financial Economics*, *43*(3), 341–372. https://doi.org/10.1016/S0304-405X(96)00890-2

Bauer, M. D., Offner, E. A., & Rudebusch, G. D. (n.d.). The Effect of U.S. Climate Policy on Financial Markets: *MONETARY POLICY*.

Bird, S., Klein, E., & Loper, E. (2009). *Natural Language Processing with Python: Analyzing Text with the Natural Language Toolkit*. O'Reilly Media, Inc.

Bistline, J., Blanford, G., Brown, M., Burtraw, D., Domeshek, M., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Marcy, C., Mayfield, E., McFarland, J., McJeon, H., … Zhao, A. (2023). Emissions and energy impacts of the Inflation Reduction Act. *Science*, *380*(6652), 1324–1327. https://doi.org/10.1126/science.adg3781

Bistline, J. E. T., Brown, M., Domeshek, M., Marcy, C., Roy, N., Blanford, G., Burtraw, D., Farbes, J., Fawcett, A., Hamilton, A., Jenkins, J., Jones, R., King, B., Kolus, H., Larsen, J., Levin, A., Mahajan, M., Mayfield, E., McFarland, J., … Zhao, A. (2023). Power sector impacts of the Inflation Reduction Act of 2022. *Environmental Research Letters*, *19*(1), 014013. https://doi.org/10.1088/1748-9326/ad0d3b

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *J. Mach. Learn. Res.*, *3*(null), 993–1022.

Bolton, P., Buchheit, L., Gulati, M., Panizza, U., di Mauro, B. W., & Zettelmeyer, J. (2023). On Debt and climate. *Oxford Open Economics*, *2*, odad005. https://doi.org/10.1093/ooec/odad005

Botzen, W., Duijndam, S., & van Beukering, P. (2021). Lessons for climate policy from behavioral biases towards COVID-19 and climate change risks. *World Development*, *137*, 105214. https://doi.org/10.1016/j.worlddev.2020.105214

Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2022). *Transition Versus Physical Climate Risk Pricing in European Financial Markets: A Text-Based Approach* (SSRN Scholarly Paper No. 4154034). Social Science Research Network. https://doi.org/10.2139/ssrn.4154034

Cao, H., Guo, L., & Zhang, L. (2020). Does oil price uncertainty affect renewable energy firms' investment? Evidence from listed firms in China. *Finance Research Letters*, *33*, 101205. https://doi.org/10.1016/j.frl.2019.06.003

Carattini, S., & Sen, S. (2019). *Carbon Taxes and Stranded Assets: Evidence from Washington State* (SSRN Scholarly Paper No. 3434841). https://doi.org/10.2139/ssrn.3434841

Cassidy, W. M. (2023). *Elections Have Consequences: The Impact of Political Agency on Climate Policy and Asset Prices* [Ph.D., The University of Chicago]. https://www.proquest.com/docview/2825333691/abstract/35C828EFEF07417APQ/1

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market Liquidity and Trading Activity. *The Journal of Finance*, *56*(2), 501–530. https://doi.org/10.1111/0022-1082.00335

Dionysiou, D. (2015). Choosing Among Alternative Long-Run Event-Study Techniques. *Journal of Economic Surveys*, *29*(1), 158–198. https://doi.org/10.1111/j.1467-6419.2012.00742.x

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging Climate Change News. *The Review of Financial Studies*, *33*(3), 1184–1216. https://doi.org/10.1093/rfs/hhz072

Faccini, R., Matin, R., & Skiadopoulos, G. S. (2023). *Dissecting Climate Risks: Are they Reflected in Stock Prices?* (SSRN Scholarly Paper No. 3795964). Social Science Research Network. https://doi.org/10.2139/ssrn.3795964

Fahmy, H. (2022). Investors' Adaptation to Climate Change: A Temporal Portfolio Choice Model with Diminishing Climate Duration Hazard. In T. Walker, S. Wendt, S. Goubran, & T. Schwartz (Eds.), *Business and Policy Solutions to Climate Change: From Mitigation to Adaptation* (pp. 239–262). Springer International Publishing. https://doi.org/10.1007/978-3-030-86803-1_11

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417. https://doi.org/10.2307/2325486

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance1. *Journal of Financial Economics*, *49*(3), 283–306. https://doi.org/10.1016/S0304-405X(98)00026-9

Fama, E. F., & French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, *83*(3), 667–689. https://doi.org/10.1016/j.jfineco.2006.01.003

Fedorova, E., & Iasakova, P. (2024). The impact of climate change news on the US stock market. *The Journal of Risk Finance*, *25*(2), 293–320. https://doi.org/10.1108/JRF-06-2023-0133

Garel, A., & Romec, A. (2020). *Investor Rewards to Environmental Responsibility: Evidence from the COVID-19 Crisis* (SSRN Scholarly Paper No. 3620109). Social Science Research Network. https://doi.org/10.2139/ssrn.3620109

Guinea, L., Puch, L. A., & Ruiz, J. (2024). Energy news shocks and their propagation to renewable and fossil fuels use. *Energy Economics*, *130*, 107289. https://doi.org/10.1016/j.eneco.2023.107289

Gürkaynak, R. S., Sack, B. P., & Swanson, E. T. (2004). Do actions speak louder than words? The response of asset prices to monetary policy actions and statements. *Finance and Economics Discussion Series*, Article 2004–66. https://ideas.repec.org//p/fip/fedgfe/2004-66.html

Horváth, R., Kalistová, A., Lyócsa, Š., Miškufová, M., & Moravcová, M. (2025). Do hurricanes cause storm on the stock market? The case of US energy companies. *International Review of Financial Analysis*, *97*, 103816. https://doi.org/10.1016/j.irfa.2024.103816

Howlett, M., & Rawat, S. (n.d.). Behavioral Science and Climate Policy. In *Oxford Research Encyclopedia of Climate Science*. Retrieved March 28, 2025, from https://oxfordre.com/climatescience/display/10.1093/acrefore/9780190228620.001.0001/acrefore-9780190228620-e-624

Hsu, Y.-J., Lu, Y.-C., & Yang, J. J. (2021). News sentiment and stock market volatility. *Review of Quantitative Finance and Accounting*, *57*(3), 1093–1122. https://doi.org/10.1007/s11156-021-00971-8

Işık, C., Kuziboev, B., Ongan, S., Saidmamatov, O., Mirkhoshimova, M., & Rajabov, A. (2024). The volatility of global energy uncertainty: Renewable alternatives. *Energy*, *297*, 131250. https://doi.org/10.1016/j.energy.2024.131250

Jiang, Y., Song, X., Harrison, J., Quegan, S., & Maynard, D. (2017). Comparing Attitudes to Climate Change in the Media using sentiment analysis based on Latent Dirichlet Allocation. In O. Popescu & C. Strapparava (Eds.), *Proceedings of the 2017 EMNLP Workshop: Natural Language Processing meets Journalism* (pp. 25–30). Association for Computational Linguistics. https://doi.org/10.18653/v1/W17-4205

Kacperczyk, M., Peng, L., & Xie, J. (n.d.). *ESG Investing and Stock Return Comovements*.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies*, *33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Li, L., Zheng, X., & Wang, S. (2024). Renewable Energy Stocks' Performance and Climate Risk: An Empirical Analysis. *Journal of Risk and Financial Management*, *17*(3), 121. https://doi.org/10.3390/jrfm17030121

Liu, H., Ferreira, S., & Karali, B. (2021). Hurricanes as news? Assessing the impact of hurricanes on the stock market returns of energy companies. *International Journal of Disaster Risk Reduction*, *66*, 102572. https://doi.org/10.1016/j.ijdrr.2021.102572

Lo, A. W. (2004). *The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective* (SSRN Scholarly Paper No. 602222). Social Science Research Network. https://papers.ssrn.com/abstract=602222

Misev, M. A., & Balles, P. (n.d.). *Natural Disasters, Investor Attention, and Non-Fundamental Green Asset Demand*.

Monasterolo, I., & de Angelis, L. (2020). Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecological Economics*, *170*, 106571. https://doi.org/10.1016/j.ecolecon.2019.106571

Monasterolo, I., Mandel, A., Battiston, S., Mazzocchetti, A., Oppermann, K., Coony, J., Stretton, S., Stewart, F., & Dunz, N. (2022). *The Role of Green Financial Sector Initiatives in the Low-Carbon Transition: A Theory of Change*. The World Bank. https://doi.org/10.1596/1813-9450-10181

Morão, H. (2024). The impact of carbon policy news on the national energy industry. *Energy Economics*, *134*, 107596. https://doi.org/10.1016/j.eneco.2024.107596

Morina, F., Ergün, U., & Hysa, E. (2021). Understanding Drivers of Renewable Energy Firm's Performance. *Environmental Research, Engineering and Management*, *77*(3), Article 3. https://doi.org/10.5755/j01.erem.77.3.29230

Mukherjee, S., Nateghi, R., & Hastak, M. (2018). A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. *Reliability Engineering and System Safety*, *175*(C), 283–305.

Noailly, J., Nowzohour, L. M., & Van Den Heuvel, M. (Eds.). (2021). *Heard the news ? Environmental policy and clean investments*. Graduate Institute of International and Development Studies, Centre for International Environmental Studies.

Nyman, R., Kapadia, S., & Tuckett, D. (2021). News and narratives in financial systems: Exploiting big data for systemic risk assessment. *Journal of Economic Dynamics and Control*, *127*, 104119. https://doi.org/10.1016/j.jedc.2021.104119

Obaid, K., & Pukthuanthong, K. (2022). A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. *Journal of Financial Economics*, *144*(1), 273–297. https://doi.org/10.1016/j.jfineco.2021.06.002

Pastor, L., Stambaugh, R., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571.

Patronella, A. M. (2021). Covering Climate Change: A Sentiment Analysis of Major Newspaper Articles from 2010 - 2020. *Inquiries Journal*, *13*(09). http://www.inquiriesjournal.com/articles/1910/covering-climate-change-a-sentiment-analysis-of-major-newspaper-articles-from-2010--2020

Pham, L., Hao, W., Truong, H., & Trinh, H. H. (2023). The impact of climate policy on U.S. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. *Energy Economics*, *119*, 106564. https://doi.org/10.1016/j.eneco.2023.106564

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021). Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections. *The Review of Corporate Finance Studies*, *10*(4), 748–787. https://doi.org/10.1093/rcfs/cfab010

Ramiah, V., Pichelli, J., & Moosa, I. (2015). Environmental regulation, the Obama effect and the stock market: Some empirical results. *Applied Economics*. https://www.tandfonline.com/doi/abs/10.1080/00036846.2014.980572

Sadorsky, P. (2012). Modeling renewable energy company risk. *Energy Policy*, *40*, 39–48. https://doi.org/10.1016/j.enpol.2010.06.064

Santi, C. (2023). Investor climate sentiment and financial markets. *International Review of Financial Analysis*, *86*, 102490. https://doi.org/10.1016/j.irfa.2023.102490

Seetharam, I. (2017). *Environmental Disasters and Stock Market Performance ∗*. https://www.semanticscholar.org/paper/Environmental-Disasters-and-Stock-Market-%E2%88%97-Seetharam/e65ddfe4b9a2c63785583f8244ed130d6343a1c6

Shiller, R. J. (2015). Irrational Exuberance. *Economics Books*. https://ideas.repec.org//b/pup/pbooks/10421.html

Shleifer, A., & Vishny, R. W. (1997). The Limits of Arbitrage. *The Journal of Finance*, *52*(1), 35–55. https://doi.org/10.1111/j.1540-6261.1997.tb03807.x

Song, Y., & Dong, J. (2024). Impact of climate policy uncertainty on corporate green investment: Examining the moderating role of financing constraints. *Frontiers in Marine Science*, *11*. https://doi.org/10.3389/fmars.2024.1456079

Stede, M., & Patz, R. (2021). The Climate Change Debate and Natural Language Processing. In A. Field, S. Prabhumoye, M. Sap, Z. Jin, J. Zhao, & C. Brockett (Eds.), *Proceedings of the 1st Workshop on NLP for Positive Impact* (pp. 8–18). Association for Computational Linguistics. https://doi.org/10.18653/v1/2021.nlp4posimpact-1.2

Stroebel, J., & Wurgler, J. (2021). *What Do You Think About Climate Finance?* (No. w29136). National Bureau of Economic Research. https://doi.org/10.3386/w29136

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Teutrine, C., Schuster, M., Bornhöft, S. C., Lueg, R., & Bouzzine, Y. D. (2024). Stock price reactions to climate science information from the Intergovernmental Panel on Climate Change: A mitigation

function of corporate and sector emissions responsibility? *Business Strategy and the Environment*, *33*(6), 5346–5365. https://doi.org/10.1002/bse.3761

Webersinke, N., Kraus, M., Bingler, J. A., & Leippold, M. (2022). *ClimateBert: A Pretrained Language Model for Climate-Related Text* (No. arXiv:2110.12010). arXiv. http://arxiv.org/abs/2110.12010

Yazici, M., & Gültekin, D. G. (2023). Framing Effects on Renewable Energy News. In H. Dincer & S. Yüksel (Eds.), *Economic Development and the Environmental Ecosystem: The Role of Energy Policy in Economic Growth* (pp. 35–46). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-26596-9_4

Yildiz, Y., & Karan, M. B. (2020). Environmental policies, national culture, and stock price crash risk: Evidence from renewable energy firms. *Business Strategy and the Environment*, *29*(6), 2374–2391. https://doi.org/10.1002/bse.2508

Zhao, W., Chen, J. J., Perkins, R., Liu, Z., Ge, W., Ding, Y., & Zou, W. (2015). A heuristic approach to determine an appropriate number of topics in topic modeling. *BMC Bioinformatics*, *16*(13), S8. https://doi.org/10.1186/1471-2105-16-S13-S8

Appendix

A1. Renewable Energy Industry Codes

Table A 1: NAICS codes for compilation of renewable energy companies

NAICS Code	Title
221122	Electric Power Distribution
221114	Solar Electric Power Generation
221115	Wind Electric Power Generation
221116	Geothermal Electric Power Generation
221117	Biomass Electric Power Generation
221118	Other Electric Power Generation
221111	Hydroelectric Power Generation
333414	Heating Equipment (except Warm Air Furnaces) Manufacturing
333611	Turbine and Turbine Generator Set Units Manufacturing
335312	Motor and Generator Manufacturing
325193	Ethyl Alcohol Manufacturing

A2. Fama-French 3-factor model

Stock return for each stock for each day is defined as:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

Where R_t is stock return for day *t*, P_t and P_{t-1} are closing prices of stock for day *t* and *(t-1).* Expected daily return for each stock is then calculated from the following equation:

$$R_{\{it\}} = \alpha_i + \beta_{\{im\}} R_{\{mt\}} + \beta_{\{is\}} SMB_t + \beta_{\{iv\}} HML_t + \epsilon_{\{it\}}$$

Where R_{it} is the expected return for stock *i* on day *t.* R_{mt} is the risk-free market rate on day *t,* SMB_t represents the size factor on day *t*, capturing the return differential between small-cap and large-cap stocks*,* HML_t represents the value factor on day *t*, capturing the return differential between value stocks (high book-to-market ratio) and growth stocks (low book-to-market ratio), α_i is the intercept term for stock *i,* and β_i is the sensitivity (beta coefficient) of stock *i* to respective factors, estimated by running an ordinary least squares regression. ϵ_{it} is the error term for stock *i* at time *t*. The abnormal return (AR_{it}) for stock *i* at day *t* is the difference between the actual and expected return:

$$AR_{it} = R_{it} - \left(\alpha_i + \beta_{\{im\}} R_{\{mt\}} + \beta_{\{is\}} SMB_t + \beta_{\{iv\}} HML_t\right)$$

This is then accumulated over the respective event window *(-t, t)* to get the CAR for security *i*:

$$\mathrm{CAR_i}(-\mathrm{t},\mathrm{t}) = \sum_{\mathrm{j}=-\mathrm{t}}^{\mathrm{t}} \mathrm{AR_{ij}}$$

The Cumulative Average Abnormal Returns (CAAR) is calculated for all securities taken together.

$$\mathrm{CAAR}(-\mathrm{t},\mathrm{t}) = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{CAR_i}(-\mathrm{t},\mathrm{t})$$

Where N denotes the number of securities of renewable energy firms in the dataset. CAARs are reported for three event windows for each news shock, very short term (-3, 1), short term (-3, 3) and medium term (-5, 5). Note that the term here signifies the time-length with respect to multifactor model methodology, which is built for very short-run analysis and might not give reliable results for windows beyond the 30-day period. In the last step, this study uses the Pattel (1976) test, to test if the CAAR are statistically significant, given by:

$$\mathrm{Z} = \frac{\sum_{\mathrm{t}=-\mathrm{t}_1}^{\mathrm{t}_2} \mathrm{SAR_{it}}}{\sqrt{\mathrm{t}_1 + \mathrm{t}_2 + 1}}$$

Where SAR_{it} is the standardized abnormal return for stock *i* at time *t.* The results are presented in the next subsection.

Table A 2: Results from FF3 model for different news textual factors.

Date	Event	CAAR [-3,1]	CAAR [-3,3]	CAAR [-5,5]
Extreme Weather Phenomena				
4/1/21	BBB announced	0.93%	-3.21%	-7.6238%***
8/10/21	IIJA passed by Senate	-1.98%	-4.00%	-8.8337%**
11/19/21	BBB passed by house	4.95%	2.8684%*	3.75%
12/19/21	Machin to vote against BBB	-2.66%	-5.3753%**	-8.1370%***
7/15/22	Machin against IRA	-2.7319%*	-3.7303%**	0.55%
7/27/22	IRA announced	9.9755%***	10.7919%***	16.4730%***
8/7/22	IRA passed	1.50%	0.91%	3.4029%***
Climate Policy				
2/17/21	Winter storms	-4.9504%***	-6.5860%***	-9.5310%***
5/25/21	Western Heat Waves	0.39%	-0.35%	0.3935%*
9/8/21	Hurricane Ida	-3.12%	-3.90%	-4.97%
11/2/21	Pacific northwest floods	1.97%	0.15%	-1.12%
2/6/22	Winter storm Landon	-2.6332%**	-1.83%	-0.78%
6/16/22	Central derecho	-2.0384%**	-2.5327%*	-1.88%
10/4/22	Hurricane Ian Aftermath	-3.4319%***	-5.1061%***	-8.3010%***
6/8/23	Canadian wildfires	-0.57%	0.44%	-0.32%
7/13/23	Drought and Heat Wave	-1.94%	-1.60%	-2.26%

8/27/23	Wildfires	1.54%	-0.37%	-3.0059%*
11/14/23	Storms and water crisis	2.42%	1.87%	-1.8548%***
Geopolitics				
4/22/21	Earth Day Summit	-1.09%	0.32%	-9.6556%**
9/21/21	UN Climate Summit talks	3.01%	0.60%	1.1277%*
10/31/21	COP26	4.6285%***	3.54%	2.43%
9/22/22	UN Climate Summit talks	-5.7357%***	-2.3094%***	-6.7876%***
11/16/22	COP27	4.27%	3.27%	3.4837%*
7/11/23	Biden's UK visit	1.41%	1.69%	-0.2461%*

Note: ∗∗∗Significant at p < 0.01, ∗∗Significant at p < 0.05, ∗Significant at p < 0.1. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAAR (-X, +X) indicates cumulative abnormal returns from X days before to X days after the event.

A3. Pairwise correlation between climate risk factors and other variables

Table A 3: Pairwise correlation between climate risk factors and other variables

	Topic1	**Topic2**	**Topic3**	**Topic4**	**Sentiment**	**article Num**	**VIX**	**crudeoil**	**Inflation**	**GDP**
Topic1	1									
Topic2	0.1381	1								
Topic3	0.4739	0.1144	1							
Topic4	0.5748	0.1313	0.7247	1						
Sentiment	-0.5176	-0.8139	-0.4849	-0.4481	1					
article Num	0.7855	0.424	0.8211	0.8447	-0.7564	1				
VIX	0.117	-0.312	-0.1073	-0.1563	0.1194	-0.1197	1			
crudeoil	0.1731	-0.2557	-0.1064	0.0803	0.0929	-0.0143	0.7885	1		
Inflation	-0.0439	-0.4433	0.0266	-0.1825	0.2825	-0.1873	0.3964	0.2371	1	
GDP	0.3865	0.2314	0.5608	0.3182	-0.403	0.5219	-0.296	-0.3305	-0.0614	1

Notes: Entries report the pairwise Pearson correlations between the daily textual and sentiment climate change risk factors, the crude oil index, CBOE VIX (volatility index), Inflation and GDP, over January 1, 2021, – December 31, 2023.

A4. BHAR

Buy and Hold Abnormal Returns (BHAR) Model

BHAR is a common approach to measuring longer-term abnormal returns in asset pricing studies. BHAR is designed to capture the cumulative performance of a stock relative to a benchmark (a market index or matched sample) over a specified period, providing insights into whether an asset outperforms or underperforms the benchmark consistently over time. For a given stock *i*, the BHAR over period *t* is typically calculated as:

$$BHAR_{i.T} = \prod_{t=1}^{T}(1 + R_{i.t}) - \prod_{t=1}^{T}(1 + R_{m.t})$$

where $R_{i.t}$ is the raw return of stock *i* on day *t* and $R_{m.t}$ is the return of the benchmark stock *m* on day *t*. The expressions $\prod_{t=1}^{T}(1 + R_{i.t})$ and $\prod_{t=1}^{T}(1 + R_{m.t})$ represent the daily cumulative (buy-and-hold)

return of each stock for treatment and benchmark group respectively over the period T. The difference generates the abnormal return per stock.

In the next step, I compute the average buy-and-hold abnormal return for treatment and benchmark group over the period T. I then use a t-test to determine the cumulative direction and statistical significance of BHAR. A significantly positive (negative) BHAR indicates that the stocks outperformed (underperformed) the benchmark over the period.

Results from the BHAR model are shown in Table A 4. The mean BHAR indicates a substantial outperformance of the renewable energy sector weighted returns by 2.05% relative to that of the benchmark with a high level of statistical significance ($p < 0.001$) after the passage of IRA. There is an increasing trend in the magnitude of cumulative abnormal returns up till 4 months from the event, with a slight decline in BHAR at 6 months mark. The result is however statistically significant at only 10%. A year after the passage of IRA, the renewable energy firms were underperforming by 1.19% relative to the benchmark, but not statistically significant. The negative BHAR had increased in magnitude to 7.47% by 18 months with a statistical significance of 10%.

In all cases, the estimated BHAR conveys the mean difference between value weighted cumulative returns of renewable energy stock and control group after the passage of IRA. It does not convey that the difference was *associated* with the passage of IRA. The results are consistent in direction and duration with those from the DiD analysis but are markedly lower in magnitude. For example, the 4-month CAR from the DiD model is about 7 basis points larger than that from BHAR. Their interpretation is also different. The abnormal returns from the DiD analysis measure the isolated effect of the IRA policy on renewable energy firms, not just the post IRA market returns which is the case with BHAR. In the latter case, the results could still have been impacted by other concurrent events internal or external to the firms such as natural disasters, macroeconomic variability, policy changes or geopolitics.

Table A 4: Long-term asset pricing results from BHAR analysis.

	Mean	**Std. Err.**	**Std. Dev.**	**95% CI**		**Pr(T><t)**
1 month	0.0405	0.0225	0.0504	0.0221	0.0632	0.0000
2 months	0.0677	0.0077	0.0396	0.0517	0.0837	0.0000
4 months	0.0650	0.0092	0.0882	0.0466	0.0834	0.0000
6 months	0.0486	0.0196	0.0519	0.0005	0.0967	0.0481
12 months	-0.0119	0.0204	0.0763	-0.0560	0.0321	0.5692
18 months	-0.0747	0.0295	0.1287	-0.1368	-0.0126	0.0210

Note: Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers.

A5. Robustness Checks

Table A 5: Robustness checks for extended term DiD event study of renewable energy firm's average cumulative returns.

	All firms	**All firms**	**All firms**
	CAR (-6, +6)	CAR (-6, +6)	CAR (-6, +6)
	(1)	(2)	(3)
Post × Treated (DiD Estimator)	0.158**	-	-
	(0.0720)	-	-
Post (after IRA)	-0.0711***	-	-
	(0.0130)	-	-
Treated (Renewable Firms)	-0.0532	-	-
	(0.0389)	-	-
Placebo x Treated	-	-0.0291	-0.000956
	-	(0.0233)	(0.0438)
Post (after placebo date)	-	0.220***	0.0449
	-	(0.0345)	(0.0430)
Treated (Renewable Firms)	-	0.0597**	-0.229***
	-	(0.0291)	(0.0463)
Climate policy factor x Treated	-	-0.0128	0.0524***
	-	(0.0259)	(0.0174)
Weather factor x Treated	-	-0.00897	-0.0108
	-	(0.0266)	(0.0215)
Geopolitics factor x Treated	-	0.0367*	0.0793***
	-	(0.0185)	(0.0192)
Sentiment Score x Treated	0.000718	-	-
	(0.00969)	-	-
Firm controls	No	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes
Time FE	No	No	No
Observations	8,666	6,777	7,100
R-squared	0.656	0.186	0.247

Note: ∗∗∗Significant at $p < 0.01$, ∗∗Significant at $p < 0.05$, ∗Significant at $p < 0.1$. Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. CAR (-X, +X) indicates cumulative abnormal trading volumes from X months before to X months after July 2022 in (1), random month December 2021 in (2) and random month December 2022 in (3).

A6. Dynamic DiD Results

Table A 6: Cumulative Abnormal Returns from the Dynamic DiD analysis.

	Coef.	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
March, 2022	0.0674225	0.0381247	1.77	0.183	-0.0092746	0.1441196
April, 2022	-0.0291325	0.0420073	-0.69	0.491	-0.1136403	0.0553753
May, 2022	0.0225675	0.0286094	0.79	0.434	-0.0349871	0.0801221
July, 2022	**0.0943417**	**0.0479076**	**1.97**	**0.055**	**-0.002036**	**0.1907194**
August, 2022	0.1615314	0.0438743	3.68	0.001	0.0732676	0.2497952

September, 2022	0.0882306	0.0476275	1.85	0.07	-0.0075836	0.1840448
October, 2022	0.0992901	0.0586409	1.69	0.097	-0.0186803	0.2172604
November, 2022	0.046401	0.0692023	0.67	0.506	-0.0928161	0.1856181
December, 2022	0.0491485	0.0620326	0.79	0.432	-0.075645	0.173942
January, 2023	0.0764756	0.0553764	1.38	0.174	-0.0349274	0.1878785
February, 2023	0.0364935	0.0578968	0.63	0.532	-0.0799799	0.1529669
March, 2023	0.0772441	0.0797513	0.97	0.338	-0.0831948	0.2376829
April, 2023	0.0072669	0.0790186	0.09	0.927	-0.1516981	0.1662319
May, 2023	0.0077208	0.0754218	0.1	0.919	-0.1440083	0.1594500
June, 2023	0.0328677	0.0667600	0.49	0.625	-0.1014362	0.1671715
July, 2023	0.0333685	0.0605265	0.55	0.584	-0.0883951	0.1551321
August, 2023	0.0062841	0.0669903	0.09	0.926	-0.1284831	0.1410513
September, 2023	-0.0914584	0.0593723	-1.54	0.13	-0.2109001	0.0279834
October, 2023	-0.0693017	0.0808958	-0.86	0.396	-0.2320431	0.0934397
November, 2023	-0.019137	0.1082508	-0.18	0.86	-0.2369096	0.1986356

Note: Cumulative returns are weighted by market cap. All values are winsorized at the 1st and 99th percentiles to mitigate the influence of extreme outliers. Reference period which is June 2022 has been omitted by design.