

The impact of climate policy on U.S. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness

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ABSTRACT

This paper investigates the green stock market reaction to climate policy events associated with the Paris Agreement and the U.S. presidential elections. We document abnormal returns, volatility and volume reactions to climate policy events among green stocks. However, the magnitude of the reactions varies between the tightening and loosening of climate policy and across subgroups of the green stock markets. Our connectedness analysis further investigates the spillover patterns among individual green stocks and confirms their heterogeneous natures when responding to the occurrence of these climate policy events. By constructing a minimum connectedness portfolio based on the estimated connectedness among these green stocks, we find that investors can substantially reduce their risks. Our findings have strong implications for policy makers in designing policies to effectively promote green investments and mitigate climate change.

1. Introduction

Climate change is one of the contemporary global challenges that can influence the well-being of nearly every country and pose serious risks to the economy and financial systems. At the same time, financial markets play an important role in mitigating climate risks by facilitating the flow of investments toward “green” or environmentally friendly economic activities that help transition to a more environmentally sustainable economy. As the market for green investments continues to grow, understanding how this market will respond to different climate policies provides useful information for policymakers to design optimal policy responses and for investors to design effective investment strategies.

While the world is working together toward achieving a low carbon global economy and mitigating the effects of climate change, the role played by the U.S. is of particular importance. The U.S. not only has a substantial global economic influence, but also is among the largest carbon emitters (Downie, 2019). Studying U.S. climate policy has strong

implications for global climate change mitigation. In the recent decade, the U.S. has seen numerous major changes related to its own climate policy. These major changes, which are rooted in the different views held by the Democratic and Republican parties on climate change, provide an interesting and unique setting to understand the impact of climate policy on the environmentally friendly financial market.

Against this background, this paper investigates how major climate policy-related events that occurred under the Obama, Trump, and Biden administrations influence the returns, volatility, volume, and spillover patterns among U.S. green stocks. These events include:

- The Paris Agreement on December 12, 2015
- The U.S. Ratification of the Paris Agreement on September 3, 2016
- The Election of President Donald J. Trump on November 8, 2016
- The Withdrawal Announcement of the Paris Agreement on June 1, 2017

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- Congressional Confirmation of President Biden's Election results on December 14, 2020
- The Passage of the U.S. Inflation Reduction Act on August 17, 2022, with generous provisions for environmentally friendly economic activities (henceforth referred to as the Biden Climate Change Bill)

Specifically, we ask the following questions. How do individual green stocks react to major climate policy events in terms of abnormal returns, volatility, and volume? In addition, how do these policies influence the spillover patterns among green stocks? Moreover, what are the implications for portfolio management and selection? To answer these questions, we derive our list of green stocks from components of the NASDAQ OMX Green Economy Index, a comprehensive stock index of companies who are actively involved in environmentally sustainable economic activities, and collect daily data on the returns, volatility, and volume of these stocks from January 2014–September 2022.

Our results show significant responses of green stocks around climate policy events. First, our event study analyses indicate that green stock returns, volatilities, and volumes respond to climate policy events. However, the magnitude of the responses varies between tightening and loosening climate policy signals and across subsectors of the green stock markets. For example, green stocks in light industries with high litigation risk experience the strongest cumulative returns around domestic climate policy events, such as the announcement of the Trump election, the announced withdrawal from the Paris Agreement, the Biden election confirmation, and the Biden Climate Change Bill. Other subgroup analyses confirm that small green firms and green firms with high idiosyncratic volatility are associated with greater reactions to climate policy events (except for the Paris Agreement Ratification). In addition, using a connectedness network approach based on a LASSO-VAR regression model, we investigate the spillovers among green stocks during the sample period from 2014 to 2022. We find that the Trump election and his subsequent announced withdrawal from the Paris Agreement has a significantly negative impact on the connectedness among environmentally friendly stocks, while the Biden Climate Change Bill has a significantly positive impact on the connectedness among the variables. Next, our subsample analysis shows that the connectedness among green firms in light industries responds most positively to the Biden Climate Change Bill, while green firms in heavy industries respond most negatively to the Trump election and his announced withdrawal from the Paris Agreement. This indicates that investors interpret tightening climate policy (i.e., the Biden Climate Change Bill) as positive news for green firms in light industries, while they view loose climate policy (i.e., the Trump election and the withdrawal from the Paris Agreement) as negative news for green firms in heavy industries. Finally, we derive the portfolio implications of our results by constructing a minimum connectedness portfolio. Our portfolio shows average hedging effectiveness of 59.83% (with the highest hedging effectiveness of 105%). Altogether, our results suggest that domestic climate policy events tend to have larger impacts on green stocks, while international climate news has smaller effects, potentially because it takes time for international climate news to materialize into national policies.

We contribute to the existing literature in the following ways. Despite the vast literature studying green stocks, the existing literature often focuses on the aggregate green stock market employing stock indices (Ahmad, 2017; Dutta, 2017; Ferrer et al., 2018; Lv et al., 2021; Reboredo, 2015; Kocaarslan and Soytas, 2021). While green stock indices have been well accepted as the performance measure of the environmentally friendly financial market, we argue that the aggregate-level analysis masks the heterogeneity of individual green stocks. Several recent papers seek to analyze green stocks at the firm level (Pástor et al., 2022; Faccini et al., 2021). However, their focus is on “green” stocks as a distinguishing category from “brown” stocks, rather than on whether different green stocks respond differently to climate events. Different from existing studies, we conduct comprehensive firm-

level analyses on the heterogeneous reactions of the green stock market subsectors to climate policy events. In addition, we document these reactions in several dimensions, including returns, volatility, volume, and connectedness. Thus, our findings add to the scarce evidence on the heterogeneous nature of green stock markets.

In addition, our event study and connectedness results have strong implications regarding investors' portfolio diversification and risk hedging, which is crucial and meaningful from a climate action perspective. While previous studies improve investors' general understanding of the overall green stock market, they offer limited implications to portfolio managers and investors who are primarily interested in disaggregate-level green investment choices. In this paper, we study 118 individual green stocks and take it one step further to quantify the risk-hedging benefits to investors by constructing a minimum connectedness portfolio based on the estimated connectedness among these individual green stocks. On average, we find that investors can reduce their risks by 59.83% when investing in green stocks through the minimum connectedness portfolio. By reducing the riskiness of green stocks, a greater amount of capital can be attracted from investors, thereby positively contributing to the development of clean energy sectors and climate change mitigation. Our findings shed light on an effective portfolio diversification and risk management strategy that is more feasible and practical for global investors. Moreover, our findings also have implications to policymakers. We identify the heterogeneous features of individual green stocks when responding to climate policy changes and their heterogeneous roles as shock transmitters and receivers in the system. Policy makers should consider their unique features and roles when designing policies to effectively promote green investments.

The remaining parts of this study are structured as follows. Section 2 provides a description of major U.S. climate policy events and a literature review of related studies. Section 3 describes the data, while Section 4 specifies the methodology. Section 5 presents the main empirical findings and discussion. Section 6 provides our concluding remarks and policy implications.

2. Events description and literature review

2.1. Major U.S. climate policy events

The Paris Agreement on December 12, 2016 is the first legally binding treaty on climate change that involves policy commitment from all governments. The agreement focuses on obtaining emission reduction, financial commitment, and eliminating the differences between developing and developed countries (Dimitrov, 2016). An important political development of the Agreement is the growing number of countries insisting on reducing the global temperature to approximate the pre-industrial levels. Two of the largest economies in the world, China and the U.S., ratified the Agreement on September 3, 2016. All developed countries also agreed to achieve a target of at least \$100 billion per year for climate finance by 2025.

However, the Republican victory of Donald J. Trump as the 45th President of the U.S. on November 8, 2016 changed the nation's views on its participation in the Paris Agreement. While the Democrats pay increasing attention to global warming, conservative Republicans are less likely to consider climate change worrisome (Ballew et al., 2019). Trump's party is a staunch supporter of the U.S. oil and gas industry (Diaz-Rainey et al., 2021) and opposes climate change mitigation domestically and internationally (Fiorino, 2022). Since Trump's election, Republicans have undone many Obama-era regulations and foreign policies to combat climate change (Asadnabizadeh, 2019; Nadja et al., 2020). While opponents view it as a severe issue, Trump supporters are less inclined to believe in global warming. The national election of Donald Trump has resulted in better views and agreement with the winners' positions (Meyer and Smyth, 2019).

Climate change became a national political issue in 2020 after

President Trump announced the U.S.'s withdrawal from the Paris Agreement on June 1, 2017, the 2019 introduction of the “litmus test,” such as the Green New Deal resolution, and the first appearance of significant party primary candidates campaigning solely on climate action (Strong, 2022). It is undeniable that Trump's influence on organizations, laws, and policies may be lessened, but his influence on environmental standards and trust has long-lasting effects (Bomberg, 2017; Jotzo et al., 2018).

Holding radically different views and beliefs on climate policy and environmental issues to Trump's administration, Joe Biden called for a bold set of climate measures and listed climate change as one of his top four priorities during his presidential election campaign in 2020. Biden's election win as the 46th U.S. president represents a mandate to address climate change. On August 17, 2022, President Joe Biden signed the Inflation Reduction Act that revealed his determination to combat climate change. The bill will devote hundreds of billions of dollars to accelerate U.S. emission cuts and to transition away from fossil fuels to clean energy.

2.2. Stock returns of environmentally friendly stocks to climate policy events

Changes in climate policy and its associated impact on green energy markets have gained increasing attention in academic research. However, the literature has documented mixed evidence regarding the effectiveness of environmental regulation and climate policies. In the U.S. context, Ramiah et al. (2015b) examine 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. In the more recent literature, Antoniuk and Leirvik (2021) investigate the effect of the Paris Agreement on the stock returns of green energy firms and find substantial abnormal returns supporting the effectiveness of the Paris Agreement. In particular, the Agreement is found to raise public awareness of global warming and support climate change legislation benefiting the overall U.S. renewable energy sector. The study also identifies greater transition-related political and market risks for utilities, energy-intensive industries, and transportation suggesting higher returns for compensation, while climate policy easing favors only the fossil energy industry. In addition, studying the industry level stock market reaction to the Trump election, Nerger et al. (2021) find that while the coal business benefited from favorable abnormal returns, other sectors experienced adverse or inconsistent reactions after the unexpected victory of Donald J. Trump on November 8, 2016. In a similar vein, Ramelli et al. (2021) examine industry level and within-industry stock price reactions. They find that the 2016 election not only boosted carbon-intensive firms, but also firms with climate-responsible practices, especially those held by long-term investors who appear to have banked on a climate policy “boomerang.” Signs of a boomerang arose during Trump's presidency and markedly came in during the 2020 presidential election.

In an international context, a number of related studies focus on the market reactions to climate policy passage, but also find mixed results. Pham et al. (2019) study the Singaporean stock market at the sector level and find that government-imposed environmental rules and policies successfully achieve their objectives. They discover that the introduction of rules and programs harms major polluters, while benefiting environmentally friendly industries. Alternatively, Ramiah et al. (2016) examine the abnormal returns of UK stocks around environmental legislation. The chemical, oil, and gas sectors react negatively to environmental laws, but other polluting industries are found to react positively, including construction and materials. Similar findings have been documented in the Australian market. Focusing on sector reactions, Ramiah et al. (2013) note that the announcement of green

policies has little impact on the greatest polluters (electricity generators) as polluters may pass on higher prices to customers. However, other businesses have seen their values eroded by green policies despite polluting less and becoming more environmentally friendly. Additional industry level evidence of ineffectual green policy can also be found in the Chinese market. As shown by Ramiah et al. (2015a), a few environmental regulations have exhibited minimal impact on risk and returns in the Chinese stock market, while others have failed to accomplish their objectives. Unexpectedly, the coal sector in China is found to have benefited from new environmental regulations in China due to a lack of regulatory enforcement. These findings are consistent with the findings of Grand and D'Elia (2005) on environmental news and stock market performance in Argentina.

While the above-mentioned studies investigate the energy market reactions to climate policies, their findings are mixed to some extent. More importantly, the existing literature overlooks the heterogeneous nature of individual green stocks when examining their response to changes in climate policy. Our study adds new evidence to the mixed findings documented in the existing literature by conducting firm-level analysis. We argue that individual green stocks are associated with unique features and, as such, may respond differently to climate policy events. Understanding the heterogeneity of green stocks is particularly important to environmentally-conscious investors when constructing diversification investment strategies, and is also important to policy makers when designing regulations to effectively promote clean energy and mitigate climate change. In addition to investigating the response of individual green stocks to climate policy events, we further extend the existing literature by exploring the evolution of spillovers among green stocks over time. Our spillover network analysis is useful in constructing a minimum connectedness portfolio that consists only of green stocks. By construction, this portfolio has low carbon intensity as all companies in this portfolio are highly engaged in environmentally friendly activities.

3. Data

We obtain a list of 118 sample green stocks from NASDAQ OMX Green Economy Index components. We use the NASDAQ OMX Green Economy Index components to guide our choice of green companies for the following reasons. First, this index is a well-established benchmark of the green economy that tracks the performance of companies across a spectrum of industries associated with the economic model around sustainable development. Previous research has employed this index to study the environmentally friendly financial sector.¹ To be included in this index, a company must be involved in the reduction of fossil-related fuels, products, services, and lifestyle and must be classified as participating in the Green Economy as determined by SustainableBusiness.com. In addition, the company must be listed on an index-eligible global stock exchange with a minimum worldwide market capitalization of \$50 million and a three-month average daily dollar trading volume of \$50,000. The company must not be under bankruptcy proceedings.² Thus, by deriving a list of green stocks from the NASDAQ OMX Green Economy Index, we are able to capture the behavior of the largest and most liquid green stocks. From this list, we extract firms who are domiciled in the U.S. and present our sampling period from 2014 to 2022 as our goal is to study the effect of various U.S. climate policies. Our final sample includes 118 firms. Table A-1 in the appendix summarizes the list of stocks in our study and the descriptive statistics. Our data set ranges from January 1, 2014 to September 16, 2022 to ensure a stable list of clean energy stocks. In addition, this period includes many

¹ See Pham (2019), Chen et al. (2022), Khalfaoui et al. (2022), Urom et al. (2022), and Mensi et al. (2022), among others.

² See https://indexes.nasdaqomx.com/docs/methodology_QGREEN.pdf for more details.

significant climate policy events including the Paris Climate Agreement and its ratification, President Trump's election and his subsequent withdrawal from the Paris Agreement, President Biden's election, and the passage of the U.S. Climate Change Bill. We collect the daily prices and volumes of these stocks from Compustat.

4. Methodology

4.1. The response of environmentally friendly stocks to climate policy: An event study

4.1.1. Abnormal returns

We investigate the market reactions of green stocks to the occurrence of the six events by using event study methodology based on a single index market model. An event falling on a non-trading day is converted to the following trading day. For example, if an event falls on Saturday in the U.S. markets, it is changed to the following Monday or Tuesday if Monday is a public holiday. Following Demirer and Kutun (2010), we employ an event window of $(-20, 20)$ around the event announcement to capture possible information leakages prior to the event, as well as post-announcement reactions. We specify the following regression model to estimate the abnormal return for each green stock.

$$R_{jt} = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt} \quad (1)$$

where R_{jt} is the return of stock j on day t , R_{mt} is the return of the CRSP equally-weighted market index on day t , and α_j , β_j are estimated parameters based on an estimation window of $t = -120$ to $t = -21$ relative to the event occurrence day.³ We specify that a minimum of 60 non-missing return observations within the estimation window are required to produce the estimates of the expected return.

The abnormal return of stock j is as follows:

$$AR_{jt} = R_{jt} - (\alpha_j + \beta_j R_{mt}) \quad (2)$$

We employ a standardized cross-sectional test (Boehmer et al., 1991) to test the null hypothesis that the event period abnormal return is zero. The cross-sectional test adjusts for event-induced changes in variance around the event date.

4.1.2. Abnormal return volatility

To examine the abnormal return volatility around the event announcement dates, we follow Beaver (1968), DeFond et al. (2007), Landsman and Maydew (2002), Landsman et al. (2012), and Devos et al. (2015) and specify the model as below:

$$AVAR_{jt} = \frac{AR_{jt}^2}{\sigma_j^2} \quad (3)$$

Abnormal return volatility measures the stock return variance over the event window period $(-20, 20)$ compared to the stock return variance over the estimation period, where AR_{jt} is defined in Eq. (2), and the denominator denotes the variance of stock j 's market model residuals calculated over the $(-120, -21)$ estimation period. If abnormal volatility is greater than one (between zero and one), the stock is considered as having greater than normal (smaller than normal) volatility. One-tailed t-statistics are calculated to test the null hypothesis that abnormal volatility is smaller than or equal to one.

³ Our results are qualitatively similar when we employ other estimation windows. For example, we use an estimation window of $(-80, -21)$ following Demirer and Kutun (2010). In addition, we also employ other estimation windows that allow for a time lag between the event and estimation windows. This helps us avoid the problem of information leakage long before the events in our estimation window (Diaz-Rainey et al., 2021; Devos et al., 2015).

4.1.3. Abnormal trading volume

When testing market responses to information disclosure or public events, the existing literature focuses not only on the abnormal returns, but also on the abnormal trading volume around the event as an indication of information flow. The volume-based metric outperforms the return-based metric in detecting the presence of investors' responses and is a more powerful measure of the impact of public disclosure (Cready and Hurtt, 2002).

To estimate abnormal trading volumes around the five events, we follow Beaver (1968), Morse (1981), and Palman et al. (1994) by defining the market-model abnormal volume as:

$$AV_{jt} = V_{jt} - (\alpha_j + \beta_j V_{mt}) \quad (4)$$

where V_{jt} is the number of shares of firm j traded on day t divided by the number of shares outstanding, and V_{mt} is the aggregate number of shares traded on day t divided by the total shares outstanding in the market on day t . AV_{jt} is the abnormal volume representing the difference between actual volume and predicted volume, where predicted volume is based on the parameters α_j and β_j estimated over the $(-120, -21)$ period relative to the announcement dates.

While the stock return metric reflects how information arrival is incorporated into stock prices, the trading volume metric shows the action of investors in translating their interpretation of information arrival into buy and sell trading activities, and the volatility metric represents the divergence and uncertainty of investors' opinions. By employing all three metrics, our event study analysis captures investor reactions to climate policy events from different aspects.

4.2. Environmentally friendly stock connectedness

The second objective of our paper is to identify the connectedness among clean energy stocks and how it evolves around major climate events. To this end, we estimate a dynamic connectedness network based on the connectedness approach by Diebold and Yilmaz (2012); Diebold and Yilmaz (2014). This framework obtains the generalized forecast error decomposition, which is a measure of spillovers across variables, from a vector autoregression (VAR) model as follows:

$$y_t = \sum_{i=1}^p B_i y_{t-i} + u_t; u_t \sim N(0, S_t) \quad (5)$$

where y_t is an $n \times 1$ vector of green stock daily returns, volatility or volume.⁴ p is the lag length with the optimal lag length determined by the Bayesian information criterion (BIC). B_i are matrices of the coefficients. u_t denotes the error terms, while S_t denotes its variance-covariance matrices. Using the Wold decomposition theorem, the moving average representation is $y_t = \sum_{i=1}^p B_i y_{t-i} + u_t = \sum_{j=0}^{\infty} A_j u_{t-j}$, where the $n \times n$ coefficient matrix A_j is calculated as: $A_j = B_1 A_{j-1} + B_2 A_{j-2} + \dots$, with $A_0 = I_n$ and $A_j = 0$ for $j < 0$.

Given the high dimensionality of our data, we estimate the VAR model in Eq. (5) using the least absolute shrinkage and selection operator (LASSO) estimation method (Tibshirani, 1996) that shrinks and selects parameters using different regularization methods. Our approach is in line with previous work by Demirer et al. (2018), Gabauer et al. (2020), and Balcilar et al. (2022) who apply the LASSO-VAR model to study the connectedness among variables in high dimensional settings.

From the LASSO-VAR model and its moving average representation, the generalized forecast error variance decomposition (GFEVD) is then given by:

⁴ Daily returns are calculated by log-differencing and daily volatilities are calculated using the Garman and Klass (1980) formula. Daily volumes are log-transformed. All series are stationary according to the augmented Dickey-Fuller unit root tests.

$$\phi_{ij,t}(H) = \frac{S_{ij,t}^{-1} \sum_{h=0}^{H-1} (e_i^T A_t S_t e_j)^2}{\sum_{h=0}^{H-1} (e_i^T A_t S_t A_t^T e_i)} \quad (6)$$

$S_{ij,t}$ denotes the standard deviation of the error term of variable j . e_i is an $n \times 1$ vector that takes a value of one for element i and zero otherwise. The spillover index from variable j to variable i is calculated as:

$$\tilde{\phi}_{ij,t}(H) = \frac{\phi_{ij,t}(H)}{\sum_{j=1}^n \phi_{ij,t}(H)} \quad (7)$$

$\tilde{\phi}_{ij,t}(H)$ represents the percent of forecast error variance in variable i that is explained by variable j . From the normalized GFEVD, we calculate various connectedness indexes to summarize the overall connectedness among the variables in the system. Specifically:

$$FROM_j = \sum_{i=1, i \neq j}^n \tilde{\phi}_{ji,t}(H) \quad (8)$$

$$TO_j = \sum_{i=1, i \neq j}^n \tilde{\phi}_{ij,t}(H) \quad (9)$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \quad (10)$$

$$PCI_{ij} = 2 * \frac{\tilde{\phi}_{ji,t}(H) + \tilde{\phi}_{ij,t}(H)}{\tilde{\phi}_{ji,t}(H) + \tilde{\phi}_{ij,t}(H) + \tilde{\phi}_{ji,t}(H) + \tilde{\phi}_{ij,t}(H)} \quad (11)$$

$$TCI_t = \frac{1}{n} \sum_{j=1}^n FROM_{jt} = \frac{1}{n} \sum_{j=1}^n TO_{jt} \quad (12)$$

where $FROM_{jt}$ captures the total spillovers from all of the other variables to variable j , TO_{jt} captures the total spillovers from variable j to all of the other variables. NET_{jt} denotes the net spillovers of variable j to all of the other variables where a positive net spillover indicates that variable j is a net shock transmitter in the system. PCI_{ij} captures the pairwise connectedness between two variables i and j that captures the overall degree of connection between two variables. By construction, $0 \leq PCI_{ij} \leq 1$. TCI_t is the total connectedness index that captures the overall spillovers among all of the variables in the system. TCI_t ranges between zero and 100 and a higher TCI_t implies stronger spillovers among the variables.

5. Empirical results

5.1. Environmentally friendly stocks and climate policy: Event study results

5.1.1. Impact of events on green stocks

We first examine the green stocks' overall return reactions to the six events and report the cumulative average abnormal returns around the event announcement days in Fig. 1. More detailed results are summarized in Table B-1 in the appendix. We focus on an event window of 20 days around the event to capture possible information leakages prior to the event, as well as post-announcement reactions.⁵ In Fig. 1a, the strongest path of cumulative abnormal returns is observed for the Biden Election Confirmation, followed by the Biden Climate Change Bill and the Paris Agreement. These events are found to have the strongest positive impact on the green stock market in both economic magnitude and statistical significance. However, the Trump Election, Paris Agreement Ratification, and the Announced Withdrawal of the Paris Agreement are documented with insignificant impacts. The confirmation of the Biden election shifted the market expectations about U.S. climate policy upward dramatically leading to more favorable market valuation

⁵ Our results are qualitatively similar when we employ alternative estimation windows. The conclusions are robust when we consider event windows such as (-5, 5).

of green stocks. Consistent positive market reaction is also observed around the announcement of the Biden Climate Change Bill reflecting climate-conscious investors' confidence in anticipating the opportunities for green firms. Alternatively, green stocks, on average, do not react significantly negatively to the opposite shock from the Trump Election. Our results are complementary to Ramelli et al. (2021) who find that the Biden election improves the value of climate-responsible firms, but the Trump election boosts not only the carbon-intensive firms, but also the climate responsible firms, especially those held by long-term investors.

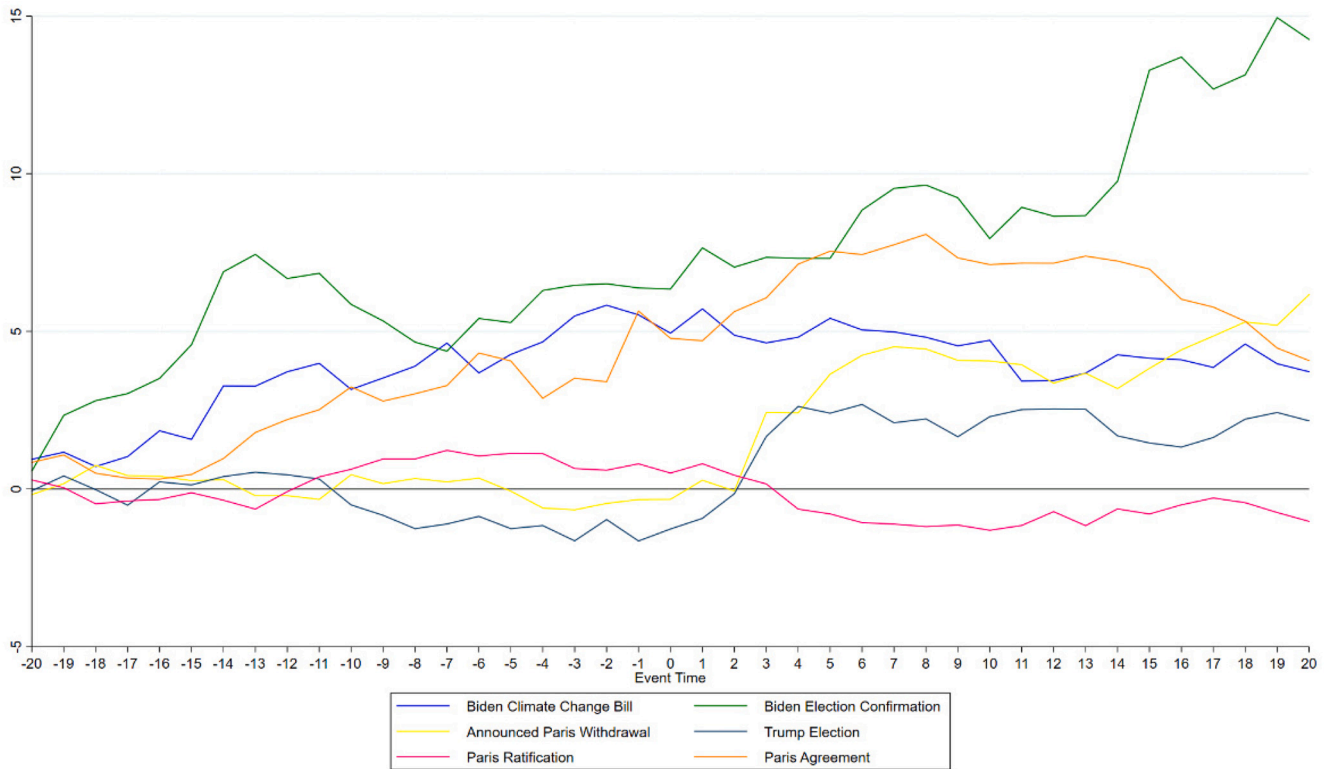
The positive cumulative impact of the Paris Agreement on green stocks highlights the importance of the transition toward green economic activities as a critical step in meeting the goals set by the Paris Agreement. Our finding is consistent with Fahmy (2022) who identifies an overall surge in investors' awareness of climate risk and attention to green investment, especially following the Paris Agreement. While the initial announcement of the Paris Agreement results in significant green stock reactions, the subsequent ratification of the Paris Agreement by China and the U.S. on September 3, 2016 demonstrates no significant positive return reactions among these stocks. Similarly, the cumulative market reaction to the announced withdrawal of the Paris Agreement also appears to be statistically insignificant. The insignificant aggregate impact of this negative shock is not surprising given that many U.S. states, cities, and companies (representing half of the U.S. economy) have agreed to continue to meet the Paris Agreement goals through alternative climate initiatives (Diaz-Rainey et al., 2021).⁶

While our cumulative average abnormal return results demonstrate significant positive return reactions to favorable climate policy events and insignificant negative return reactions to unfavorable events, we find that the average abnormal volatilities are affected in the opposite way. As shown in Fig. 1b, negative shocks (Trump Election and Announced Withdrawal of Paris Agreement) are found to increase the average abnormal volatilities of green stocks significantly. These findings confirm the validity of abnormal volatility metrics in capturing the uncertainty and divergence in investors' opinions that arise from these unfavorable shocks. Different from the abnormal return metrics that reflect the increased information content conveyed by the events to the stock market, abnormal volatility metrics better capture the increased uncertainty associated with these events. Our results suggest that the election victory of Donald Trump and the withdrawal from the Paris Agreement impose great concern and uncertainty in the green stock market leading to divergent opinions among investors. However, climate policy events that are favorable to climate change mitigation are found to have no statistically significant impact on green stocks' abnormal volatility confirming these positive shocks are associated with less uncertainty and greater consensus among green investors.

Next, we explore the abnormal trading volume around the announcement dates of the six events and plot the paths of their cumulative reactions in Fig. 1c. Our abnormal trading volume metric shows how investors translate their interpretation of news events into buy and sell trading activities. Although a visual inspection on Fig. 1c suggests the upward trending cumulative paths for all six events, the cumulative abnormal volumes are only statistically significant around the news announcements for the Biden Election Confirmation, Ratification Paris Agreement, and Trump Election. The cumulative average abnormal effects are relatively short-lived for Ratification Paris Agreement and Trump Election in terms of statistical significance (cumulative results become statistically insignificant one or two weeks after the announcements). We also find a delayed overall reaction in trading

⁶ Diaz-Rainey et al. (2021) identify unexpected negative reaction among U.S. oil and gas firms to the withdrawal from the Paris Agreement and they attribute this finding to the effort by those U.S. states, cities, and companies (representing half of the U.S. economy) who agreed to continue to meet the Paris Agreement goals through initiatives, such as "We Are Still In" and the U.S. Climate Alliance.

Cumulative average abnormal returns



Average abnormal volatility

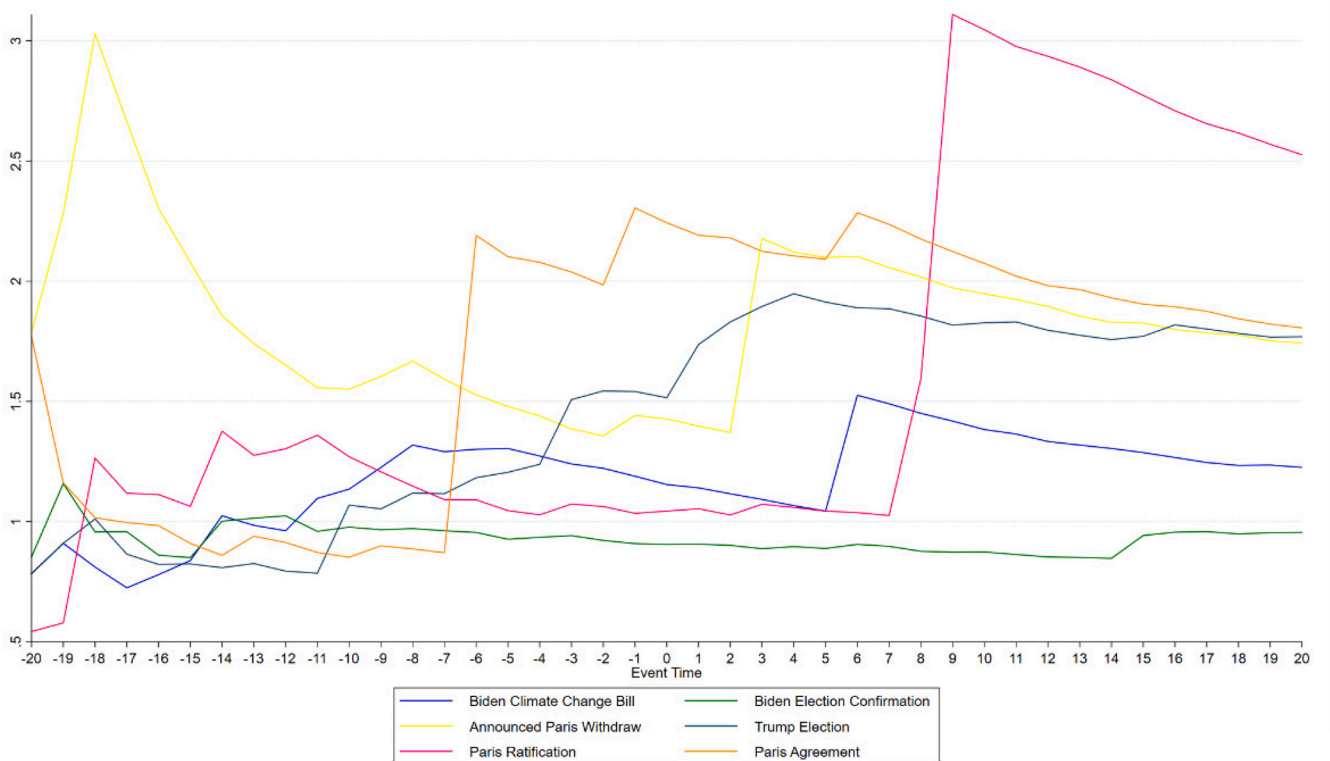


Fig. 1. Cumulative average abnormal return, average abnormal volatility, and average abnormal volume from event day -20 to event day 20 . (a) Cumulative average abnormal returns. (b) Average abnormal volatility. (c) Cumulative average abnormal volume.

Note: Fig. 1 plots the cumulative average abnormal returns, volatility, and volume of 118 sample green stocks from day -20 to day 20 around the announcements of the six studied events. Detailed results and test statistics are presented in Table B in the appendix. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Cumulative average abnormal volume

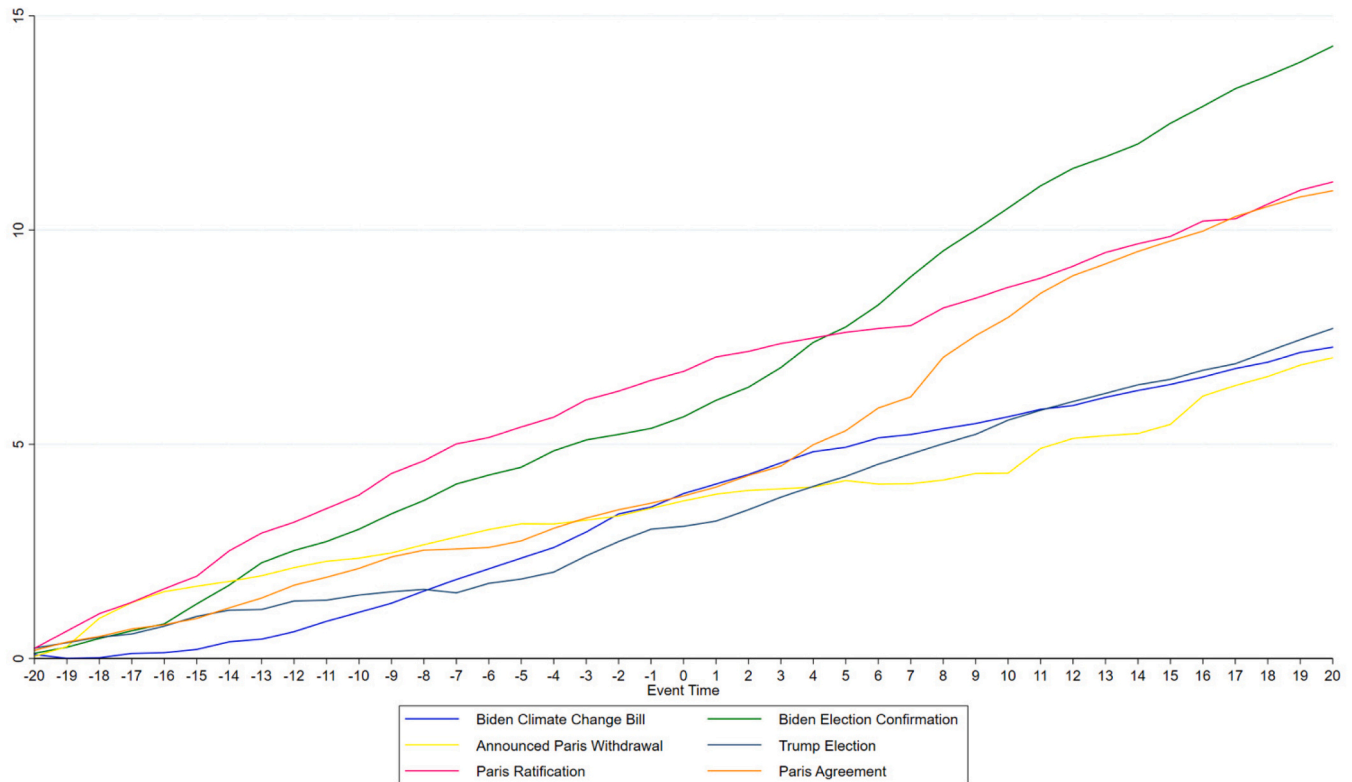


Fig. 1. (continued).

activities to the Announced Withdrawal of Paris Agreement. Specifically, the cumulative average abnormal volumes appear to become statistically significant about one week after the announcement. Overall, our mixed evidence from the aggregate market reaction to climate policy events in returns, volume, and volatility metrics highlights the importance of conducting further disaggregate level analyses to uncover the possible heterogeneity of green stocks.

5.1.2. Impact of events on green stocks across subsamples

This section conducts further analyses to investigate whether green stocks have homogenous reactions to climate events. To do this, we group individual clean energy stocks into different subsamples and re-examine the abnormal returns, volatility, and volume reactions for each subsample separately.

First, we group the green stocks by their industry classifications. Specifically, we distinguish between heavy and light industries following Nguyen and Phan (2020), and between high and low litigation risk industries following Chen et al. (2015). Our rationale for this classification stems from the fact that carbon intensity and litigation risk may cause differential effects of climate change policy on firm performance (Nguyen and Phan, 2020; Fard et al., 2020). Table A-2 in the appendix provides the definitions of the industry classifications. Our results are presented in Fig. C-1 in the appendix.⁷ For abnormal returns, green stocks in light industries with low litigation risk (Group 1) experience the strongest cumulative reactions among all three groups around

the announcements of the Paris Agreement. Green stocks in light industries with high litigation risk (Group 3) experience the strongest cumulative reactions around the announcements of the Trump Election, Announced Withdrawal of Paris Agreement, Biden Election, and Biden Climate Change Bill. Interestingly, green stocks in different groups tend to have different reactions to the negative shocks. When responding to Trump Election and Announced Withdrawal of Paris Agreement, green firms in light industries are associated with positive cumulative abnormal returns, on average, while green firms in heavy industries are associated with negative cumulative abnormal returns. This result indicates that environmental conscious investors have stronger confidence in green firms in light industries and believe those firms are less affected by loosened climate policy (i.e., Trump Election and Announced Withdrawal of Paris Agreement). This result also explains why we find an insignificant overall impact of Trump Election and Announced Withdrawal of Paris Agreement in the previous aggregate level analysis. For the Confirmation of Biden Election and Biden Climate Change Bill, all green stocks appear to gain following the announcements with the most substantial gain observed in light industries with high litigation risk. Specifically, we find the 20 days cumulative abnormal returns reach 43.58% and 10.80%, respectively. The results of abnormal volume and volatility appear to be less statistically significant and mixed in Fig. C-1.

In addition, we explore how firm sizes influence their reaction to climate policy events. We define large firms as those whose average market capitalization is above the sample median and small firms as those whose average market capitalization is below the sample median. Comparing the results between large firms and small firms in Fig. C-2, we find stronger cumulative abnormal return reactions among small

⁷ Full version of detailed results is available upon request.

green firms for all climate policy events except for Ratification of Paris Agreement (of which the results are insignificant). Consistent findings are identified for cumulative abnormal volatility and volume. Small green firms are found to have stronger cumulative abnormal volume and volatility reactions even as the statistical significance becomes weaker in some cases. The inverse size and stock return reaction relationship has been well established in the literature since the seminal work of [Banz \(1981\)](#). In a more recent study by [Ramelli et al. \(2021\)](#), firm size has also been documented to have a negative relation with stock return reactions to the 2016 Trump Election and the 2020 Biden Election.

Moreover, we consider the impact of idiosyncratic risk on firms' reactions to climate policy events.⁸ To this end, we estimate the firms' idiosyncratic volatility (IVOL) using the method in [Fu \(2009\)](#). Next, we define firms with high idiosyncratic risks as those whose IVOL is above the sample median and low idiosyncratic risk firms as those whose IVOL is below the sample median. As shown in [Fig. C-3](#), high IVOL green firms are associated with stronger cumulative abnormal returns in response to the Paris Agreement, Announced Withdrawal of Paris Agreement, Biden Election, and Biden Climate Change Bill in terms of both economic and statistical significance. The general trends hold in cumulative abnormal volatility and volume reactions. However, the results become weaker in statistical significance. Overall, our result complements [Roy et al. \(2022\)](#) who find that IVOL is positively related to the excess returns of clean energy stocks indicating clean energy stocks are influenced by the group of pessimistic investors who underprice the high IVOL clean energy stocks.

Viewed collectively, our subsample analyses uncover different reactions to different climate policy events conditional upon the characteristics of the individual green stocks and the nature of the events. These results highlight the importance of further exploring the heterogeneous roles played by individual green stocks when responding to climate policy events, thereby influencing the patterns of spillovers within the green stock market. We further address this question in the connectedness analysis.

5.2. Connectedness among green stocks

5.2.1. Connectedness among green stocks

In this section, we discuss the connectedness among green stocks. First, we estimate a static connectedness network among the variables. [Table 1](#) presents the summary statistics of the connectedness degree measures among the variables, while [Fig. 2](#) presents their histograms. The total connectedness index (TCI) is 87.8%, 81.4%, and 74.7% for returns, volatility, and volume respectively. This suggests a high degree of spillovers across the variables. The median values for the FROM connectedness, that captures the spillovers to a specific variable from all other variables, are 92.7%, 87.7%, and 90.1% in returns, volatility, and volume, respectively. The median values for the TO connectedness, that captures the spillovers from a specific variable to all other variables, are 94.46%, 90.54%, and 77.5% in returns, volatility, and volume, respectively. These results indicate that, on average, the variables receive and transmit a substantial amount of shocks from and to the system. The NET connectedness, which captures whether a variable is a net shock receiver or transmitter in the system, varies widely in the returns, volatility, and volume network. For example, the range of the NET connectedness is between -52.08 and 69.29% in returns, between -58 and 114.20% in volatility, and between -32.46% and 49.86% in volume. This suggests heterogeneous roles of individual stocks as shock transmitters and receivers in the system. [Table 2](#) presents the top and bottom-ranked firms with respect to the FROM, TO, and NET connectedness indexes. The table reports that energy and utility companies, such as Emerson Electric Co. (EMR), Essential Utilities Inc. (WTRG), American Water Works Co. Inc. (AWK), and Nextera Energy Inc. (NEE) tend to be the largest shock

Table 1
Connectedness degree measures – Summary statistics.

Connectedness index	Min	P25	Median	Mean	P75	Max
<i>(a) Return connectedness</i>						
FROM	27.2	88.6	92.7	87.8	94.5	95.8
TO	3.58	58.21	94.46	87.81	123.64	165.06
NET	-52.08	-29.14	1.56	0.00	29.06	69.29
TCI	87.8%					
<i>(b) Volatility connectedness</i>						
FROM	12.6	80.7	87.7	81.4	90.7	93.8
TO	2.41	42.94	90.54	81.38	121.18	208.02
NET	-58.00	-31.20	-7.30	0.00	30.40	114.20
TCI	81.4%					
<i>(c) Volume connectedness</i>						
FROM	27.6	72.8	90.1	74.7	84.0	88.7
TO	11.1	56.4	77.5	74.7	94.8	138.0
NET	-32.46	-14.61	-2.02	0.00	10.87	49.86
TCI	74.7%					

Note: [Table 1](#) presents the summary statistics of the connectedness degree measures among the variables for 118 sample green firms.

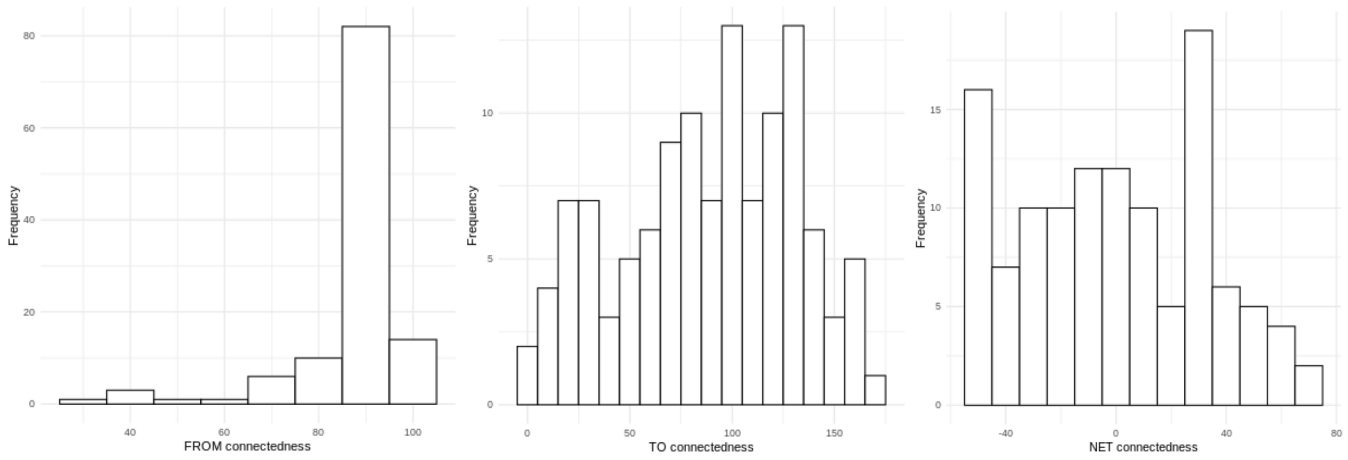
transmitters and receivers in the system. This indicates the significant role of the energy and utility sectors in driving the green economy. This finding is in line with previous research that highlighted the role of green energy on sustainable development. For example, [Li et al. \(2022\)](#) argue that green energy significantly accelerates green growth. [Mamidi et al. \(2021\)](#) suggest that households who adapt clean energy experience an increase in the household development index. [Hao et al. \(2021\)](#) and [Ulucak \(2020\)](#) find that green energy and green technological innovation promotes green growth.

[Fig. 3](#) presents the connectedness network among the variables. Red (blue) nodes indicate net shock receivers (transmitters). The node sizes indicate the size of the net spillovers. The shapes of the nodes (square, triangle, and circle) indicate the subsamples. Specifically, square nodes indicate firms who are in light industries with low litigation risk. Triangular nodes indicate firms who are in heavy industries with low litigation risk. Circle nodes indicate firms who are in light industries with high litigation risk. Oval nodes indicate the remaining firms. The arrows indicate the direction of spillovers between any two stocks, while the thickness of the arrows indicates the strength of the pairwise spillover index (PCI). Black arrows indicate a PCI of at least 0.5. [Fig. 3](#) demonstrates that firms in light industries with low litigation risk (the square nodes in the figure) are the dominant shock transmitters and receivers in the system. In contrast, the linkage between other firms is smaller. This is expected, as most firms (78 of 118 firms in our sample) are in light industries with low litigation risk. Note that the node sizes, which indicate the magnitudes of the NET connectedness index, are smaller in the volume connectedness network. This suggests a more balanced transmission of shocks in volume compared to returns and volatility shock. Finally, [Fig. 3](#) notes that the pairwise connectedness indexes among the firms are the largest in returns, followed by volatility and volume. This suggests that volume connectedness may not be the main drivers of spillovers among environmentally friendly stocks.

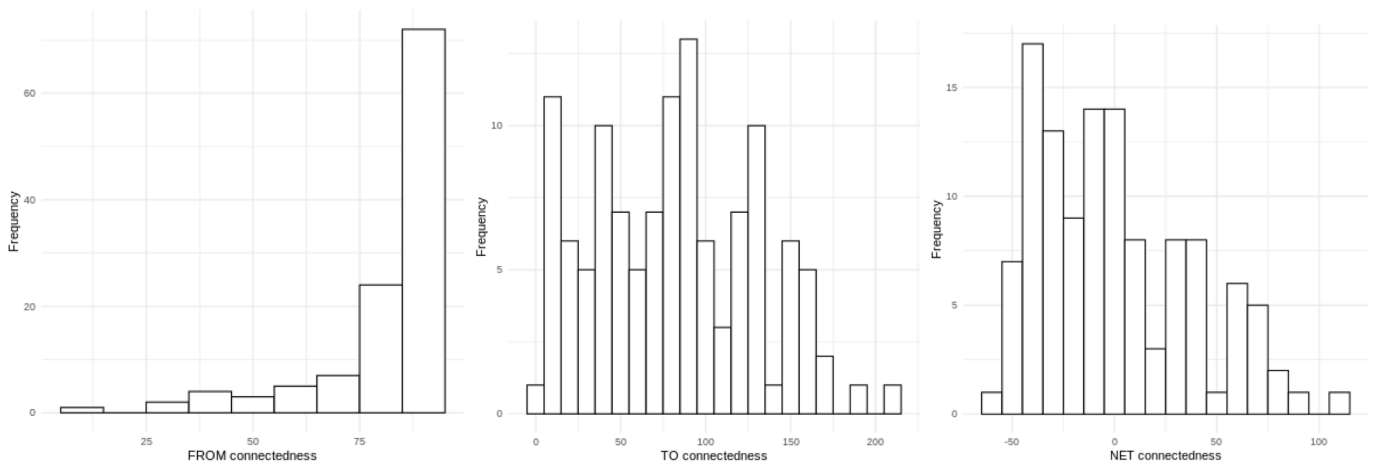
In addition to the static connectedness indexes, we calculate the dynamic connectedness among the variables in our model by estimating the LASSO-VAR connectedness model with a rolling window of 200 days (one trading year). [Fig. 4](#) presents the time-varying total connectedness indexes (TCI). The figure illustrates that the TCI are time varying in returns, volatility, and volume, where volatility connectedness experiences larger ups and downs than return and volume connectedness. Note that all the TCI are larger than 50% throughout the sampling period indicating a high degree of spillovers among environmentally friendly stocks. The TCI is high between 2014 and mid-2016 corresponding to the timing of the 2014–2016 oil glut. In addition, this period is

⁸ We thank an anonymous reviewer for this suggestion.

Return connectedness



Volatility connectedness



Volume connectedness

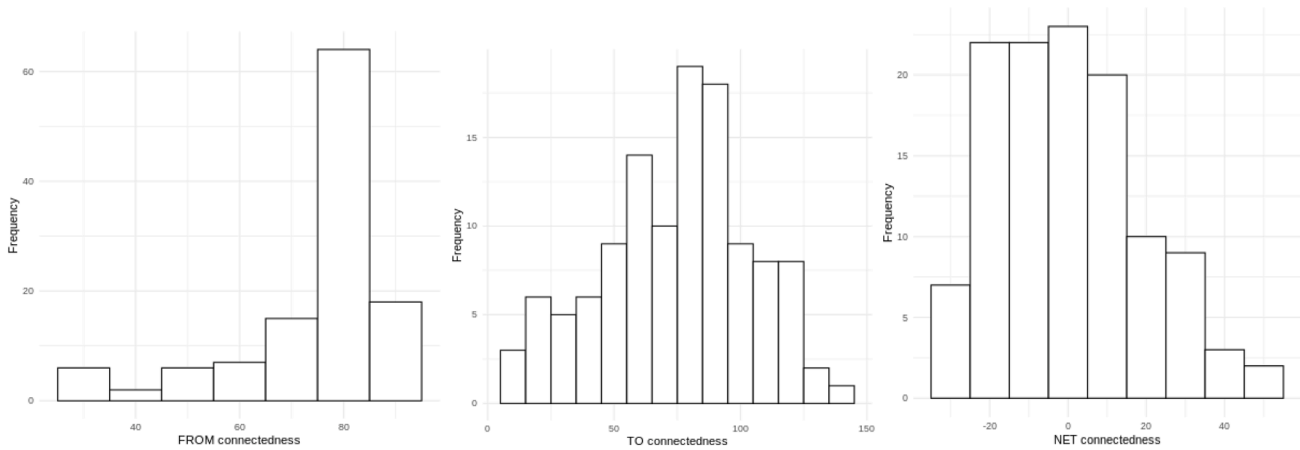


Fig. 2. Distribution of the FROM, TO, and NET connectedness indexes. (a) Return connectedness. (b) Volatility connectedness. (c) Volume connectedness. Note: The figure shows the distribution of the FROM, TO, and NET connectedness indexes across the 118 firms in our sample.

Table 2
Connectedness degree measures – Top and Bottom firms.

	Firm name	Ticker	Value of sorting measure
<i>(a) Return connectedness degree measures</i>			
FROM connectedness	Highest	IDEX Corp	IEX 95.8361
		Emerson Electric Co	EMR 95.81766
		Energys	ENS 95.76512
		Donaldson Co Inc	DCI 95.71638
		Xylem Inc	XYL 95.66191
	Lowest	Hudson Technologies Inc	HDSN 51.46982
		Blink Charging Co	BLNK 44.45628
		Gevo Inc	GEVO 37.937
		Ocean Power Technologies Inc	OPTT 35.41683
		Workhorse Group Inc	WKHS 27.17357
TO connectedness	Highest	Energys	ENS 165.0563
		IDEX Corp	IEX 163.3537
		Emerson Electric Co	EMR 160.3932
		Donaldson Co Inc	DCI 157.2757
		Xylem Inc	XYL 156.4396
	Lowest	Hudson Technologies Inc	HDSN 8.149614
		Blink Charging Co	BLNK 7.07677
		Gevo Inc	GEVO 5.75067
		Ocean Power Technologies Inc	OPTT 4.758366
		Workhorse Group Inc	WKHS 3.582453
NET connectedness	Highest	Energys	ENS 69.29115
		IDEX Corp	IEX 67.51764
		Emerson Electric Co	EMR 64.57555
		Donaldson Co Inc	DCI 61.55932
		Xylem Inc	XYL 60.77765
	Lowest	Fuelcell Energy Inc	FCEL -49.4848
		Hain Celestial Group Inc	HAIN -49.829
		Tesla Inc	TSLA -50.5719
		Ultralife Corp	ULBI -52.0128
		Nextera Energy Inc	NEE -52.0769
<i>(b) Volatility connectedness degree measure</i>			
FROM connectedness	Highest	Simon Property Group Inc	SPG 92.9073
		Nextera Energy Inc	NEE 92.95312
		Ecolab Inc	ECL 93.1322
		American Water Works Co Inc	AWK 93.26248
		Emerson Electric Co	EMR 93.7885
	Lowest	Blink Charging Co	BLNK 12.64475
		Amtech Systems Inc	ASYS 31.16729
		Hudson Technologies Inc	HDSN 34.97313
		Fuelcell Energy Inc	FCEL 35.57263
		Ocean Power Technologies Inc	OPTT 37.54321
TO connectedness	Highest	Emerson Electric Co	EMR 208.0195
		Nextera Energy Inc	NEE 186.3047
		American Water Works Co Inc	AWK 173.0135
		Essential Utilities Inc	WTRG 172.3715
		Corning Inc	GLW 164.3656
	Lowest	Hudson Technologies Inc	HDSN 9.173792
		Amrys Inc	AMRS 9.064416
		Ultralife Corp	ULBI 8.809833
		Amtech Systems Inc	ASYS 6.373383
		Blink Charging Co	BLNK 2.414834
NET connectedness	Highest	Emerson Electric Co	EMR 114.231
		Nextera Energy Inc	NEE 93.35161
		Essential Utilities Inc	WTRG 80.27938
		American Water Works Co Inc	AWK 79.75099

Table 2 (continued)

	Firm name	Ticker	Value of sorting measure
FROM connectedness	Lowest	Corning Inc	GLW 72.25797
		Natural Grocers Vitamin Ctge	NGVC -45.8616
		Artesian Resources Preformed Line Products Co	ARTNA -46.7291
		PLPC -50.9251	
		Gaia Inc	GAIA -54.978
	Highest	Digi International Inc	DGII -58.0339
		Mueller Industries Franklin Electric Co Inc	MLE 88.66172
		FELE 88.30844	
		Cisco Systems Inc California Water Service Gp	CSCO 88.14719
		CWT 87.99901	
TO connectedness	Lowest	American States Water Co	AWR 87.76242
		Amtech Systems Inc	ASYS 33.48579
		Lifeway Foods Inc	LWAY 32.46913
		Ocean Power Technologies Inc	OPTT 31.84969
		Gevo Inc	GEVO 28.05592
	Highest	Blink Charging Co	BLNK 27.57762
		Cisco Systems Inc	CSCO 138.0032
		Nextera Energy Inc	NEE 128.5953
		Mueller Industries Franklin Electric Co Inc	MLE 125.5953
		FELE 124.8059	
NET connectedness	Lowest	California Water Service Gp	CWT 122.2542
		Blink Charging Co	BLNK 16.35705
		Ultralife Corp	ULBI 16.29824
		Hudson Technologies Inc	HDSN 14.07597
		Lifeway Foods Inc	LWAY 12.41734
	Highest	Workhorse Group Inc	WKHS 11.11927
		Cisco Systems Inc	CSCO 49.856
		Nextera Energy Inc	NEE 46.12342
		Mueller Industries	MLE 36.93357
		Simon Property Group Inc	SPG 36.55076

Note: Table 2 presents the top and bottom-ranked green firms with respect to the FROM, TO, and NET connectedness indexes. Firm name, ticker, and value of connectedness degree measures are illustrated in the columns.

characterized by high climate policy uncertainty. Moreover, there was a significant increase in connectedness at the beginning of the COVID-19 pandemic in 2020. Note that the TCI declines toward the end of 2020. However, it has not reverted to its pre-pandemic level. Finally, our results note an increase in the total connectedness index at the beginning of 2022 that could be explained by the greater uncertainty in the energy and financial markets following the Russia-Ukraine war. The high connectedness among green stocks during crisis periods is in line with previous studies that note higher financial contagion during extreme market movement (Baker et al., 2020; Ahmad et al., 2021; Akhtar-uzzaman et al., 2021).

5.2.2. Cumulative abnormal connectedness around climate policy events
To analyze how connectedness among clean energy stocks evolves

Fig. 3. Connectedness network. (a) Return connectedness. (b) Volatility connectedness. (c) Volume connectedness.

Note: The figure shows the average connectedness network among the variables. Red (blue) nodes indicate net shock receivers (transmitters). The node sizes indicate the size of the net spillovers. The shapes of the nodes (square, triangle, and circle) indicate the subsamples. Specifically, square nodes indicate firms who are in light industries with low litigation risks. Triangular nodes indicate firms who are in heavy industries with low litigation risks. Circle nodes indicate firms who are in light industries with high litigation risks. Oval nodes indicate the remaining firms. The arrows indicate the direction of spillovers between any two stocks, while the thickness of the arrows indicates the strength of the pairwise spillover index (PCI). Black arrows indicate a PCI of at least 0.5. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Volatility connectedness

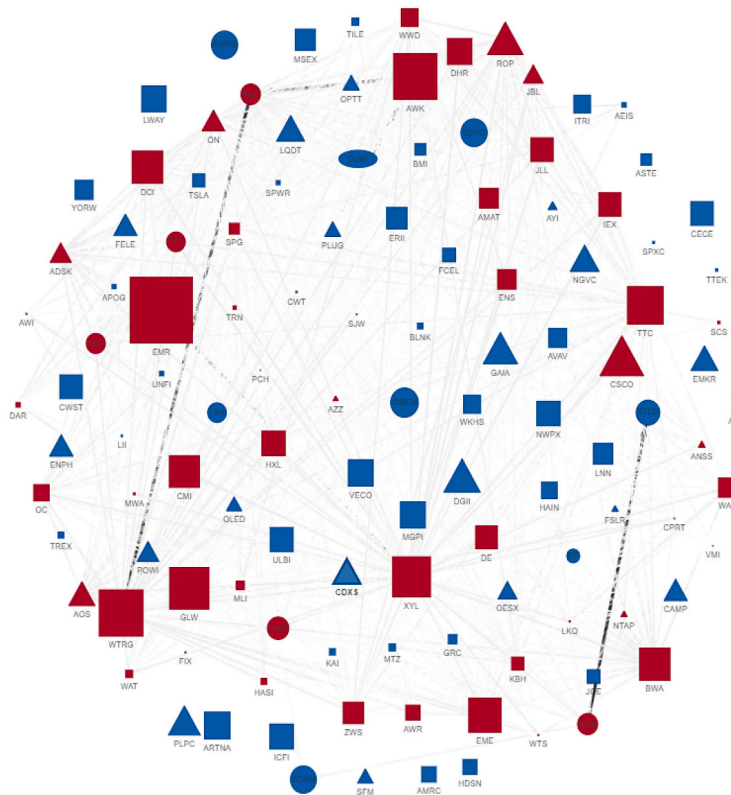


Fig. 3. (continued).

around climate policy events, we calculate the abnormal connectedness for each day in the event window. We define *abnormal connectedness* as the difference between the total connectedness and its conditional mean over the estimation window of $t = -120$ to $t = -21$ relative to the event occurrence day. Then, we determine the cumulative average abnormal connectedness over the event window.⁹

Fig. 5 presents the cumulative abnormal connectedness (CAC) in the event window of 20 days around the events, while Tables E-1–E-3 in the appendix present the results of the hypothesis tests as to whether the CAC is significantly different from zero. We find that the Trump election and his subsequent announced withdrawal from the Paris Agreement has a significantly negative impact on the connectedness among the environmentally friendly stocks, while the Biden Climate Change Bill has a significantly positive impact on the connectedness among the variables. One explanation is that these events signal changes in the direction of climate policies in the U.S. This triggers significant responses of environmentally friendly stocks, thereby altering their spillover patterns around the events. Fig. 5 also shows that the effects of other events, such as the Paris Agreement and its Ratification and the Biden Election Confirmation, exhibit less consistent effects on the returns, volatility, and volume connectedness among environmentally

friendly stocks. This is in line with the fact that the Paris Agreement represents an international event. Thus, it tends to have a smaller effect on the U.S. financial market. This result corroborates with Faccini et al. (2021) who finds that news about U.S. climate policy is more likely to be priced in the stock market than news about international events. Finally, the small CAC in response to the Paris Ratification and the Biden Election Confirmation implies that investors do not interpret these events as significant changes in climate policy when compared to the other events.

5.2.3. Robustness checks – Subsample analysis

In this section, we analyze how the connectedness among environmentally friendly stocks varies across subsamples. First, we group the green stocks by the nature of their industries along two dimensions: carbon intensity and litigation risk. Fig. F-1 presents the time-varying total connectedness index by industry. The figures illustrate that the total connectedness indexes (TCI) tend to move in the same direction, and the TCI among firms in light industries with low litigation risk is the largest among all of the industries. This is consistent with our previous findings that firms in light industries with low litigation risk are the largest transmitters and receivers of shocks among environmentally friendly stocks. Moreover, the high total connectedness index in light industries with low litigation risk reflects the higher concentration of green firms in these industries. Thus, shocks from one green firm spill over more easily to other green firms. In contrast, green firms in other industries (i.e., those in heavy industries or industries with high

⁹ The methodology for the connectedness event study is based on Campbell et al. (2012) and González-Urteaga and Rubio (2022).

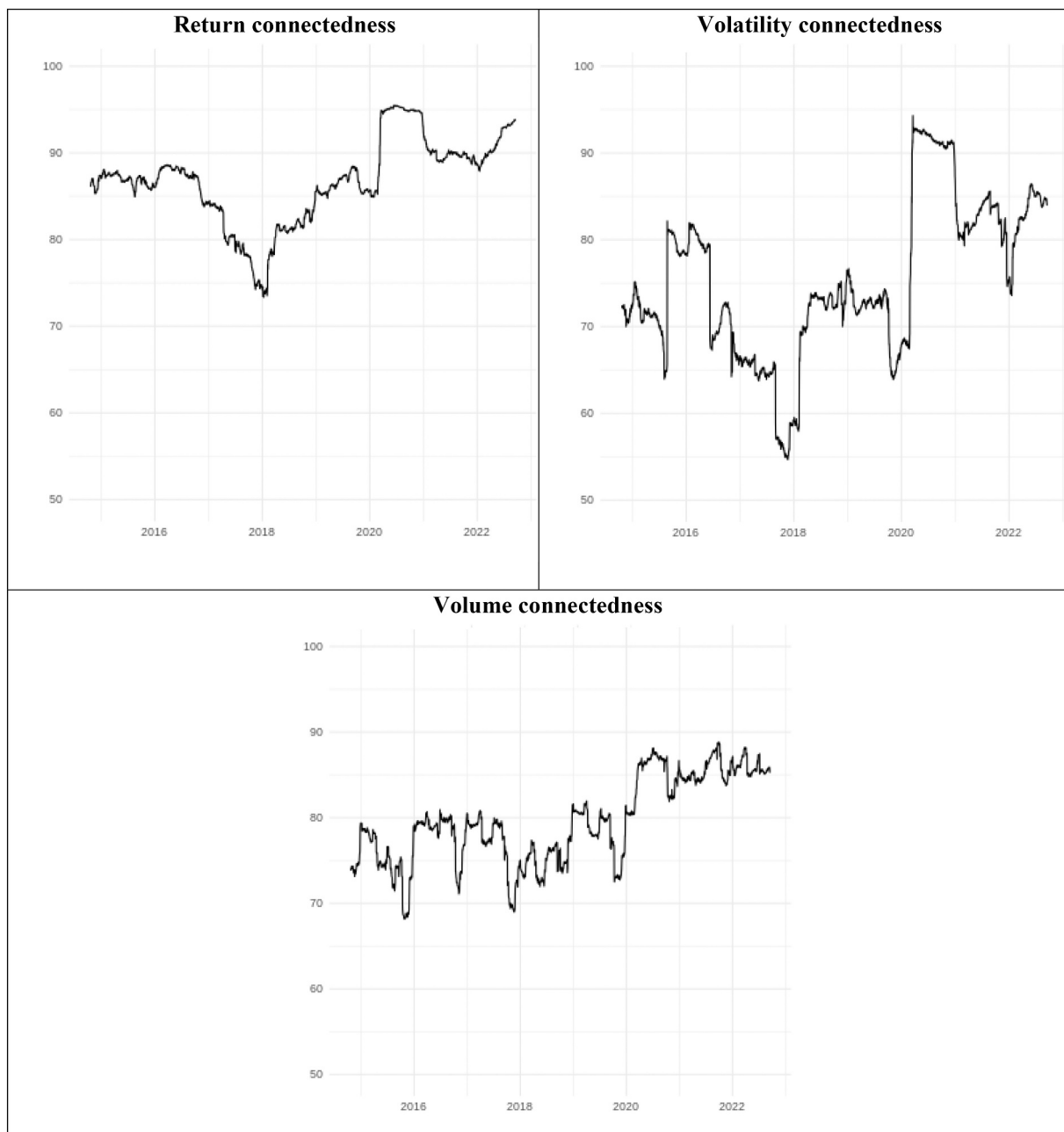


Fig. 4. Time-varying total connectedness indexes. (a) Return connectedness. (b) Volatility connectedness. (c) Volume connectedness.

Note: The figure shows the time-varying total connectedness indexes among clean energy stocks for the whole sample. The x-axis indicates time, while the y-axis indicates the spillover values.

litigation risk) represent smaller shares in the total number of firms in the industries. Therefore, their performance may be driven by the industries' overall performance that includes both green and brown firms. Fig. G-1 present the cumulative abnormal connectedness (CAC) of firms in different industries in response to the events. The figure indicates that the CAC among green firms in light industries responds most positively to the Biden Climate Change Bill, while green firms in heavy industries respond most negatively to the Trump election and his announced withdrawal from the Paris Agreement. This indicates that investors interpret tightening climate policy (i.e., the Biden Climate Change Bill) as positive news for green firms in light industries, while they view loose climate policy (i.e., the Trump election and the withdrawal from the Paris Agreement) as negative news for green firms in heavy industries.

In addition, we explore the differences in the connectedness between large and small firms. Fig. F-2 presents the total connectedness index

(TCI) by firm size. The figure illustrates that large firms are more interconnected with one another as indicated by their larger total connectedness index. Moreover, we consider the impact of idiosyncratic risk (IVOL) on firms' connectedness. Fig. F-3 presents the total connectedness by firms' IVOL, which shows a greater connectedness among firms with low idiosyncratic risk. This is in line with the fact that large firms tend to have lower idiosyncratic risk in our sample. Thus, the higher TCI among firms with low IVOL reflects the fact that these firms tend to be larger in size. This provides indirect evidence of the larger role of firm size in driving the connectedness among green stocks than firms' idiosyncratic risk. The lower connectedness among firms with higher IVOL is also in line with the negative relationship between idiosyncratic risk and stock returns (Ang et al., 2009; Fu, 2009; Stambaugh et al., 2015; Qadan and Shuval, 2022). Figs. G-2 and G-3 present the cumulative abnormal connectedness (CAC) of large vs. small and high vs. low

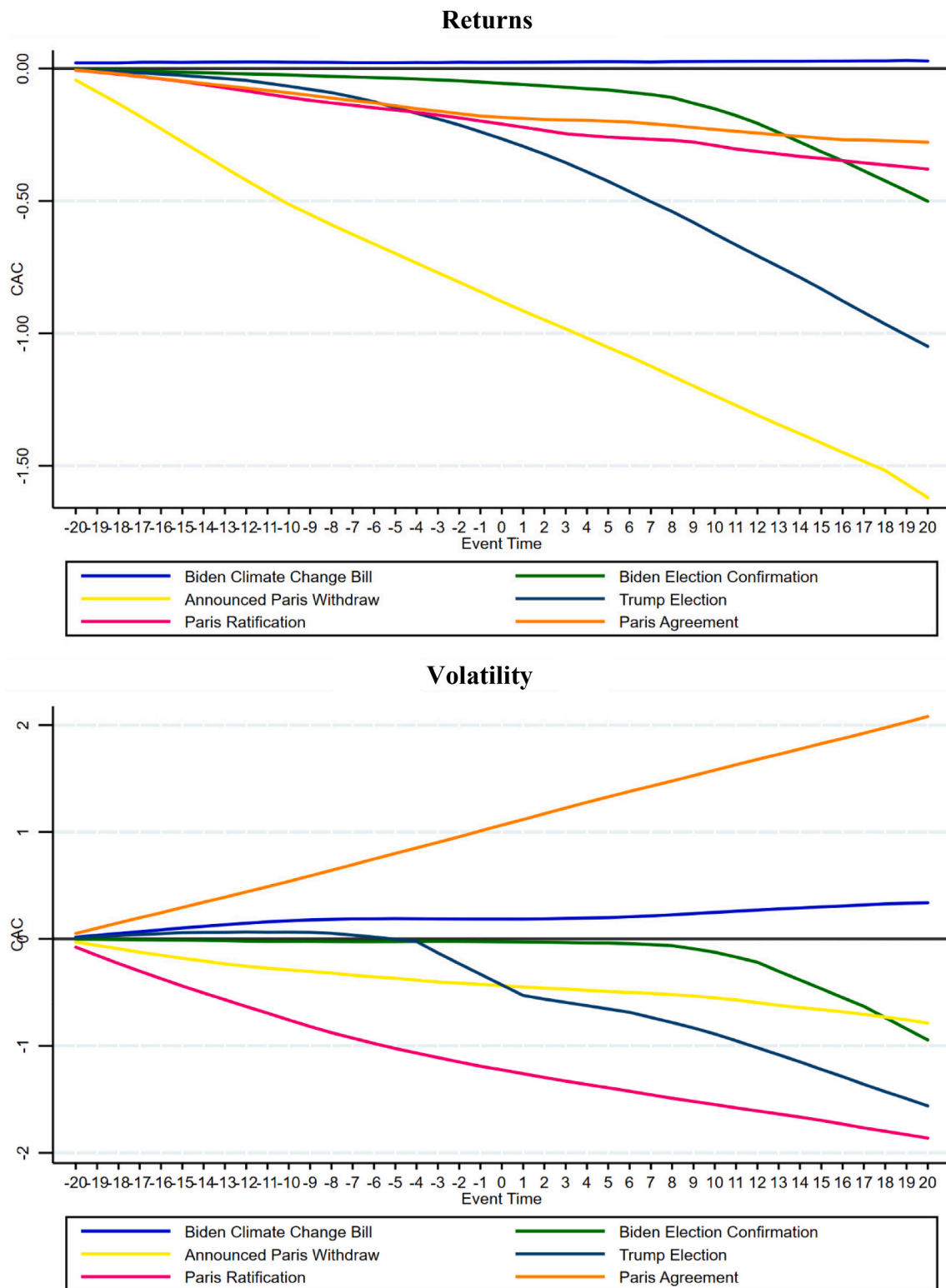


Fig. 5. Cumulative abnormal connectedness from event day -20 to event day 20. (a) Returns. (b) Volatility. (c) Volume. Note: Fig. 5 presents the cumulative abnormal connectedness (CAC) in the event window of 20 days around the six studied events.

IVOL firms around climate events. Overall, our conclusions in Section 5.2.2 still hold; however, large firms tend to be more sensitive to the events than small firms.

5.3. Portfolio analysis

In this section, we explore the implications of our connectedness

results for portfolio management and construction. To this end, we build a minimum connectedness portfolio. The portfolio weights of the assets vary according to their connectedness with other variables. Following Tiwari et al. (2022) and Broadstock et al. (2020), we first calculate the pairwise connectedness index (PCI) between two assets using the formula in Eq. (11). Next, using these pairwise connectedness indices, we create a minimum connectedness portfolio (MCP). In this portfolio,

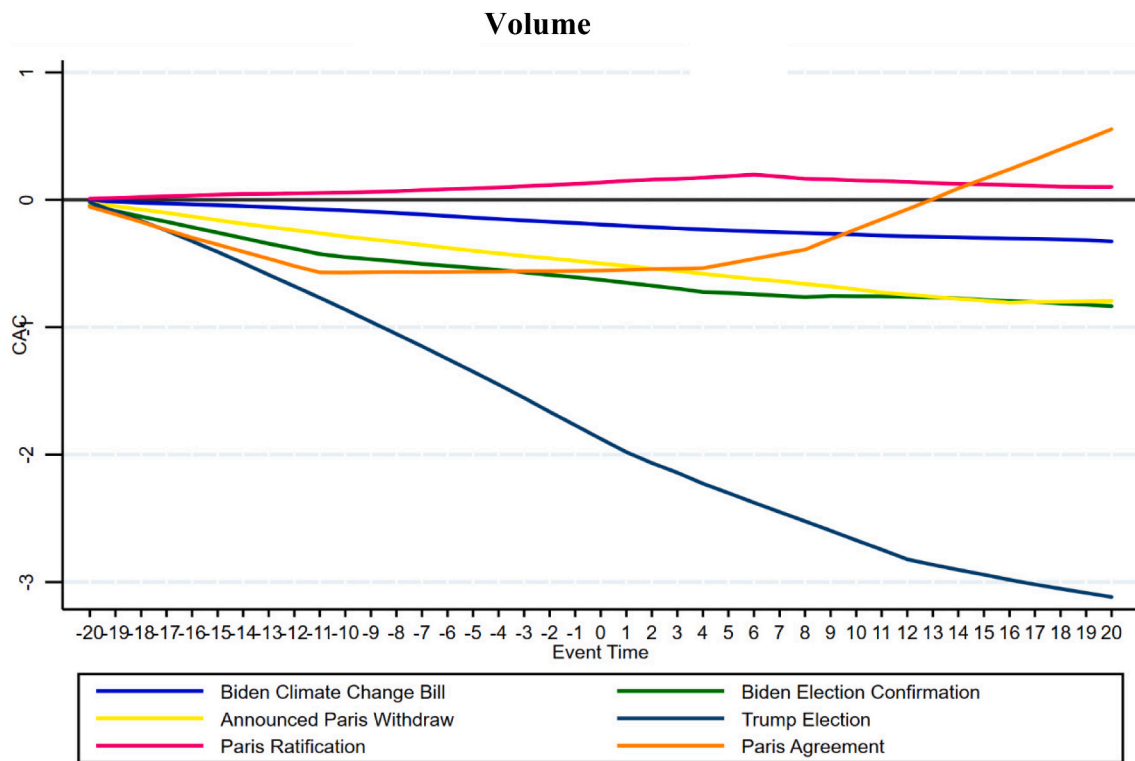


Fig. 5. (continued).

variables that do not influence others and are not influenced by others will be given a higher weight in the portfolio. The portfolio weight matrix can be expressed as follows:

$$w = \frac{PCI_t^{-1} * I}{I * PCI_t^{-1} * I}$$

where PCI_t is the pairwise connectedness matrix and I is the identity matrix. w minimizes the interconnectedness across variables and offers a portfolio that is more resilient to network shocks. Fig. 6 presents the distribution of the minimum connectedness portfolio's hedging effectiveness against each stock in our sample, and Table H-1 presents the

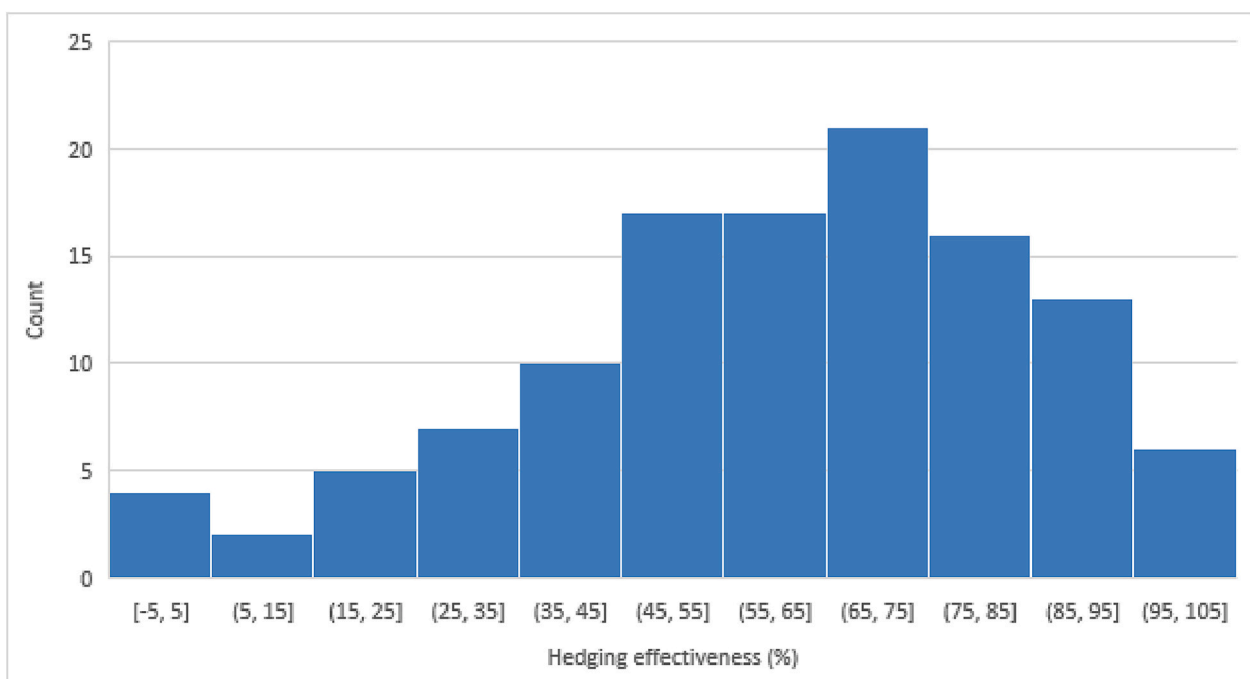


Fig. 6. Histogram of the hedging effectiveness from the minimum connectedness portfolio.

Note: Fig. 6 presents the distribution of the minimum connectedness portfolio's hedging effectiveness against each green stock in our sample. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

numeric values of the portfolio weights and the hedging effectiveness for each stock. We define hedging effectiveness as the amount of variance reduction from the portfolio compared to an unhedged position of the individual stocks. We find that the minimum connectedness portfolio provides hedging benefits for most clean energy stocks in the portfolio, where the highest hedging effectiveness is 105%. On average, the minimum connectedness portfolio offers hedging effectiveness of 59.83% suggesting that investors can reduce the variance of their portfolio by 59.83% by investing in the minimum connectedness portfolio as opposed to investing in the individual green stocks. Most of the hedging effectiveness in [Table H-1](#) is statistically significant at the 1% significance level.¹⁰

6. Conclusion

The development of environmentally friendly activities is key to alleviating the effect of climate change and keeping global temperature increases within 2 °C. This study examines the impact of recent climate policy events associated with the Paris Agreement and the U.S. Presidential Elections on the U.S. green stock market. Our paper contributes to the literature by analyzing the responses of green stocks to climate policy events with respect to a wide range of measures, including their returns, volatility, volume, and connectedness at the firm-level. We document the heterogeneous responses of green stocks to climate policies providing useful insights for environmentally conscious investors and policymakers.

Our empirical findings can be summarized as follows. First, in terms of cumulative average abnormal returns, green stocks respond positively to the initial announcement of the Paris Agreement on December 12, 2015, Congress confirmation of Biden's presidential election results on 14 December 2020 and the Biden Climate Change Bill on August 17, 2022. While we find insignificant cumulative average abnormal returns to the Trump election on November 8, 2016 and his subsequent announcement to withdraw from the Paris Agreement on June 1, 2017, the increased uncertainty from these negative shocks is effectively captured by the abnormal volatility metric. In addition, we find heterogeneous responses of green stock subgroups to the climate policy events. Generally, green firms in light industries with high litigation risk, small green firms, and green firms with high idiosyncratic volatility tend to exhibit stronger cumulative reactions when compared with other green firms.

In addition to identifying how individual green stocks react to the studied events, we also analyze how the spillover patterns among these stocks change around the events. Our results suggest that the Trump election and his subsequent announced withdrawal from the Paris Agreement have a significantly negative impact on the connectedness among environmentally friendly stocks, while the Biden Climate Change Bill has a significantly positive impact on the connectedness among the variables. Moreover, the connectedness among green firms in light industries respond most positively to the Biden Climate Change Bill, while green firms in heavy industries respond most negatively to the Trump election and his announced withdrawal from the Paris Agreement. This indicates that investors interpret tightening climate policy (i.e., the Biden Climate Change Bill) as positive news for green firms in light industries,

while they view loose climate policy (i.e., the Trump election and the withdrawal from the Paris Agreement) as negative news for green firms in heavy industries. Finally, the connectedness among large firms and firms with low idiosyncratic risks are larger than that among smaller firms and firms with high idiosyncratic risks. Thus, while small green firms and green firms with high idiosyncratic risk may respond more strongly to climate policy events, larger firms are still the main driver of spillovers within the environmentally friendly financial markets.

Our results have a strong implication for risk hedging and portfolio management. As an important extension, we perform a formal test to quantify the risk hedging benefits to investors by constructing a minimum connectedness portfolio. Specifically, we assign weights to each individual stock based on its connectedness with other stocks. By construction, our minimum connectedness portfolio is more resilient to network shocks (i.e., such as climate policy events and natural disasters). Our portfolio shows average hedging effectiveness of 59.83% (with the highest hedging effectiveness of 105%). Thus, when compared to investments in individual clean energy stocks, a minimum connectedness portfolio reduces the variance return by 59.83%, on average.

In summary, we find that the studied events significantly influence green stock markets. However, their influences vary across different stock characteristics. This provides evidence for the value-added of using firm-level data to analyze the clean energy stock market compared to an aggregate analysis using stock indexes. Our results have several implications for investors and policymakers. Specifically, environmentally friendly investors should incorporate climate risks into their portfolios as green stocks respond significantly to climate events. Moreover, investors can take advantage of the heterogeneous behavior of green stocks to design an effective portfolio management strategy. In fact, our minimum connectedness portfolio, which is constructed based on the connectedness among individual green stocks, provides substantial hedging benefits to almost all of the clean energy stocks studied. For policymakers, our results illustrate that climate policy changes can influence investor awareness about the transition and physical risks of climate change. Specifically, signals of more stringent climate policy, such as global commitments like the Paris Agreement or the election of pro-environmental government officials, can positively influence the green stock market, which could increase the financial flow toward environmentally friendly activities. Our paper offers several suggestions for future research. For example, future studies could focus on documenting the longer-term impact of climate policy stringency on clean energy stock markets and analyzing how the impact of climate policy stringency on clean energy firms varies across countries.

CRedit authorship contribution statement

Linh Pham: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Wei Hao:** Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft, Writing – review & editing, Project administration. **Ha Truong:** Formal analysis, Writing – original draft. **Hai Hong Trinh:** Writing – original draft.

¹⁰ In addition to the minimum connectedness portfolio analysis, we also calculate the hedging ratios and hedging effectiveness based on a bivariate DCC multivariate GARCH model of [Engle \(2002\)](#). Our results indicate that green stocks can be used to hedge among themselves, and the hedging effectiveness varies across the pairs of stocks considered. We thank an anonymous reviewer for this suggestion.

Appendix A. List of green stocks

Table A-1

List of green stocks and summary statistics.

Company name	Ticker	Average daily closing prices	SD of daily closing prices	Average daily volumes	SD of daily volumes
Advanced Energy Inds Inc	AEIS	3.93	0.51	12.60	0.48
Aerovironment Inc	AVAV	3.89	0.52	12.18	0.61
Ameresco Inc	AMRC	2.64	0.89	11.70	0.90
American States Water Co	AWR	4.03	0.36	12.03	0.46
American Water Works Co Inc	AWK	4.51	0.42	13.65	0.40
Amtech Systems Inc	ASYS	1.99	0.33	10.86	1.01
Apogee Enterprises Inc	APOG	3.69	0.25	12.17	0.58
Applied Materials Inc	AMAT	3.78	0.66	16.13	0.45
Armstrong World Industries	AWI	4.17	0.31	12.98	0.59
Artesian Resources	ARTNA	3.49	0.25	9.83	0.62
Astec Industries Inc	ASTE	3.85	0.24	11.69	0.53
Badger Meter Inc	BMI	4.10	0.30	11.51	0.63
Blink Charging Co	BLNK	0.74	1.77	11.80	2.49
Borgwarner Inc	BWA	3.77	0.21	14.42	0.46
California Water Service Gp	CWT	3.65	0.35	12.22	0.48
Casella Waste Sys Inc	CWST	3.03	1.02	12.15	0.58
Ceco Environmental Corp	CECE	2.12	0.33	11.51	0.67
Comfort Systems USA Inc	FIX	3.67	0.52	12.20	0.54
Copart Inc	CPRT	4.10	0.50	13.69	0.66
Corning Inc	GLW	3.31	0.26	15.61	0.50
Cummins Inc	CMI	5.07	0.25	14.06	0.43
Danaher Corp	DHR	4.83	0.47	14.77	0.45
Darling Ingredients Inc	DAR	3.16	0.62	14.00	0.48
Deere & Co	DE	4.99	0.52	14.59	0.46
Donaldson Co Inc	DCI	3.81	0.20	13.04	0.49
Emcor Group Inc	EME	4.24	0.34	12.59	0.45
Emerson Electric Co	EMR	4.20	0.20	14.97	0.41
Energy Recovery Inc	ERII	2.16	0.56	12.57	0.68
Energys	ENS	4.24	0.15	12.39	0.48
Essential Utilities Inc	WTRG	3.57	0.23	13.52	0.49
Fuelcell Energy Inc	FCEL	0.76	0.95	15.16	1.55
Gorman-Rupp Co	GRC	3.44	0.13	10.67	0.56
Hain Celestial Group Inc	HAIN	3.66	0.44	13.77	0.63
Hannon Armstrong Sust Infr	HASI	3.23	0.44	12.65	0.78
Hexcel Corp	HXL	3.97	0.22	13.29	0.53
Hudson Technologies Inc	HDSN	1.03	0.77	12.28	1.28
Icf International Inc	ICFI	4.06	0.38	11.33	0.51
Idex Corp	IEX	4.82	0.39	12.74	0.46
Interface Inc	TILE	2.78	0.31	12.79	0.56
Itron Inc	ITRI	4.02	0.31	12.45	0.54
Jones Lang Lasalle Inc	JLL	4.98	0.25	12.65	0.45
Kadant Inc	KAI	4.41	0.55	10.71	0.52
Kb Home	KBH	3.16	0.40	14.56	0.56
Lennox International Inc	LII	5.21	0.41	12.66	0.44
Lifeway Foods Inc	LWAY	1.91	0.68	9.68	1.02
Lindsay Corp	LNN	4.56	0.25	11.30	0.58
Lkq Corp	LKQ	3.50	0.24	14.43	0.48
Mastec Inc	MTZ	3.75	0.52	13.62	0.51
Mgp Ingredients Inc	MGPI	3.67	0.76	11.49	0.81
Middlesex Water Co	MSEX	3.81	0.51	10.82	0.62
Mueller Industries	MLI	3.53	0.25	12.16	0.48
Mueller Water Products Inc	MWA	2.39	0.17	13.71	0.48
Northwest Pipe Co	NWPX	3.10	0.37	10.64	0.62
Owens Corning	OC	4.07	0.31	13.95	0.49
Potlatchdeltic Corp	PCH	3.74	0.18	12.66	0.56
Simon Property Group Inc	SPG	5.00	0.31	14.39	0.57
Sjw Group	SJW	3.90	0.33	11.23	0.61
Spx Technologies Inc	SPXC	3.69	0.59	12.48	0.62
St Joe Co	JOE	3.10	0.39	12.38	0.65
Steelcase Inc	SCS	2.69	0.17	13.29	0.51
Sunpower Corp	SPWR	2.68	0.63	14.76	0.60
Tesla Inc	TSLA	5.88	0.56	16.02	0.86

(continued on next page)

Table A-1 (continued)

Company name	Ticker	Average daily closing prices	SD of daily closing prices	Average daily volumes	SD of daily volumes
Tetra Tech Inc	TTEK	4.03	0.62	12.59	0.46
Toro Co	TTC	4.29	0.20	12.81	0.55
Trex Co Inc	TREX	4.23	0.38	12.93	0.73
Trinity Industries Inc	TRN	3.32	0.32	14.08	0.63
Ultralife Corp	ULBI	1.78	0.33	10.01	1.11
United Natural Foods Inc	UNFI	3.50	0.64	13.43	0.70
Valmont Industries Inc	VMI	5.01	0.26	11.80	0.57
Veeco Instruments Inc	VECO	2.98	0.41	12.80	0.57
Wabtec Corp	WAB	4.38	0.15	13.67	0.58
Waters Corp	WAT	5.22	0.37	13.02	0.43
Watts Water Technologies Inc	WTS	4.39	0.36	11.84	0.48
Woodward Inc	WWD	4.31	0.34	12.62	0.53
Workhorse Group Inc	WKHS	0.74	1.51	12.86	2.69
Xylem Inc	XYL	4.13	0.40	13.80	0.43
York Water Co	YORW	3.50	0.29	10.18	0.57
Zurn Elkay Water Solution Corp	ZWS	3.33	0.26	13.38	0.56
Acuity Brands Inc	AYI	5.05	0.28	12.92	0.56
Ansys Inc	ANSS	5.07	0.55	12.96	0.43
Autodesk Inc	ADSK	4.77	0.61	14.38	0.49
Azz Inc	AZZ	3.85	0.17	11.71	0.50
Calamp Corp	CAMP	2.63	0.44	12.69	0.67
Cisco Systems Inc	CSCO	3.63	0.29	16.91	0.39
Codexis Inc	CDXS	2.08	0.84	12.24	1.07
Digi International Inc	DGII	2.55	0.33	11.54	0.66
Emcore Corp	EMKR	1.63	0.37	12.03	0.99
Enphase Energy Inc	ENPH	2.56	1.75	14.12	1.05
First Solar Inc	FSLR	4.06	0.31	14.45	0.58
Franklin Electric Co Inc	FELE	3.86	0.33	11.93	0.50
Gaia Inc	GAIA	2.15	0.34	10.81	0.89
Jabil Inc	JBL	3.39	0.38	14.19	0.58
Liquidity Services Inc	LQDT	2.23	0.50	12.01	0.83
Natural Grocers Vitamin Ctge	NGVC	2.66	0.44	11.50	0.62
Netapp Inc	NTAP	3.90	0.37	14.74	0.50
Ocean Power Technologies Inc	OPIT	0.30	0.73	12.66	1.66
On Semiconductor Corp	ON	2.92	0.60	15.58	0.47
Orion Energy Systems Inc	OESX	0.90	0.71	11.55	1.09
Plug Power Inc	PLUG	1.48	1.09	15.71	1.16
Power Integrations Inc	POWI	4.23	0.26	12.22	0.59
Preformed Line Products Co	PLPC	4.01	0.23	8.78	0.87
Roper Technologies Inc	ROP	5.57	0.41	12.99	0.41
Smith (A.O.)	AOS	4.06	0.20	13.71	0.59
Sprouts Farmers Market	SFM	3.20	0.19	14.36	0.55
Universal Display Corp	OLED	4.55	0.67	13.21	0.60
Aes Corp (The)	AES	2.71	0.30	15.49	0.39
Amyris Inc	AMRS	1.10	0.89	13.70	1.44
Clearway Energy Inc	CWEN	3.12	0.41	12.38	0.60
Commercial Metals	CMC	3.02	0.29	14.01	0.48
Ecolab Inc	ECL	5.00	0.26	13.88	0.44
Futurefuel Corp	FF	2.51	0.24	11.73	0.64
Gevo Inc	GEVO	0.34	1.03	13.97	1.82
Lsb Industries Inc	LXU	2.21	0.90	12.37	0.85
Nextera Energy Inc	NEE	4.84	0.39	14.78	0.68
Nucor Corp	NUE	4.09	0.33	14.67	0.40
Schnitzer Steel Inds	SCHN	3.23	0.36	12.57	0.48
Steel Dynamics Inc	STLD	3.49	0.44	14.70	0.44
Clean Energy Fuels Corp	CLNE	1.39	0.60	14.28	0.82
All companies		3.45	1.27		

Table A.2
Firm classification definitions.

Classification criterion	Definition
Carbon intensity	Heavy industries are those who are in one of the following sectors: (1) Oil, Gas & Consumable Fuels; (2) Electric Utilities; (3) Gas Utilities; (4) Independent Power Producers & Energy Traders; (5) multi-Utilities; (6) Chemicals; (7) Construction Materials; (8) Metals & Mining; and (9) Paper & Forest Products. Light industries include all other industries (Nguyen and Phan, 2020).
Litigation risk	Industries with high litigation risks are those with one of the following SICs: 2833–2838, 3570–3577, 3600–3674, 5200–5961, 7370–7374, and 8731–8734. Others are classified as low litigation risk industries (Chen et al., 2015).
Size	Large firms are those whose average market capitalization is above the sample median. Small firms are those whose average market capitalization is below the sample median.
Idiosyncratic volatility (IVOL)	High volatility firms are those whose IVOL is above the sample median. Low volatility firms are those whose IVOL is below the sample median. We calculate IVOL using the Fama and French (1993) five-factor model following Fu (2009).

Appendix B. Cumulative abnormal returns, volatility, and volume test statistics

Table B-1
Cumulative average abnormal return.

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
-20	0.85 [0.00]***	0.29 [0.39]	-0.05 [0.90]	-0.18 [0.39]	0.57 [0.00]***	0.94 [0.00]***
-19	1.08 [0.00]***	0.04 [1.00]	0.42 [0.02]**	0.17 [0.51]	2.34 [0.00]***	1.17 [0.00]***
-18	0.50 [0.06]*	-0.47 [0.65]	-0.02 [0.46]	0.75 [0.22]	2.80 [0.00]***	0.71 [0.00]***
-17	0.35 [0.05]*	-0.38 [0.44]	-0.51 [0.97]	0.43 [0.57]	3.03 [0.00]***	1.03 [0.00]***
-16	0.31 [0.03]**	-0.33 [0.44]	0.23 [0.13]	0.41 [0.71]	3.51 [0.00]***	1.85 [0.00]***
-15	0.46 [0.01]***	-0.12 [0.82]	0.13 [0.61]	0.27 [0.71]	4.58 [0.00]***	1.57 [0.00]***
-14	0.97 [0.00]***	-0.35 [0.29]	0.40 [0.39]	0.30 [0.64]	6.89 [0.00]***	3.27 [0.00]***
-13	1.79 [0.00]***	-0.64 [0.19]	0.53 [0.51]	-0.21 [0.78]	7.44 [0.00]***	3.26 [0.00]***
-12	2.20 [0.00]***	-0.08 [0.72]	0.45 [0.69]	-0.21 [0.93]	6.68 [0.00]***	3.72 [0.00]***
-11	2.51 [0.00]***	0.39 [0.61]	0.32 [0.71]	-0.33 [0.83]	6.84 [0.00]***	3.99 [0.00]***
-10	3.24 [0.00]***	0.63 [0.37]	-0.50 [0.27]	0.45 [0.14]	5.86 [0.00]***	3.16 [0.00]***
-9	2.79 [0.00]***	0.95 [0.20]	-0.83 [0.19]	0.17 [0.60]	5.33 [0.01]***	3.52 [0.00]***
-8	3.02 [0.00]***	0.95 [0.17]	-1.26 [0.08]*	0.34 [0.44]	4.66 [0.04]**	3.89 [0.00]***
-7	3.28 [0.00]***	1.23 [0.06]*	-1.11 [0.26]	0.23 [0.47]	4.37 [0.13]	4.63 [0.00]***
-6	4.31 [0.00]***	1.05 [0.14]	-0.87 [0.79]	0.35 [0.35]	5.41 [0.02]**	3.68 [0.00]***
-5	4.06 [0.00]***	1.13 [0.18]	-1.26 [0.26]	-0.07 [0.62]	5.28 [0.03]**	4.27 [0.00]***
-4	2.88 [0.03]**	1.13 [0.23]	-1.16 [0.43]	-0.60 [0.97]	6.30 [0.01]***	4.67 [0.00]***
-3	3.52 [0.02]**	0.65 [0.58]	-1.64 [0.32]	-0.66 [0.88]	6.46 [0.00]***	5.49 [0.00]***
-2	3.40 [0.04]**	0.60 [0.58]	-0.97 [0.94]	-0.46 [0.80]	6.51 [0.00]***	5.83 [0.00]***
-1	5.64 [0.03]**	0.80 [0.35]	-1.65 [0.28]	-0.33 [0.65]	6.38 [0.00]***	5.52 [0.00]***
0	4.78 [0.10]*	0.51 [0.66]	-1.27 [0.47]	-0.33 [0.57]	6.34 [0.00]***	4.94 [0.00]***
1	4.70 [0.08]*	0.80 [0.54]	-0.93 [0.98]	0.28 [0.25]	7.65 [0.00]***	5.72 [0.00]***
2	5.63 [0.02]**	0.44 [0.67]	-0.15 [0.42]	-0.06 [0.45]	7.04 [0.00]***	4.88 [0.00]***
3	6.06 [0.01]**	0.16 [0.92]	1.67 [0.01]**	2.43 [0.14]	7.35 [0.00]***	4.63 [0.00]***
4	7.13 [0.00]***	-0.64 [0.45]	2.62 [0.00]***	2.42 [0.15]	7.32 [0.00]***	4.81 [0.00]***
5	7.54 [0.00]***	-0.79 [0.39]	2.41 [0.00]***	3.64 [0.01]**	7.32 [0.01]**	5.42 [0.00]***
6	7.44 [0.01]***	-1.07 [0.30]	2.68 [0.00]***	4.24 [0.00]***	8.85 [0.01]***	5.05 [0.00]***
7	7.75 [0.00]***	-1.11 [0.25]	2.10 [0.01]***	4.51 [0.00]***	9.53 [0.00]***	4.98 [0.00]***
8	8.08 [0.00]***	-1.19 [0.23]	2.23 [0.01]***	4.44 [0.00]***	9.64 [0.00]***	4.81 [0.00]***
9	7.33 [0.00]***	-1.14 [0.29]	1.66 [0.03]**	4.08 [0.00]***	9.24 [0.00]***	4.54 [0.00]***
10	7.12 [0.00]***	-1.31 [0.22]	2.30 [0.01]***	4.06 [0.00]***	7.94 [0.03]**	4.72 [0.01]***
11	7.17 [0.00]***	-1.16 [0.27]	2.52 [0.01]***	3.94 [0.01]***	8.93 [0.01]***	3.42 [0.04]**
12	7.16 [0.01]***	-0.72 [0.48]	2.54 [0.00]***	3.36 [0.04]**	8.65 [0.01]***	3.44 [0.04]**
13	7.39 [0.02]**	-1.16 [0.37]	2.53 [0.01]***	3.67 [0.03]**	8.67 [0.02]**	3.67 [0.03]**
14	7.23 [0.02]**	-0.63 [0.60]	1.69 [0.03]**	3.18 [0.11]	9.76 [0.00]***	4.26 [0.01]***
15	6.98 [0.04]**	-0.79 [0.50]	1.46 [0.06]*	3.83 [0.08]*	13.28 [0.00]***	4.15 [0.02]**
16	6.02 [0.12]	-0.50 [0.56]	1.33 [0.08]*	4.41 [0.03]**	13.70 [0.00]***	4.10 [0.02]**
17	5.77 [0.22]	-0.28 [0.66]	1.63 [0.06]**	4.85 [0.01]***	12.68 [0.00]***	3.86 [0.03]**
18	5.32 [0.24]	-0.43 [0.59]	2.22 [0.03]**	5.30 [0.00]***	13.14 [0.00]***	4.60 [0.01]**
19	4.47 [0.42]	-0.74 [0.48]	2.43 [0.02]**	5.19 [0.01]***	14.95 [0.00]***	3.97 [0.06]*
20	4.07 [0.55]	-1.03 [0.38]	2.16 [0.03]**	6.17 [0.00]***	14.26 [0.00]***	3.72 [0.10]

Table B-2
Average abnormal volatility.

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
-20	1.77 [0.07]*	0.54 [0.00]***	0.78 [0.28]	1.79 [0.40]	0.85 [0.38]	0.78 [0.19]
-19	1.16 [0.48]	0.58 [0.00]***	0.91 [0.61]	2.28 [0.09]*	1.16 [0.30]	0.91 [0.60]
-18	1.02 [0.93]	1.26 [0.65]	1.01 [0.96]	3.03 [0.00]***	0.96 [0.71]	0.81 [0.13]
-17	1.00 [0.98]	1.12 [0.79]	0.86 [0.40]	2.66 [0.00]***	0.96 [0.73]	0.72 [0.00]***
-16	0.98 [0.90]	1.11 [0.76]	0.82 [0.18]	2.30 [0.00]***	0.86 [0.16]	0.78 [0.01]***
-15	0.91 [0.42]	1.06 [0.84]	0.82 [0.14]	2.08 [0.00]***	0.85 [0.10]	0.84 [0.17]
-14	0.86 [0.18]	1.38 [0.41]	0.81 [0.07]*	1.86 [0.01]***	1.00 [0.99]	1.02 [0.84]
-13	0.94 [0.58]	1.28 [0.50]	0.83 [0.07]*	1.74 [0.01]***	1.01 [0.92]	0.98 [0.89]
-12	0.91 [0.41]	1.30 [0.42]	0.79 [0.02]**	1.65 [0.01]***	1.02 [0.85]	0.96 [0.70]
-11	0.87 [0.17]	1.36 [0.30]	0.79 [0.01]***	1.56 [0.01]***	0.96 [0.73]	1.10 [0.42]
-10	0.85 [0.10]*	1.27 [0.40]	1.07 [0.71]	1.55 [0.01]***	0.98 [0.83]	1.13 [0.32]
-9	0.90 [0.27]	1.21 [0.48]	1.05 [0.76]	1.60 [0.01]***	0.97 [0.75]	1.23 [0.10]
-8	0.89 [0.20]	1.15 [0.59]	1.12 [0.48]	1.67 [0.00]***	0.97 [0.79]	1.32 [0.02]**
-7	0.87 [0.12]	1.09 [0.72]	1.12 [0.46]	1.59 [0.00]***	0.96 [0.71]	1.29 [0.03]**
-6	2.19 [0.37]	1.09 [0.70]	1.18 [0.24]	1.53 [0.01]***	0.95 [0.64]	1.30 [0.02]**
-5	2.10 [0.37]	1.05 [0.84]	1.20 [0.17]	1.48 [0.01]**	0.93 [0.42]	1.30 [0.02]**
-4	2.08 [0.36]	1.03 [0.89]	1.24 [0.09]*	1.44 [0.02]**	0.93 [0.49]	1.27 [0.02]**
-3	2.04 [0.35]	1.07 [0.73]	1.51 [0.00]***	1.39 [0.02]**	0.94 [0.51]	1.24 [0.04]**
-2	1.98 [0.35]	1.06 [0.75]	1.54 [0.00]***	1.36 [0.03]**	0.92 [0.35]	1.22 [0.05]**
-1	2.30 [0.22]	1.03 [0.86]	1.54 [0.00]***	1.44 [0.02]**	0.91 [0.26]	1.19 [0.08]*
0	2.24 [0.22]	1.04 [0.81]	1.52 [0.00]***	1.43 [0.02]**	0.90 [0.23]	1.15 [0.13]
1	2.19 [0.22]	1.05 [0.76]	1.74 [0.00]***	1.40 [0.02]**	0.91 [0.22]	1.14 [0.16]
2	2.18 [0.20]	1.03 [0.87]	1.83 [0.00]***	1.37 [0.02]**	0.90 [0.18]	1.12 [0.23]
3	2.12 [0.20]	1.07 [0.66]	1.89 [0.00]***	2.18 [0.18]	0.89 [0.11]	1.09 [0.32]
4	2.11 [0.19]	1.06 [0.71]	1.95 [0.00]***	2.12 [0.19]	0.90 [0.13]	1.07 [0.46]
5	2.09 [0.18]	1.04 [0.77]	1.91 [0.00]***	2.10 [0.18]	0.89 [0.10]*	1.04 [0.62]
6	2.28 [0.11]	1.04 [0.80]	1.89 [0.00]***	2.10 [0.16]	0.91 [0.19]	1.53 [0.30]
7	2.24 [0.12]	1.03 [0.86]	1.89 [0.00]***	2.06 [0.16]	0.90 [0.16]	1.49 [0.31]
8	2.18 [0.12]	1.59 [0.29]	1.86 [0.00]***	2.02 [0.16]	0.88 [0.08]*	1.45 [0.34]
9	2.12 [0.13]	3.11 [0.20]	1.82 [0.00]***	1.97 [0.17]	0.87 [0.07]*	1.42 [0.36]
10	2.07 [0.13]	3.05 [0.20]	1.83 [0.00]***	1.95 [0.17]	0.87 [0.07]*	1.38 [0.38]
11	2.02 [0.14]	2.98 [0.20]	1.83 [0.00]***	1.92 [0.16]	0.86 [0.05]**	1.36 [0.39]
12	1.98 [0.14]	2.94 [0.19]	1.80 [0.00]***	1.89 [0.16]	0.85 [0.03]**	1.33 [0.42]
13	1.97 [0.14]	2.89 [0.19]	1.78 [0.00]***	1.86 [0.17]	0.85 [0.02]**	1.32 [0.42]
14	1.93 [0.14]	2.84 [0.19]	1.76 [0.00]***	1.83 [0.17]	0.85 [0.02]**	1.30 [0.43]
15	1.90 [0.14]	2.77 [0.19]	1.77 [0.00]***	1.83 [0.16]	0.94 [0.36]	1.29 [0.45]
16	1.89 [0.13]	2.71 [0.20]	1.82 [0.00]***	1.80 [0.16]	0.96 [0.49]	1.27 [0.47]
17	1.88 [0.13]	2.66 [0.20]	1.80 [0.00]***	1.78 [0.16]	0.96 [0.50]	1.25 [0.49]
18	1.84 [0.14]	2.62 [0.20]	1.78 [0.00]***	1.78 [0.15]	0.95 [0.40]	1.23 [0.50]
19	1.82 [0.14]	2.57 [0.20]	1.77 [0.00]***	1.75 [0.16]	0.95 [0.46]	1.24 [0.49]
20	1.81 [0.14]	2.53 [0.20]	1.77 [0.00]***	1.74 [0.15]	0.95 [0.46]	1.22 [0.50]

Table B-3
Cumulative average abnormal volume.

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
-20	0.19 [0.67]	0.24 [0.96]	0.24 [0.84]	0.05 [0.01]***	0.57 [0.00]***	0.09 [0.38]
-19	0.38 [0.93]	0.64 [0.21]	0.37 [0.59]	0.28 [0.04]**	2.34 [0.00]***	0.00 [0.00]***
-18	0.51 [0.76]	1.05 [0.22]	0.50 [0.19]	0.94 [0.79]	2.80 [0.00]***	0.02 [0.00]***
-17	0.69 [0.99]	1.31 [0.24]	0.57 [0.10]	1.31 [0.90]	3.03 [0.00]***	0.12 [0.01]**
-16	0.79 [0.53]	1.63 [0.18]	0.76 [0.15]	1.56 [0.78]	3.51 [0.00]***	0.14 [0.01]***
-15	0.94 [0.42]	1.92 [0.08]*	0.98 [0.13]	1.69 [0.92]	4.58 [0.00]***	0.21 [0.02]**
-14	1.18 [0.30]	2.51 [0.08]*	1.13 [0.12]	1.80 [0.65]	6.89 [0.00]***	0.39 [0.08]*
-13	1.41 [0.28]	2.93 [0.07]*	1.14 [0.06]*	1.93 [0.55]	7.44 [0.00]***	0.45 [0.09]*
-12	1.71 [0.45]	3.18 [0.10]*	1.34 [0.03]**	2.12 [0.58]	6.68 [0.00]***	0.63 [0.16]
-11	1.90 [0.25]	3.50 [0.06]**	1.36 [0.02]**	2.27 [0.55]	6.84 [0.00]***	0.87 [0.33]
-10	2.10 [0.36]	3.81 [0.04]**	1.48 [0.01]***	2.34 [0.36]	5.86 [0.00]***	1.08 [0.26]
-9	2.37 [0.45]	4.32 [0.03]**	1.56 [0.00]***	2.46 [0.39]	5.33 [0.01]***	1.29 [0.36]
-8	2.53 [0.42]	4.61 [0.03]**	1.61 [0.00]***	2.66 [0.48]	4.66 [0.04]**	1.58 [0.68]
-7	2.56 [0.33]	5.01 [0.04]**	1.53 [0.00]***	2.83 [0.53]	4.37 [0.13]	1.84 [0.93]
-6	2.59 [0.22]	5.16 [0.06]*	1.75 [0.00]***	3.01 [0.62]	5.41 [0.02]**	2.09 [0.78]
-5	2.75 [0.25]	5.40 [0.06]*	1.86 [0.00]***	3.14 [0.53]	5.28 [0.03]**	2.34 [0.63]
-4	3.04 [0.31]	5.63 [0.06]**	2.02 [0.00]***	3.14 [0.38]	6.30 [0.01]***	2.59 [0.56]
-3	3.28 [0.31]	6.04 [0.05]**	2.40 [0.00]***	3.23 [0.32]	6.46 [0.00]***	2.95 [0.42]
-2	3.47 [0.33]	6.24 [0.05]**	2.73 [0.01]**	3.33 [0.32]	6.51 [0.00]***	3.37 [0.30]
-1	3.63 [0.34]	6.49 [0.04]**	3.02 [0.03]**	3.50 [0.29]	6.38 [0.00]***	3.53 [0.42]
0	3.79 [0.37]	6.70 [0.04]**	3.09 [0.02]**	3.68 [0.32]	6.34 [0.00]***	3.85 [0.44]
1	4.00 [0.42]	7.04 [0.03]**	3.21 [0.02]**	3.83 [0.35]	7.65 [0.00]***	4.07 [0.43]
2	4.27 [0.48]	7.17 [0.04]**	3.47 [0.01]**	3.92 [0.31]	7.04 [0.00]***	4.29 [0.41]
3	4.49 [0.55]	7.35 [0.05]**	3.77 [0.02]**	3.96 [0.22]	7.35 [0.00]***	4.57 [0.38]
4	4.99 [0.96]	7.48 [0.06]*	4.02 [0.02]**	4.00 [0.16]	7.32 [0.00]***	4.83 [0.36]
5	5.32 [0.87]	7.61 [0.07]*	4.25 [0.02]**	4.15 [0.16]	7.32 [0.01]**	4.93 [0.43]
6	5.85 [0.71]	7.70 [0.12]	4.53 [0.03]**	4.07 [0.08]*	8.85 [0.01]***	5.15 [0.38]
7	6.10 [0.68]	7.77 [0.18]	4.77 [0.04]**	4.08 [0.04]**	9.53 [0.00]***	5.23 [0.42]
8	7.03 [0.78]	8.18 [0.13]	5.01 [0.06]*	4.16 [0.03]**	9.64 [0.00]***	5.36 [0.44]
9	7.54 [0.69]	8.41 [0.14]	5.23 [0.06]*	4.32 [0.03]**	9.24 [0.00]***	5.48 [0.45]
10	7.96 [0.60]	8.66 [0.13]	5.56 [0.10]	4.33 [0.02]**	7.94 [0.03]**	5.64 [0.46]
11	8.52 [0.49]	8.88 [0.14]	5.79 [0.13]	4.90 [0.04]**	8.93 [0.01]***	5.82 [0.41]
12	8.94 [0.39]	9.16 [0.11]	6.00 [0.15]	5.14 [0.05]**	8.65 [0.01]***	5.90 [0.42]
13	9.21 [0.33]	9.48 [0.10]	6.19 [0.19]	5.20 [0.04]**	8.67 [0.02]**	6.10 [0.39]
14	9.50 [0.33]	9.68 [0.10]	6.39 [0.25]	5.25 [0.03]**	9.76 [0.00]***	6.25 [0.37]
15	9.75 [0.32]	9.85 [0.11]	6.52 [0.20]	5.46 [0.03]**	13.28 [0.00]***	6.40 [0.38]
16	9.97 [0.29]	10.21 [0.13]	6.73 [0.21]	6.13 [0.07]*	13.70 [0.00]***	6.57 [0.37]
17	10.31 [0.25]	10.26 [0.19]	6.88 [0.21]	6.37 [0.08]*	12.68 [0.00]***	6.77 [0.31]
18	10.55 [0.25]	10.61 [0.21]	7.17 [0.24]	6.58 [0.09]*	13.14 [0.00]***	6.91 [0.30]
19	10.77 [0.23]	10.93 [0.16]	7.44 [0.30]	6.85 [0.12]	14.95 [0.00]***	7.14 [0.26]
20	10.92 [0.25]	11.12 [0.16]	7.70 [0.30]	7.02 [0.11]	14.26 [0.00]***	7.27 [0.25]

Note: Table B provides cumulative average abnormal returns, volatility, and volume of 118 green stocks to the six studied events on each day over the event window. In Tables B-1 and B-3, statistical significance is reported based on the standardized cross-sectional test. In Table B-2, statistical significance is reported based on one-tailed t-statistics. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels.

Appendix C. Cumulative abnormal returns, volatility, and volume among the subsample of green stocks

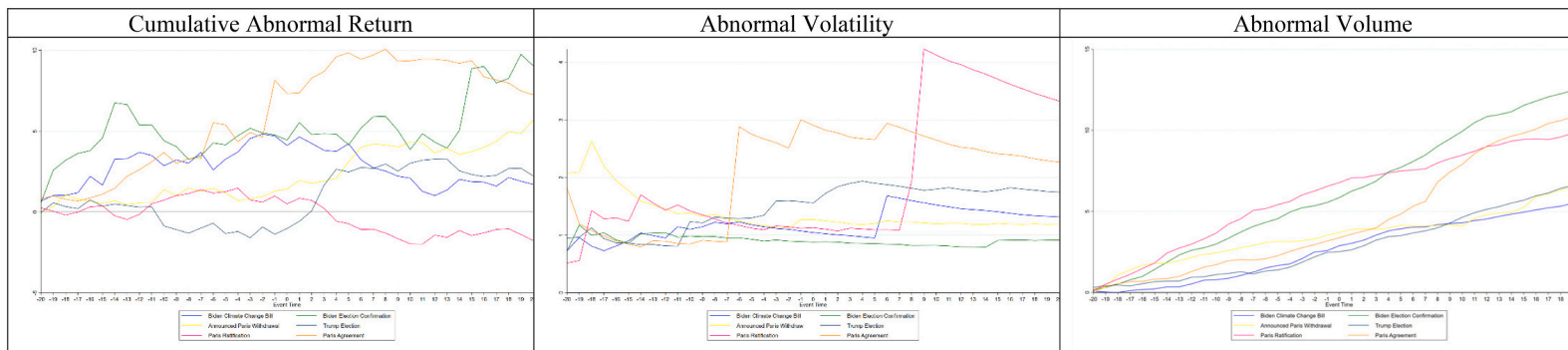
Company name	Ticker	Return NET connectedness	Volatility NET connectedness	Volume NET connectedness
Advanced Energy Inds Inc	AEIS			
Aerovironment Inc	AVAV			
Ameresco Inc	AMRC			
American States Water Co	AWR			
American Water Works Co Inc	AWK			
Amtech Systems Inc	ASYS			
Apogee Enterprises Inc	APOG			
Applied Materials Inc	AMAT			
Armstrong World Industries	AWI			
Artesian Resources	ARTNA			
Astec Industries Inc	ASTE			
Badger Meter Inc	BMI			
Blink Charging Co	BLNK			
Borgwarner Inc	BWA			
California Water Service Gp	CWT			
Casella Waste Sys Inc	CWST			
Ceco Environmental Corp	CECE			
Comfort Systems Usa Inc	FIX			
Copart Inc	CPRT			
Coming Inc	GLW			
Cummins Inc	CMI			
Danaher Corp	DHR			
Darling Ingredients Inc	DAR			
Deere & Co	DE			
Donaldson Co Inc	DCI			
Emcor Group Inc	EME			
Emerson Electric Co	EMR			
Energy Recovery Inc	ERII			
Enersys	ENS			
Essential Utilities Inc	WTRG			
Fuelcell Energy Inc	FCEL			
Gorman-Rupp Co	GRC			
Hain Celestial Group Inc	HAIN			
Hannon Armstrong Sust Infr	HASI			
Hexcel Corp	HXL			
Hudson Technologies Inc	HDSN			
Icf International Inc	ICFI			
Ilex Corp	IEX			
Interface Inc	TILE			
Itron Inc	ITRI			
Jones Lang Lasalle Inc	JLL			
Kadant Inc	KAI			
Kb Home	KBH			
Lennox International Inc	LII			
Lifeway Foods Inc	LWAY			
Lindsay Corp	LNN			
Lkq Corp	LKQ			
Mastec Inc	MTZ			
Mgp Ingredients Inc	MGPI			
Middlesex Water Co	MSEX			
Mueller Industries	MLI			
Mueller Water Products Inc	MWA			
Northwest Pipe Co	NWPX			
Owens Corning	OC			
Potlatchdeltic Corp	PCH			
Simon Property Group Inc	SPG			
Sjw Group	SJW			
Spx Technologies Inc	SPXC			
St Joe Co	JOE			

Fig. C-1. Cumulative abnormal returns, volatility, and volume of clean energy stocks around the announcement of the events – Subsector analysis.

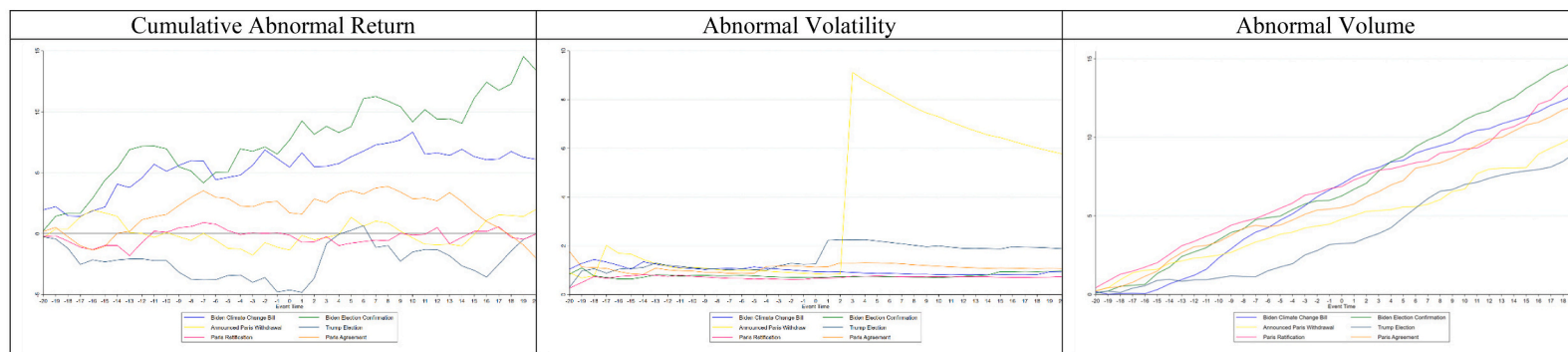
Company name	Ticker	Return NET connectedness	Volatility NET connectedness	Volume NET connectedness
Steelcase Inc	SCS			
Sunpower Corp	SPWR			
Tesla Inc	TSLA			
Tetra Tech Inc	TTEK			
Toro Co	TTC			
Trex Co Inc	TREX			
Trinity Industries Inc	TRN			
Ultralife Corp	ULBI			
United Natural Foods Inc	UNFI			
Valmont Industries Inc	VMI			
Veeco Instruments Inc	VECO			
Wabtec Corp	WAB			
Waters Corp	WAT			
Watts Water Technologies Inc	WTS			
Woodward Inc	WWD			
Workhorse Group Inc	WKHS			
Xylem Inc	XYL			
York Water Co	YORW			
Zum Elkay Water Soluti Corp	ZWS			
Acuity Brands Inc	AYI			
Ansys Inc	ANSS			
Autodesk Inc	ADSK			
Azz Inc	AZZ			
Calamp Corp	CAMP			
Cisco Systems Inc	CSCO			
Codexis Inc	CDXS			
Digi International Inc	DGHI			
Emcore Corp	EMKR			
Enphase Energy Inc	ENPH			
First Solar Inc	FSLR			
Franklin Electric Co Inc	FELE			
Gaia Inc	GAIA			
Jabil Inc	JBL			
Liquidity Services Inc	LQDT			
Natural Grocers Vitamin Ctge	NGVC			
Netapp Inc	NTAP			
Ocean Power Technologies Inc	OPTT			
On Semiconductor Corp	ON			
Orion Energy Systems Inc	OESX			
Plug Power Inc	PLUG			
Power Integrations Inc	POWI			
Preformed Line Products Co	PLPC			
Roper Technologies Inc	ROP			
Smith (A. O.)	AOS			
Sprouts Farmers Market	SFM			
Universal Display Corp	OLED			
Aes Corp (The)	AES			
Amyris Inc	AMRS			
Clearway Energy Inc	CWEN			
Commercial Metals	CMC			
Ecolab Inc	ECL			
Futurefuel Corp	FF			
Gevo Inc	GEVO			
Lsb Industries Inc	LXU			
Nextera Energy Inc	NEE			
Nucor Corp	NUE			
Schnitzer Steel Inds	SCHN			
Steel Dynamics Inc	STLD			
Clean Energy Fuels Corp	CLNE			

Fig. C-1. (continued).

Part I: Group 1 – Light industries with low litigation risks



Part II: Group 2: Heavy industries with low litigation risks



Part III: Group 3: Light industries with high litigation risks

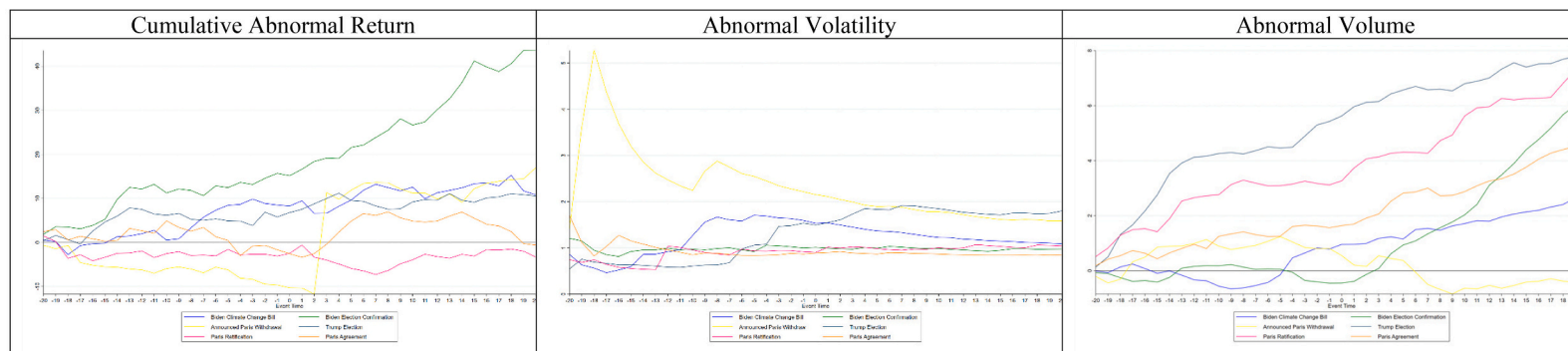
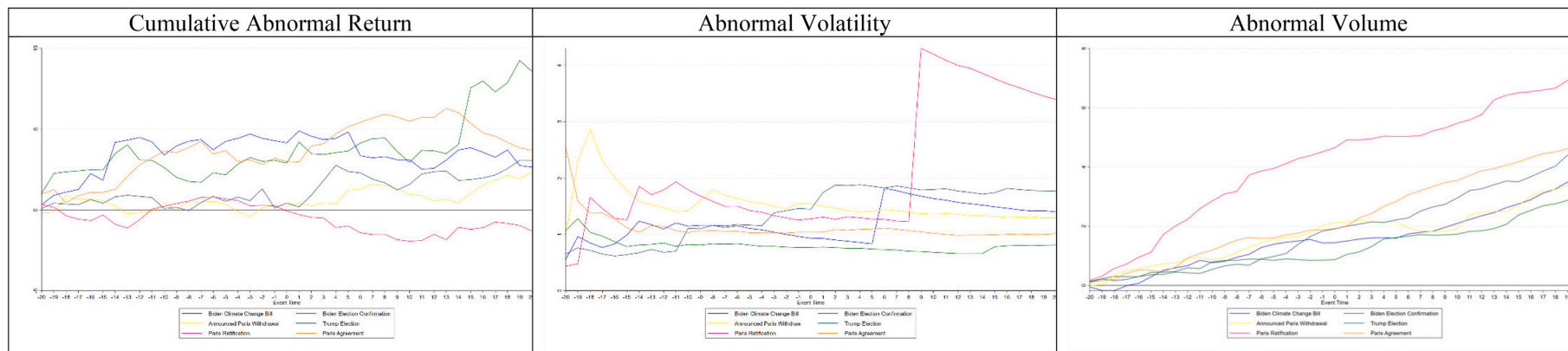


Fig. C-2. Cumulative abnormal returns, volatility, and volume of clean energy stocks around the announcement of the events – Large v. Small firms.

Part I: Large firms



Part II: Small firms

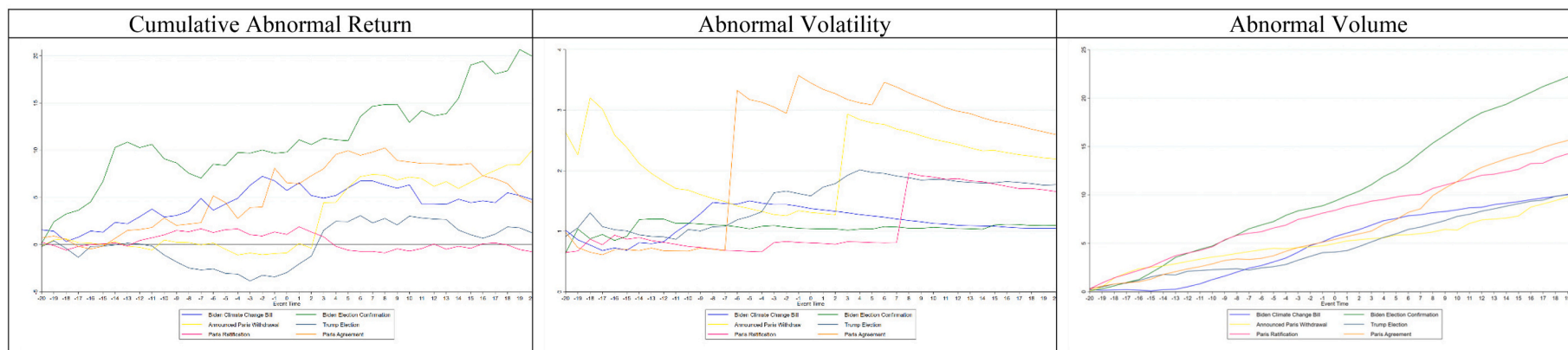


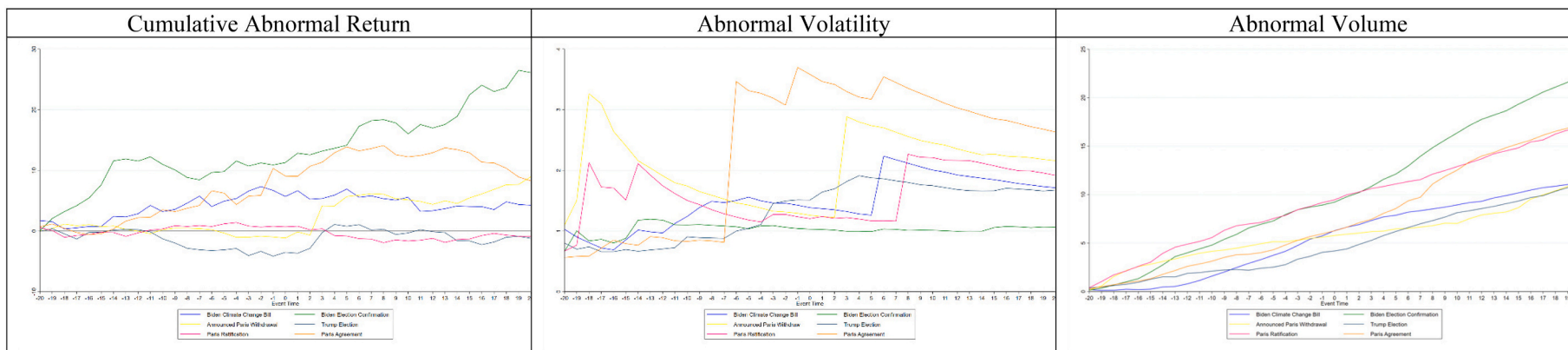
Fig. C-3. Cumulative abnormal returns, volatility, and volume of clean energy stocks around the announcement of the events – High v. low volatility firms.

Appendix D. Connectedness net shock transmitter and receivers

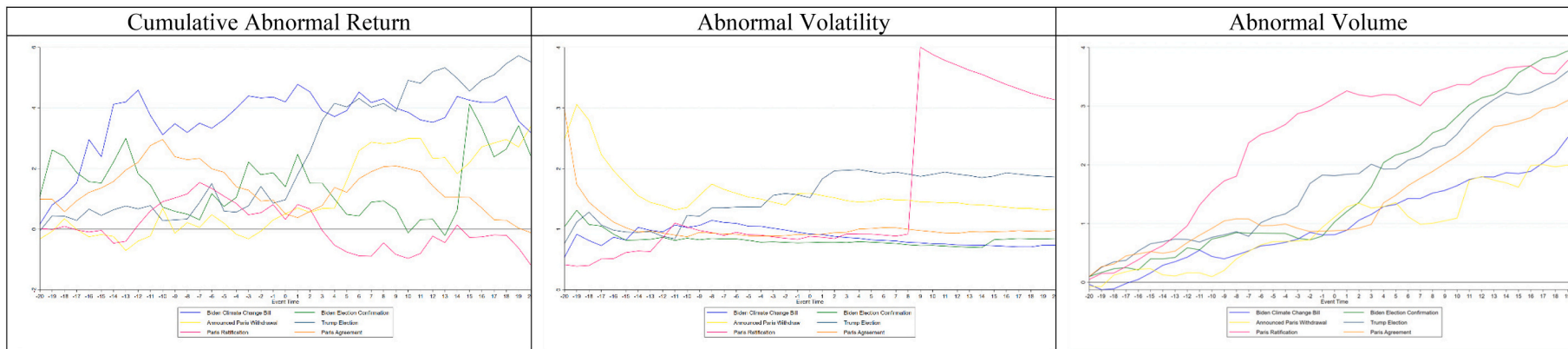
Table D-1

NET connectedness indexes of clean energy stocks.

Part I: High volatility firms



Part II: Low volatility firms



Note: The table reports the NET connectedness indexes in returns, volatility, and volume for all clean energy stocks. Blue bars indicate positive values, while red bars indicate negative values. The length of the bars indicates the magnitude of the NET connectedness indexes.

Appendix E. Cumulative abnormal connectedness test statistics

Table E-1

Cumulative abnormal return connectedness.

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
-20	-0.01 [0.00]***	-0.01 [0.00]***	0.00 [0.00]***	-0.04 [0.00]***	0.00 [0.00]***	0.02 [0.10]
-19	-0.01 [0.00]***	-0.01 [0.00]***	-0.01 [0.00]***	-0.09 [0.00]***	0.00 [0.00]***	0.02 [0.10]
-18	-0.02 [0.00]***	-0.02 [0.00]***	-0.01 [0.00]***	-0.13 [0.00]***	-0.01 [0.00]***	0.02 [0.10]
-17	-0.03 [0.00]***	-0.03 [0.00]***	-0.02 [0.00]***	-0.18 [0.00]***	-0.01 [0.00]***	0.02 [0.07]*
-16	-0.04 [0.00]***	-0.04 [0.00]***	-0.02 [0.00]***	-0.23 [0.00]***	-0.01 [0.00]***	0.02 [0.07]*
-15	-0.05 [0.00]***	-0.05 [0.00]***	-0.03 [0.00]***	-0.28 [0.00]***	-0.01 [0.00]***	0.02 [0.08]*
-14	-0.06 [0.00]***	-0.06 [0.00]***	-0.03 [0.00]***	-0.33 [0.00]***	-0.02 [0.00]***	0.02 [0.07]*
-13	-0.07 [0.00]***	-0.07 [0.00]***	-0.04 [0.00]***	-0.37 [0.00]***	-0.02 [0.00]***	0.02 [0.06]*
-12	-0.07 [0.00]***	-0.08 [0.00]***	-0.05 [0.00]***	-0.42 [0.00]***	-0.02 [0.00]***	0.02 [0.06]*
-11	-0.08 [0.00]***	-0.10 [0.00]***	-0.06 [0.00]***	-0.47 [0.00]***	-0.02 [0.00]***	0.02 [0.06]*
-10	-0.09 [0.00]***	-0.11 [0.00]***	-0.07 [0.00]***	-0.51 [0.00]***	-0.02 [0.00]***	0.02 [0.07]*
-9	-0.10 [0.00]***	-0.12 [0.00]***	-0.08 [0.00]***	-0.55 [0.00]***	-0.03 [0.00]***	0.02 [0.07]*
-8	-0.11 [0.00]***	-0.13 [0.00]***	-0.09 [0.00]***	-0.59 [0.00]***	-0.03 [0.00]***	0.02 [0.08]*
-7	-0.12 [0.00]***	-0.14 [0.00]***	-0.11 [0.00]***	-0.63 [0.00]***	-0.03 [0.00]***	0.02 [0.09]*
-6	-0.13 [0.00]***	-0.15 [0.00]***	-0.13 [0.00]***	-0.66 [0.00]***	-0.03 [0.00]***	0.02 [0.09]*
-5	-0.14 [0.00]***	-0.16 [0.00]***	-0.15 [0.00]***	-0.70 [0.00]***	-0.04 [0.00]***	0.02 [0.09]*
-4	-0.15 [0.00]***	-0.17 [0.00]***	-0.17 [0.00]***	-0.73 [0.00]***	-0.04 [0.00]***	0.02 [0.08]*
-3	-0.16 [0.00]***	-0.18 [0.00]***	-0.19 [0.00]***	-0.77 [0.00]***	-0.04 [0.00]***	0.02 [0.08]*
-2	-0.17 [0.00]***	-0.19 [0.00]***	-0.21 [0.00]***	-0.81 [0.00]***	-0.05 [0.00]***	0.02 [0.07]*
-1	-0.18 [0.00]***	-0.20 [0.00]***	-0.24 [0.00]***	-0.84 [0.00]***	-0.05 [0.00]***	0.02 [0.07]*
0	-0.18 [0.00]***	-0.21 [0.00]***	-0.27 [0.00]***	-0.88 [0.00]***	-0.06 [0.00]***	0.02 [0.07]*
1	-0.19 [0.00]***	-0.22 [0.00]***	-0.29 [0.00]***	-0.92 [0.00]***	-0.06 [0.00]***	0.02 [0.07]*
2	-0.19 [0.00]***	-0.23 [0.00]***	-0.32 [0.00]***	-0.95 [0.00]***	-0.07 [0.00]***	0.02 [0.07]*
3	-0.19 [0.00]***	-0.25 [0.00]***	-0.36 [0.00]***	-0.98 [0.00]***	-0.07 [0.00]***	0.02 [0.06]*
4	-0.20 [0.00]***	-0.25 [0.00]***	-0.39 [0.00]***	-1.02 [0.00]***	-0.08 [0.00]***	0.03 [0.05]*
5	-0.20 [0.00]***	-0.26 [0.00]***	-0.43 [0.00]***	-1.05 [0.00]***	-0.08 [0.00]***	0.03 [0.05]*
6	-0.20 [0.00]***	-0.26 [0.00]***	-0.46 [0.00]***	-1.09 [0.00]***	-0.09 [0.00]***	0.03 [0.05]*
7	-0.21 [0.00]***	-0.27 [0.00]***	-0.50 [0.00]***	-1.12 [0.00]***	-0.10 [0.00]***	0.02 [0.06]*
8	-0.22 [0.00]***	-0.27 [0.00]***	-0.54 [0.00]***	-1.16 [0.00]***	-0.11 [0.00]***	0.03 [0.04]**
9	-0.22 [0.00]***	-0.28 [0.00]***	-0.58 [0.00]***	-1.20 [0.00]***	-0.13 [0.00]***	0.03 [0.04]**
10	-0.23 [0.00]***	-0.29 [0.00]***	-0.62 [0.00]***	-1.24 [0.00]***	-0.15 [0.00]***	0.03 [0.04]**
11	-0.24 [0.00]***	-0.30 [0.00]***	-0.67 [0.00]***	-1.27 [0.00]***	-0.18 [0.00]***	0.03 [0.04]**
12	-0.24 [0.00]***	-0.31 [0.00]***	-0.71 [0.00]***	-1.31 [0.00]***	-0.21 [0.00]***	0.03 [0.04]**
13	-0.25 [0.00]***	-0.32 [0.00]***	-0.75 [0.00]***	-1.34 [0.00]***	-0.24 [0.00]***	0.03 [0.03]**
14	-0.26 [0.00]***	-0.33 [0.00]***	-0.79 [0.00]***	-1.38 [0.00]***	-0.28 [0.00]***	0.03 [0.04]**
15	-0.26 [0.00]***	-0.34 [0.00]***	-0.83 [0.00]***	-1.41 [0.00]***	-0.31 [0.00]***	0.03 [0.03]**
16	-0.27 [0.00]***	-0.35 [0.00]***	-0.88 [0.00]***	-1.45 [0.00]***	-0.35 [0.00]***	0.03 [0.03]**
17	-0.27 [0.00]***	-0.36 [0.00]***	-0.92 [0.00]***	-1.48 [0.00]***	-0.39 [0.00]***	0.03 [0.03]**
18	-0.27 [0.00]***	-0.36 [0.00]***	-0.96 [0.00]***	-1.52 [0.00]***	-0.42 [0.00]***	0.03 [0.03]**
19	-0.28 [0.00]***	-0.37 [0.00]***	-1.01 [0.00]***	-1.57 [0.00]***	-0.46 [0.00]***	0.03 [0.02]**
20	-0.28 [0.00]***	-0.38 [0.00]***	-1.05 [0.00]***	-1.62 [0.00]***	-0.50 [0.00]***	0.03 [0.03]**

Table E-2

Cumulative abnormal volatility connectedness.

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
-20	0.05 [0.00]***	-0.08 [0.00]***	0.01 [0.00]***	-0.03 [0.00]***	0.00 [0.00]***	0.02 [0.00]***
-19	0.10 [0.00]***	-0.15 [0.00]***	0.02 [0.00]***	-0.06 [0.00]***	0.00 [0.00]***	0.03 [0.00]***
-18	0.15 [0.00]***	-0.23 [0.00]***	0.03 [0.00]***	-0.09 [0.00]***	-0.01 [0.00]***	0.05 [0.00]***
-17	0.20 [0.00]***	-0.30 [0.00]***	0.04 [0.00]***	-0.12 [0.00]***	-0.01 [0.00]***	0.07 [0.00]***
-16	0.24 [0.00]***	-0.37 [0.00]***	0.05 [0.00]***	-0.15 [0.00]***	-0.01 [0.00]***	0.08 [0.00]***
-15	0.29 [0.00]***	-0.44 [0.00]***	0.06 [0.00]***	-0.18 [0.00]***	-0.01 [0.00]***	0.10 [0.00]***
-14	0.34 [0.00]***	-0.51 [0.00]***	0.06 [0.00]***	-0.21 [0.00]***	-0.01 [0.00]***	0.12 [0.00]***
-13	0.39 [0.00]***	-0.57 [0.00]***	0.06 [0.00]***	-0.23 [0.00]***	-0.02 [0.00]***	0.13 [0.00]***
-12	0.44 [0.00]***	-0.63 [0.00]***	0.06 [0.00]***	-0.26 [0.00]***	-0.02 [0.00]***	0.15 [0.00]***
-11	0.49 [0.00]***	-0.69 [0.00]***	0.06 [0.00]***	-0.27 [0.00]***	-0.02 [0.00]***	0.16 [0.00]***
-10	0.54 [0.00]***	-0.76 [0.00]***	0.06 [0.00]***	-0.29 [0.00]***	-0.02 [0.00]***	0.17 [0.00]***
-9	0.59 [0.00]***	-0.82 [0.00]***	0.06 [0.00]***	-0.31 [0.00]***	-0.02 [0.00]***	0.18 [0.00]***
-8	0.64 [0.00]***	-0.88 [0.00]***	0.05 [0.00]***	-0.32 [0.00]***	-0.03 [0.00]***	0.18 [0.00]***
-7	0.69 [0.00]***	-0.93 [0.00]***	0.03 [0.00]***	-0.34 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
-6	0.75 [0.00]***	-0.98 [0.00]***	0.02 [0.00]***	-0.36 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
-5	0.80 [0.00]***	-1.03 [0.00]***	0.00 [0.00]***	-0.37 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
-4	0.85 [0.00]***	-1.07 [0.00]***	-0.02 [0.00]***	-0.39 [0.00]***	-0.02 [0.00]***	0.19 [0.00]***
-3	0.90 [0.00]***	-1.11 [0.00]***	-0.13 [0.00]***	-0.40 [0.00]***	-0.02 [0.00]***	0.19 [0.00]***
-2	0.95 [0.00]***	-1.15 [0.00]***	-0.23 [0.00]***	-0.41 [0.00]***	-0.02 [0.00]***	0.19 [0.00]***
-1	1.01 [0.00]***	-1.19 [0.00]***	-0.33 [0.00]***	-0.43 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***

(continued on next page)

Table E-2 (continued)

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
0	1.06 [0.00]***	-1.22 [0.00]***	-0.43 [0.00]***	-0.44 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
1	1.12 [0.00]***	-1.26 [0.00]***	-0.53 [0.00]***	-0.45 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
2	1.17 [0.00]***	-1.30 [0.00]***	-0.56 [0.00]***	-0.46 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
3	1.22 [0.00]***	-1.33 [0.00]***	-0.59 [0.00]***	-0.47 [0.00]***	-0.03 [0.00]***	0.19 [0.00]***
4	1.28 [0.00]***	-1.36 [0.00]***	-0.63 [0.00]***	-0.48 [0.00]***	-0.04 [0.00]***	0.19 [0.00]***
5	1.33 [0.00]***	-1.39 [0.00]***	-0.66 [0.00]***	-0.49 [0.00]***	-0.04 [0.00]***	0.20 [0.00]***
6	1.38 [0.00]***	-1.42 [0.00]***	-0.69 [0.00]***	-0.50 [0.00]***	-0.05 [0.00]***	0.21 [0.00]***
7	1.43 [0.00]***	-1.46 [0.00]***	-0.73 [0.00]***	-0.51 [0.00]***	-0.05 [0.00]***	0.21 [0.00]***
8	1.48 [0.00]***	-1.49 [0.00]***	-0.78 [0.00]***	-0.52 [0.00]***	-0.06 [0.00]***	0.22 [0.00]***
9	1.53 [0.00]***	-1.52 [0.00]***	-0.83 [0.00]***	-0.53 [0.00]***	-0.09 [0.00]***	0.24 [0.00]***
10	1.58 [0.00]***	-1.55 [0.00]***	-0.89 [0.00]***	-0.55 [0.00]***	-0.13 [0.00]***	0.25 [0.00]***
11	1.63 [0.00]***	-1.58 [0.00]***	-0.95 [0.00]***	-0.57 [0.00]***	-0.17 [0.00]***	0.26 [0.00]***
12	1.68 [0.00]***	-1.61 [0.00]***	-1.02 [0.00]***	-0.60 [0.00]***	-0.22 [0.00]***	0.27 [0.00]***
13	1.73 [0.00]***	-1.64 [0.00]***	-1.08 [0.00]***	-0.62 [0.00]***	-0.30 [0.00]***	0.28 [0.00]***
14	1.78 [0.00]***	-1.67 [0.00]***	-1.15 [0.00]***	-0.64 [0.00]***	-0.38 [0.00]***	0.29 [0.00]***
15	1.83 [0.00]***	-1.70 [0.00]***	-1.22 [0.00]***	-0.66 [0.00]***	-0.47 [0.00]***	0.30 [0.00]***
16	1.87 [0.00]***	-1.73 [0.00]***	-1.29 [0.00]***	-0.68 [0.00]***	-0.55 [0.00]***	0.31 [0.00]***
17	1.92 [0.00]***	-1.77 [0.00]***	-1.36 [0.00]***	-0.71 [0.00]***	-0.63 [0.00]***	0.32 [0.00]***
18	1.98 [0.00]***	-1.80 [0.00]***	-1.43 [0.00]***	-0.73 [0.00]***	-0.74 [0.00]***	0.33 [0.00]***
19	2.03 [0.00]***	-1.83 [0.00]***	-1.49 [0.00]***	-0.76 [0.00]***	-0.84 [0.00]***	0.33 [0.00]***
20	2.08 [0.00]***	-1.86 [0.00]***	-1.56 [0.00]***	-0.79 [0.00]***	-0.95 [0.00]***	0.34 [0.00]***

Table E-3

Cumulative abnormal volume connectedness.

Event time	Paris Agreement (12 Dec 2015)	Ratification of Paris Agreement (3 Sep 2016)	Trump Election (8 Nov 2016)	Announced Withdrawal of Paris Agreement (1 Jun 2017)	Biden Election Congress Confirmation (14 Dec 2020)	Biden Climate Change Bill (17 Aug 2022)
-20	-0.06 [0.00]***	0.01 [0.00]***	-0.02 [0.00]***	-0.03 [0.00]***	-0.05 [0.00]***	-0.01 [0.00]***
-19	-0.11 [0.00]***	0.02 [0.00]***	-0.09 [0.00]***	-0.05 [0.00]***	-0.09 [0.00]***	-0.02 [0.00]***
-18	-0.17 [0.00]***	0.02 [0.00]***	-0.17 [0.00]***	-0.08 [0.00]***	-0.13 [0.00]***	-0.02 [0.00]***
-17	-0.24 [0.00]***	0.03 [0.00]***	-0.24 [0.00]***	-0.10 [0.00]***	-0.17 [0.00]***	-0.03 [0.00]***
-16	-0.30 [0.00]***	0.03 [0.00]***	-0.32 [0.00]***	-0.13 [0.00]***	-0.22 [0.00]***	-0.04 [0.00]***
-15	-0.35 [0.00]***	0.04 [0.00]***	-0.41 [0.00]***	-0.16 [0.00]***	-0.26 [0.00]***	-0.04 [0.00]***
-14	-0.41 [0.00]***	0.05 [0.00]***	-0.50 [0.00]***	-0.19 [0.00]***	-0.30 [0.00]***	-0.05 [0.00]***
-13	-0.46 [0.00]***	0.05 [0.00]***	-0.59 [0.00]***	-0.21 [0.00]***	-0.34 [0.00]***	-0.06 [0.00]***
-12	-0.52 [0.00]***	0.05 [0.00]***	-0.68 [0.00]***	-0.24 [0.00]***	-0.38 [0.00]***	-0.07 [0.00]***
-11	-0.57 [0.00]***	0.05 [0.00]***	-0.77 [0.00]***	-0.26 [0.00]***	-0.43 [0.00]***	-0.07 [0.00]***
-10	-0.57 [0.00]***	0.06 [0.00]***	-0.86 [0.00]***	-0.29 [0.00]***	-0.45 [0.00]***	-0.08 [0.00]***
-9	-0.57 [0.00]***	0.06 [0.00]***	-0.96 [0.00]***	-0.31 [0.00]***	-0.47 [0.00]***	-0.09 [0.00]***
-8	-0.57 [0.00]***	0.07 [0.00]***	-1.05 [0.00]***	-0.33 [0.00]***	-0.48 [0.00]***	-0.10 [0.00]***
-7	-0.57 [0.00]***	0.08 [0.00]***	-1.15 [0.00]***	-0.35 [0.00]***	-0.50 [0.00]***	-0.11 [0.00]***
-6	-0.57 [0.00]***	0.08 [0.00]***	-1.25 [0.00]***	-0.38 [0.00]***	-0.52 [0.00]***	-0.13 [0.00]***
-5	-0.56 [0.00]***	0.09 [0.00]***	-1.35 [0.00]***	-0.40 [0.00]***	-0.53 [0.00]***	-0.14 [0.00]***
-4	-0.56 [0.00]***	0.10 [0.00]***	-1.45 [0.00]***	-0.42 [0.00]***	-0.55 [0.00]***	-0.15 [0.00]***
-3	-0.56 [0.00]***	0.11 [0.00]***	-1.55 [0.00]***	-0.44 [0.00]***	-0.57 [0.00]***	-0.16 [0.00]***
-2	-0.56 [0.00]***	0.12 [0.00]***	-1.66 [0.00]***	-0.46 [0.00]***	-0.59 [0.00]***	-0.17 [0.00]***
-1	-0.56 [0.00]***	0.12 [0.00]***	-1.77 [0.00]***	-0.48 [0.00]***	-0.61 [0.00]***	-0.18 [0.00]***
0	-0.56 [0.00]***	0.14 [0.00]***	-1.88 [0.00]***	-0.50 [0.00]***	-0.63 [0.00]***	-0.19 [0.00]***
1	-0.55 [0.00]***	0.15 [0.00]***	-1.98 [0.00]***	-0.52 [0.00]***	-0.65 [0.00]***	-0.20 [0.00]***
2	-0.54 [0.00]***	0.16 [0.00]***	-2.07 [0.00]***	-0.54 [0.00]***	-0.67 [0.00]***	-0.22 [0.00]***
3	-0.54 [0.00]***	0.16 [0.00]***	-2.14 [0.00]***	-0.56 [0.00]***	-0.70 [0.00]***	-0.22 [0.00]***
4	-0.54 [0.00]***	0.17 [0.00]***	-2.23 [0.00]***	-0.58 [0.00]***	-0.72 [0.00]***	-0.23 [0.00]***
5	-0.50 [0.00]***	0.19 [0.00]***	-2.30 [0.00]***	-0.60 [0.00]***	-0.73 [0.00]***	-0.24 [0.00]***
6	-0.46 [0.00]***	0.20 [0.00]***	-2.38 [0.00]***	-0.62 [0.00]***	-0.74 [0.00]***	-0.25 [0.00]***
7	-0.43 [0.00]***	0.18 [0.00]***	-2.45 [0.00]***	-0.64 [0.00]***	-0.75 [0.00]***	-0.25 [0.00]***
8	-0.39 [0.00]***	0.17 [0.00]***	-2.52 [0.00]***	-0.66 [0.00]***	-0.76 [0.00]***	-0.26 [0.00]***
9	-0.31 [0.00]***	0.16 [0.00]***	-2.60 [0.00]***	-0.68 [0.00]***	-0.75 [0.00]***	-0.27 [0.00]***
10	-0.23 [0.00]***	0.15 [0.00]***	-2.67 [0.00]***	-0.70 [0.00]***	-0.76 [0.00]***	-0.27 [0.00]***
11	-0.15 [0.00]***	0.15 [0.00]***	-2.75 [0.00]***	-0.73 [0.00]***	-0.76 [0.00]***	-0.28 [0.00]***
12	-0.07 [0.00]***	0.14 [0.00]***	-2.82 [0.00]***	-0.74 [0.00]***	-0.76 [0.00]***	-0.29 [0.00]***
13	0.01 [0.00]***	0.13 [0.00]***	-2.86 [0.00]***	-0.76 [0.00]***	-0.77 [0.00]***	-0.29 [0.00]***
14	0.09 [0.00]***	0.12 [0.00]***	-2.90 [0.00]***	-0.78 [0.00]***	-0.77 [0.00]***	-0.29 [0.00]***
15	0.16 [0.00]***	0.12 [0.00]***	-2.94 [0.00]***	-0.79 [0.00]***	-0.79 [0.00]***	-0.30 [0.00]***
16	0.24 [0.00]***	0.12 [0.00]***	-2.98 [0.00]***	-0.81 [0.00]***	-0.79 [0.00]***	-0.30 [0.00]***
17	0.32 [0.00]***	0.11 [0.00]***	-3.02 [0.00]***	-0.80 [0.00]***	-0.80 [0.00]***	-0.31 [0.00]***
18	0.40 [0.00]***	0.10 [0.00]***	-3.05 [0.00]***	-0.80 [0.00]***	-0.81 [0.00]***	-0.31 [0.00]***
19	0.47 [0.00]***	0.10 [0.00]***	-3.09 [0.00]***	-0.80 [0.00]***	-0.82 [0.00]***	-0.32 [0.00]***
20	0.55 [0.00]***	0.10 [0.00]***	-3.12 [0.00]***	-0.79 [0.00]***	-0.83 [0.00]***	-0.33 [0.00]***

Note: Table E provides cumulative abnormal connectedness of 118 green stocks to the six studied events on each day over the event window. Statistical significance is reported based on the standardized cross-sectional test. The symbols *, **, and *** denote statistical significance at the 0.10, 0.05, and 0.01 levels.F.

Appendix F. Total connectedness index by subsamples

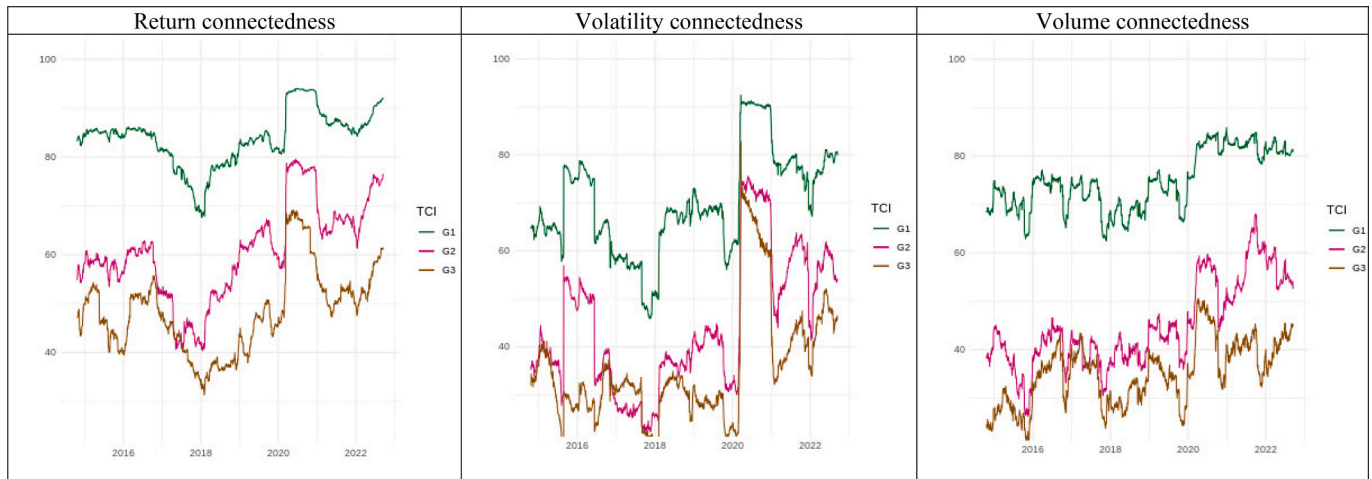


Fig. F-1. Total connectedness by industries.

Note: G1 are firms who are in light industries with low litigation risk, G2 are firms who are in heavy industries with low litigation risk, and G3 are firms who are in light industries with high litigation risk.

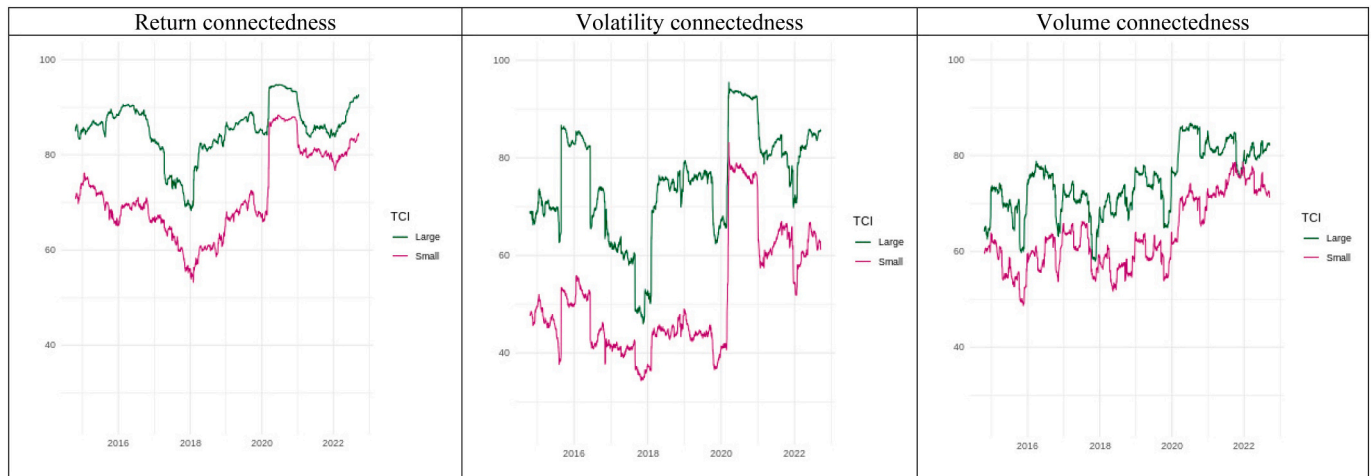


Fig. F-2. Total connectedness index by size.

Note: Large firms refer to those green firms whose average market capitalization is above the sample median, and small firms are those whose average market capitalization is below the sample median.

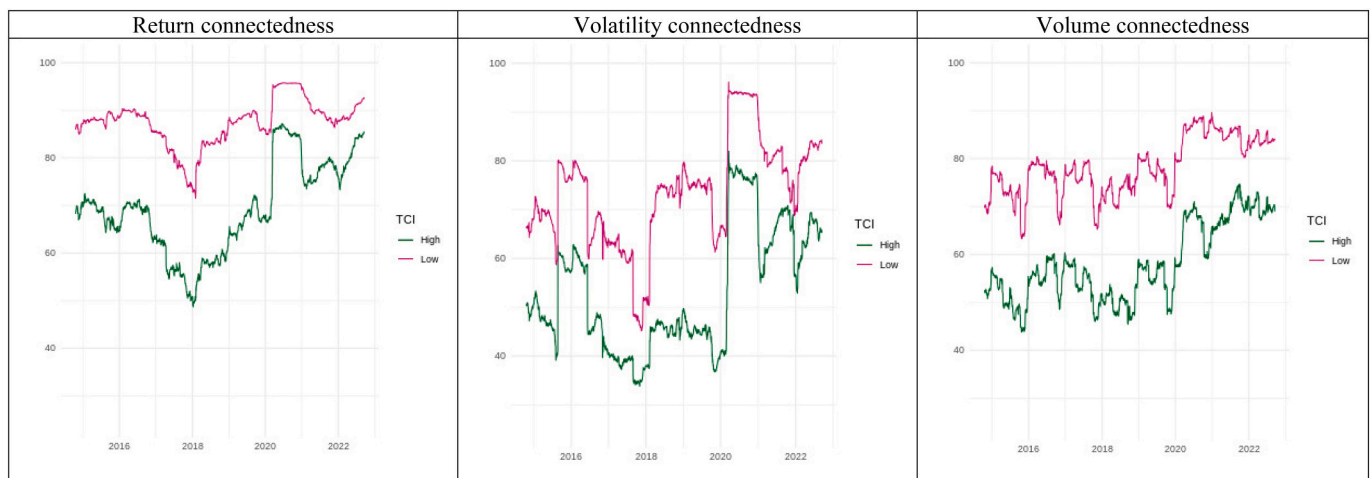
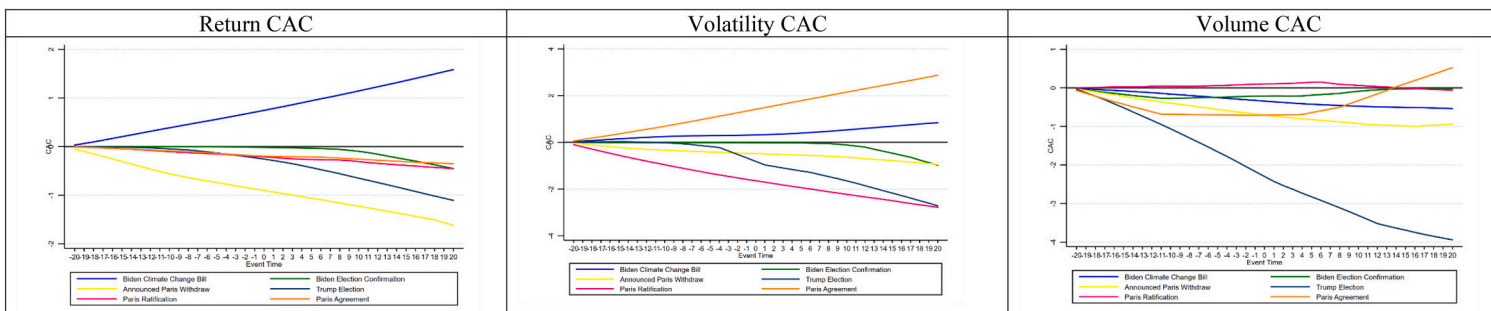


Fig. F-3. Total connectedness index by IVOL.

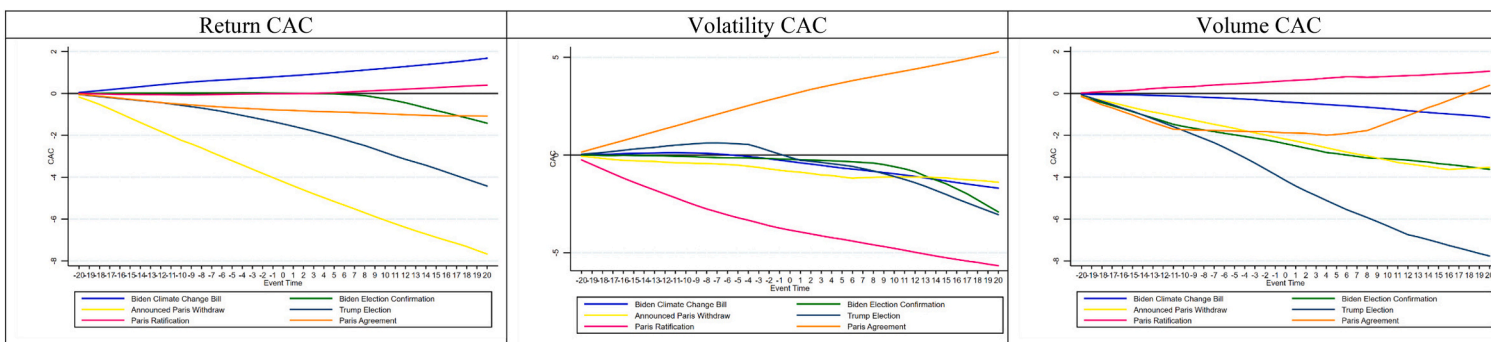
Note: high IVOL firms refer to those green firms whose IVOL is above the sample median, while low IVOL firms are those whose IVOL is below the sample median.

Appendix G. Cumulative abnormal connectedness by subsamples

Part I: Group 1 – Light industries with low litigation risks



Part II: Group 2: Heavy industries with low litigation risks



Part III: Group 3: Light industries with high litigation risks

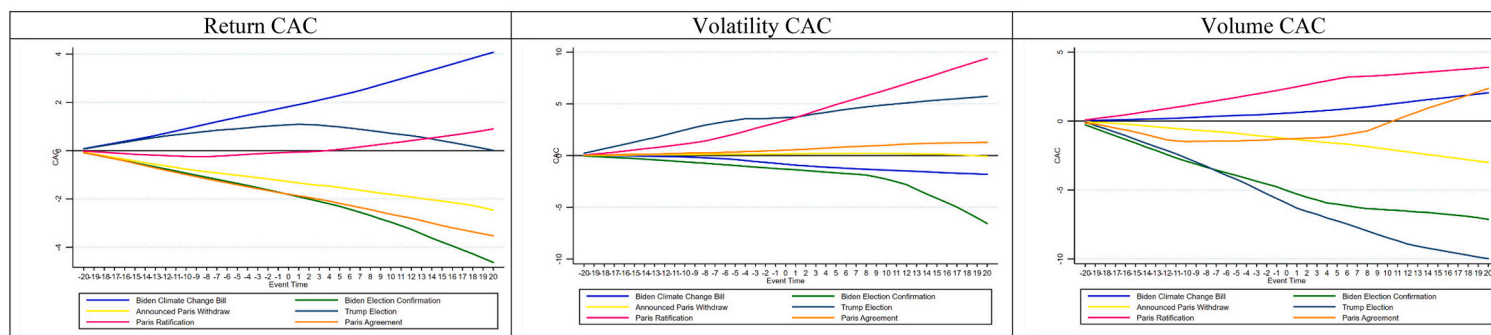
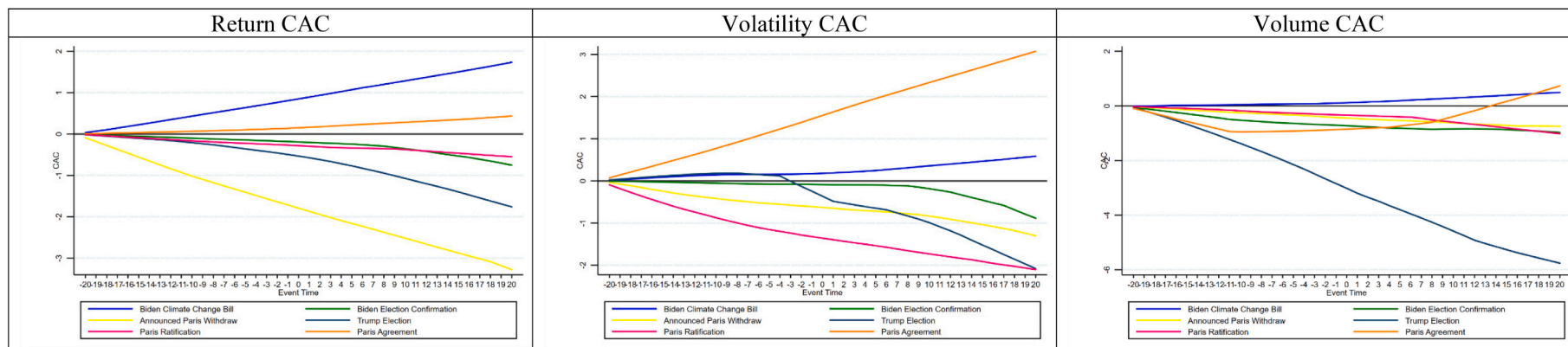


Fig. G-1. Cumulative abnormal connectedness (CAC) of clean energy stocks around the announcement of the events – Subsector analysis.

Part I: Large firms



Part II: Small firms

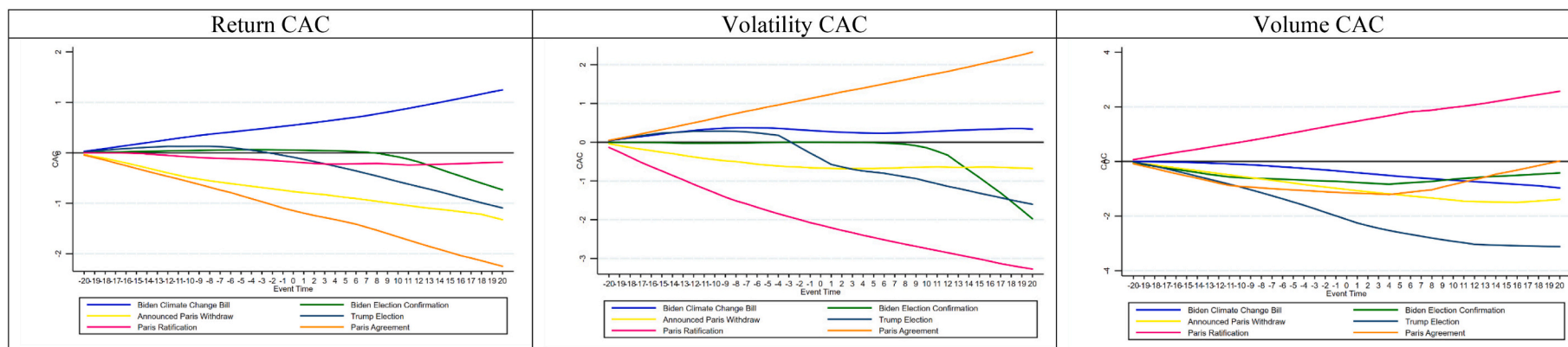
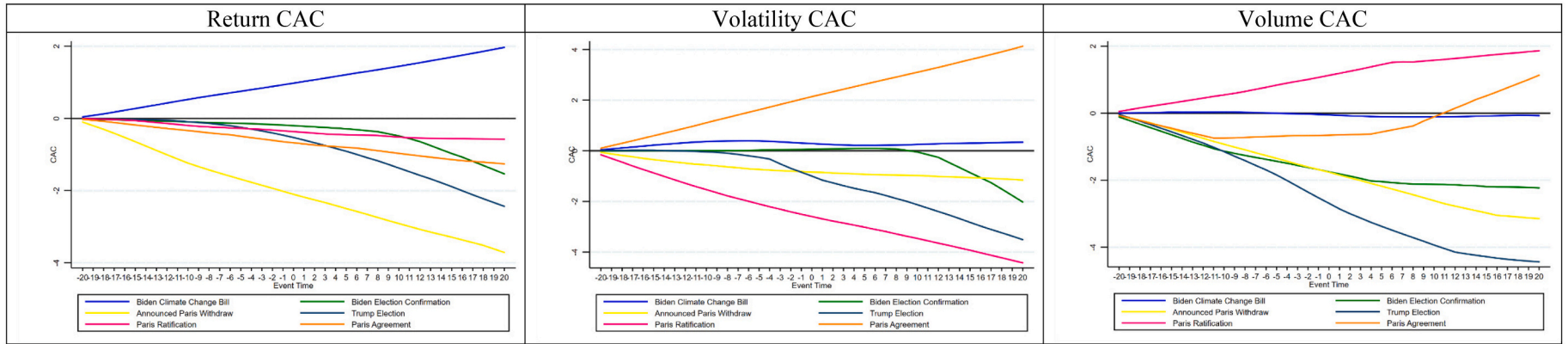


Fig. G-2. Cumulative abnormal connectedness of clean energy stocks around the announcement of the events – Large v. Small firms.

Part I: High volatility firms



Part II: Low volatility firms

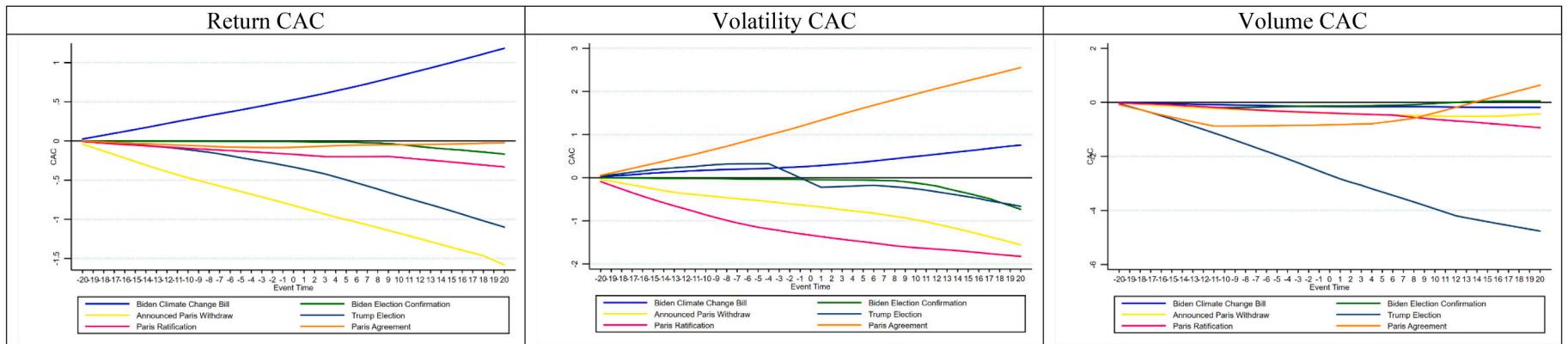


Fig. G-3. Cumulative abnormal connectedness (CAC) of clean energy stocks around the announcement of the events – High v. Low volatility firms.

Appendix H. Portfolio analysis

Table H-1

Minimum connectedness portfolio performance.

Stock	Summary statistics of dynamic portfolio weights				Hedging effectiveness	
	Mean	Std. Dev.	p5	p95	HE (%)	p-value
ADSK	0.9524	0.9365	0.0000	2.7640	59.357	0.000
AEIS	0.8339	1.1588	0.0000	3.3900	69.119	0.000
AES	0.7571	0.8086	0.0000	2.0925	48.151	0.000
AMAT	1.0597	1.3896	0.0000	4.1235	64.89	0.000
AMRC	0.9371	0.8577	0.0000	2.3595	79.227	0.000
AMRS	0.9464	0.7373	0.0000	2.1533	97.188	0.000
ANSS	0.4231	0.7764	0.0000	2.1659	35.877	0.000
AOS	1.1243	1.3283	0.0000	3.7588	57.297	0.000
APOG	0.7630	0.7644	0.0000	2.2671	71.652	0.000
ARTNA	0.5231	0.6294	0.0000	1.7501	25.005	0.000
ASTE	0.9709	1.0561	0.0000	3.0210	66.334	0.000
ASYS	0.8726	0.7158	0.0000	2.1133	83.662	0.000
AVAV	1.0602	0.7555	0.0000	2.2292	73.546	0.000
AWI	1.0214	1.0960	0.0000	3.0105	43.368	0.000
AWK	0.4850	0.8801	0.0000	2.3721	-4.99	0.024
AWR	0.7838	1.0360	0.0000	2.9120	24.922	0.000
AYI	1.1159	0.7907	0.0000	2.5154	60.764	0.000
AZZ	0.8002	0.8414	0.0000	2.3592	53.421	0.000
BLNK	0.8527	0.6453	0.0000	2.0034	98.429	0.000
BMI	1.0242	0.9792	0.0000	2.8750	64.579	0.000
BWA	1.0560	1.1897	0.0000	3.3679	53.655	0.000
CAMP	0.5414	0.5726	0.0000	1.6031	79.394	0.000
CDXS	0.7059	0.6509	0.0000	2.0249	84.958	0.000
CECE	1.0301	0.8052	0.0000	2.2678	77.44	0.000
CLNE	0.8712	0.6508	0.0000	1.9861	89.892	0.000
CMC	1.0798	1.3633	0.0000	3.8493	66.397	0.000
CMI	1.1283	1.1521	0.0000	3.3274	25.459	0.000
CPRT	1.0133	1.0262	0.0000	3.0075	58.415	0.001
CSCO	0.9457	1.0479	0.0000	2.9999	18.061	0.212
CWEN	0.5263	0.6268	0.0000	1.7841	68.764	0.000
CWST	0.8668	0.7234	0.0000	2.0108	49.477	0.000
CWT	0.5869	0.9961	0.0000	2.8141	28.948	0.000
DAR	0.7133	0.8148	0.0000	2.2808	61.317	0.000
DCI	1.1047	1.4189	0.0000	3.9498	21.15	0.003
DE	1.4106	1.0338	0.0000	3.1240	38.795	0.000
DGII	0.9785	0.7875	0.0000	2.4107	70.529	0.000
DHR	0.8165	0.9395	0.0000	2.8005	3.981	0.107
ECL	0.9753	1.1582	0.0000	3.4521	13.511	0.185
EME	0.4485	1.2644	0.0000	2.8577	37.777	0.000
EMKR	0.7237	0.5874	0.0000	1.7773	78.926	0.000
EMR	1.3924	1.9878	0.0000	5.8794	31.034	0.000
ENPH	0.7805	0.6632	0.0000	1.9157	92.19	0.000
ENS	0.8579	1.2379	0.0000	2.9495	56.468	0.000
ERII	0.9426	0.7903	0.0000	2.3579	86.414	0.000
FCEL	0.6800	0.6281	0.0000	1.7781	97.762	0.000
FELE	0.6333	1.1627	0.0000	2.9105	48.568	0.000
FF	0.5921	0.6704	0.0000	1.8586	74.654	0.000
FIX	1.0768	1.2569	0.0000	3.6718	60.178	0.000
FSLR	0.6276	0.7545	0.0000	2.0610	74.287	0.000
GAIA	0.8069	0.6089	0.0000	1.7452	76.231	0.000
GEVO	0.7744	0.6492	0.0000	2.0747	98.855	0.000
GLW	0.7167	1.0893	0.0000	3.0594	37.949	0.000
GRC	1.0932	1.2928	0.0000	4.0688	55.103	0.000
HAIN	0.7630	0.5897	0.0000	1.7788	70.656	0.000
HASI	0.5588	0.7240	0.0000	1.9141	59.604	0.000
HDSN	0.8227	0.5806	0.0000	1.8248	91.128	0.000
HXL	1.0563	1.0874	0.0000	3.1530	60.231	0.000
ICFI	0.8060	0.7281	0.0000	2.0083	39.022	0.000
IEX	0.4952	1.0867	0.0000	3.1310	-5.324	0.719
ITRI	0.9510	1.0131	0.0000	3.1355	69.201	0.000
JBL	0.7759	1.0370	0.0000	2.9514	53.579	0.000
JLL	0.9820	0.9983	0.0000	2.8878	56.609	0.000
JOE	0.8307	0.7132	0.0000	1.9196	44.849	0.000
KAI	1.2424	1.0047	0.0000	3.1131	49.814	0.000
KBH	0.5665	0.8789	0.0000	2.4240	74.807	0.000
LII	1.1725	1.1188	0.0000	3.0228	15.689	0.000
LKQ	0.9882	1.0516	0.0000	2.8818	52.378	0.000
LNN	1.0331	0.9185	0.0000	2.7700	47.04	0.000
LQDT	0.9180	0.5723	0.0000	1.8834	83.018	0.000
LWAY	0.7943	0.5514	0.0000	1.7025	85.538	0.000
LXU	0.9008	0.6491	0.0000	1.9202	92.595	0.000

(continued on next page)

Table H-1 (continued)

Stock	Summary statistics of dynamic portfolio weights				Hedging effectiveness	
	Mean	Std. Dev.	p5	p95	HE (%)	p-value
MGPI	0.8525	0.5114	0.0000	1.5872	73.315	0.000
MLI	0.5867	1.4436	0.0000	3.0987	54.867	0.000
MSEX	0.4885	0.7125	0.0000	1.8138	41.18	0.000
MTZ	1.0041	1.3407	0.0000	3.9709	72.238	0.000
MWA	0.8219	1.0834	0.0000	3.0238	47.98	0.000
NEE	0.6852	0.7873	0.0000	2.1681	80.963	0.006
NGVC	0.5592	0.4655	0.0000	1.4489	82.495	0.000
NTAP	0.8251	0.9434	0.0000	2.4822	53.692	0.000
NUE	0.8669	1.4136	0.0000	3.7909	54.317	0.000
NWPX	0.8494	0.7500	0.0000	2.1727	72.131	0.000
OC	1.2458	1.2159	0.0000	3.3301	53.122	0.000
OESX	0.8826	0.7165	0.0000	1.9480	86.784	0.000
OLED	0.7751	0.7711	0.0000	2.2122	76.963	0.000
ON	0.4241	0.8786	0.0000	2.4315	75.446	0.000
OPTT	0.8160	0.6302	0.0000	1.9615	98.324	0.000
PCH	0.8541	0.8025	0.0000	2.2597	52.258	0.000
PLPC	0.7948	0.6839	0.0000	1.9395	67.193	0.000
PLUG	0.5601	0.6320	0.0000	1.7217	90.304	0.000
POWI	0.4654	0.6547	0.0000	1.6440	72.231	0.000
ROP	1.0264	1.2205	0.0000	3.4942	0.712	0.267
SCHN	1.0512	1.1910	0.0000	3.6875	74.746	0.000
SCS	0.9987	0.9846	0.0000	2.9726	66.374	0.000
SFM	0.5199	0.4715	0.0000	1.3490	59.826	0.000
SJW	1.0184	0.8161	0.0000	2.3273	40.951	0.000
SPG	0.7087	0.9937	0.0000	2.5335	63.766	0.000
SPWR	0.5620	0.8554	0.0000	2.3462	88.518	0.000
SPXC	0.9403	1.1562	0.0000	3.3414	86.111	0.000
STLD	1.3750	1.7467	0.0000	5.4202	64.585	0.000
TILE	0.6046	0.9886	0.0000	2.7974	72.492	0.000
TREX	0.9957	0.9455	0.0000	2.6663	82.502	0.000
TRN	0.8198	1.0125	0.0000	2.9572	66.041	0.000
TSLA	1.0097	0.8807	0.0000	2.6772	92.412	0.000
TTC	1.1523	1.0047	0.0000	2.9324	52.005	0.837
TTEK	0.5611	0.9392	0.0000	2.7412	39.802	0.000
ULBI	0.8591	0.6032	0.0000	1.8196	76.242	0.000
UNFI	0.7542	0.5544	0.0000	1.7207	84.771	0.000
VECO	0.6937	0.7259	0.0000	2.0752	78.821	0.000
VMI	0.9522	1.0397	0.0000	2.9413	32.366	0.000
WAB	1.0130	1.1168	0.0000	3.1207	49.308	0.000
WAT	0.8162	0.7995	0.0000	2.3068	21.368	0.035
WKHS	0.8175	0.6064	0.0000	1.8053	97.397	0.000
WTRG	0.6272	0.8666	0.0000	2.3617	8.299	0.687
WTS	0.8983	1.1392	0.0000	3.2771	32.291	0.000
WWD	1.2660	1.4647	0.0000	4.2940	54.806	0.000
XYL	0.9725	1.2710	0.0000	3.7491	24.509	0.000
YORW	0.5028	0.8407	0.0000	2.3581	44.029	0.000
ZWS	0.6642	1.0519	0.0000	2.5913	70.555	0.000

Note: Table H-1 presents the summary statistics of the dynamic portfolio weights, the numerical values of the portfolio weights, and the hedging effectiveness for each stock. Hedging effectiveness is defined as the amount of variance reduction from the portfolio compared to an unhedged position of the individual stocks.

Appendix I. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eneco.2023.106564>.

References

- Ahmad, W., 2017. On the dynamic dependence and investment performance of crude oil and clean energy stocks. *Res. Int. Bus. Financ.* 42, 376–389.
- Ahmad, W., Kutan, A.M., Gupta, S., 2021. Black swan events and COVID-19 outbreak: sector level evidence from the U.S., UK, and European stock markets. *Int. Rev. Econ. Financ.* 75, 546–557.
- Akhtaruzzaman, M., Boubaker, S., Sensory, A., 2021. Financial contagion during COVID-19 crisis. *Financ. Res. Lett.* 38, 101604.
- Ang, A., Hodrick, R.J., Xing, Y., Zhang, X., 2009. High idiosyncratic volatility and low returns: international and further U.S. evidence. *J. Financ. Econ.* 91 (1), 1–23.
- Antoniuk, Y., Leirvik, T., 2021. Climate change events and stock market returns. *J. Sustain. Finance Invest.* 1–26.
- Asadnabizadeh, M., 2019. Climate change in the foreign policy of the trump administration. *Environ. Policy Law* 49 (2/3), 195–202. <https://doi.org/10.3233/EPL-190157>.
- Baker, S.R., Bloom, N., Davis, S.J., Kost, K., Sammon, M., Viratyosin, T., 2020. The unprecedented stock market reaction to COVID-19. *Rev. Asset Pricing Stud.* 10 (4), 742–758.
- Balcilar, M., Ozdemir, H., Agan, B., 2022. Effects of COVID-19 on cryptocurrency and emerging market connectedness: empirical evidence from quantile, frequency, and lasso networks. *Physica A* 604, 127885.
- Ballew, M.T., Leiserowitz, A., Roser-Renouf, C., Rosenthal, S.A., Kotcher, J.E., Marlon, J. R., Lyon, E., Goldberg, M.H., Maibach, E.W., 2019. Climate change in the American mind: data, tools, and trends. *Environ. Sci. Policy Sustain. Dev.* 61 (3), 4–18. <https://doi.org/10.1080/00139157.2019.1589300>.
- Banz, R., 1981. The relation between return and market value of common stocks. *J. Financ. Econ.* 9, 3–18.
- Beaver, W.H., 1968. The information content of annual earnings announcements. *J. Account. Res.* 6, 67–92. <https://doi.org/10.2307/2490070>.
- Boehmer, E., Musumeci, J., Poulsen, A.B., 1991. Event-study methodology under conditions of event-induced variance. *J. Financ. Econ.* 30 (2), 253–272. [https://doi.org/10.1016/0304-405X\(91\)90032-F](https://doi.org/10.1016/0304-405X(91)90032-F).
- Bombardier, E., 2017. Environmental politics in the Trump era: an early assessment. *Environ. Polit.* 26 (5), 956–963. <https://doi.org/10.1080/09644016.2017.1332543>.
- Broadstock, D.C., Chatziantoniou, I., Gabauer, D., 2020. Minimum connectedness portfolios and the market for green bonds: advocating socially responsible investment (SRI) activity. In: Available at SSRN 3793771.

- Campbell, J.Y., Lo, A.W., MacKinlay, A.C., 2012. The econometrics of financial markets. In: *The Econometrics of Financial Markets*. Princeton University Press.
- Chen, Y., Gul, F.A., Veeraraghavan, M., Zolotoy, L., 2015. Executive equity risk-taking incentives and audit pricing. *Account. Rev.* 90 (6), 2205–2234.
- Chen, Y., Zhu, X., Chen, J., 2022. Spillovers and hedging effectiveness of non-ferrous metals and sub-sectoral clean energy stocks in time and frequency domain. *Energy Econ.* 106070.
- Cready, W.M., Hurr, D.N., 2002. Assessing investor response to information events using return and volume metrics. *Account. Rev.* 77 (4), 891–909. <https://doi.org/10.2308/accr.2002.77.4.891>.
- DeFond, M., Hung, M., Trezevant, R., 2007. Investor protection and the information content of annual earnings announcements: international evidence. *J. Account. Econ.* 43 (1), 37–67. <https://doi.org/10.1016/j.jacceco.2006.09.001>.
- Demirer, R., Kutun, A.M., 2010. The behavior of crude oil spot and futures prices around OPEC and SPR announcements: an event study perspective. *Energy Econ.* 32 (6), 1467–1476.
- Demirer, M., Diebold, F.X., Liu, L., Yilmaz, K., 2018. Estimating global bank network connectedness. *J. Appl. Econ.* 33 (1), 1–15.
- Devos, E., Hao, W., Prevost, A.K., Wongchoti, U., 2015. Stock return synchronicity and the market response to analyst recommendation revisions. *J. Bank. Financ.* 58, 376–389. <https://doi.org/10.1016/j.jbankfin.2015.04.021>.
- Diaz-Rainey, I., Gehricke, S.A., Roberts, H., Zhang, R., 2021. Trump vs. Paris: the impact of climate policy on U.S. listed oil and gas firm returns and volatility. *Int. Rev. Financ. Anal.* 76, 101746. <https://doi.org/10.1016/j.irfa.2021.101746>.
- Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. *Int. J. Forecasting* 28 (1), 57–66.
- Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. *J. Econ.* 182 (1), 119–134.
- Dimitrov, R.S., 2016. The Paris Agreement on climate change: behind closed doors. *Global Environ. Polit.* 16 (3), 1–11. https://doi.org/10.1162/GLEP_a_00361.
- Downie, C., 2019. Business Battles in the U.S. Energy Sector: Lessons for a Clean Energy Transition.
- Dutta, A., 2017. Oil price uncertainty and clean energy stock returns: New evidence from crude oil volatility index. *J. Clean. Prod.* 164, 1157–1166. <https://doi.org/10.1016/j.jclepro.2017.07.050>.
- Engle, R., 2002. Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *J. Bus. Econ. Stat.* 20 (3), 339–350.
- Faccini, R., Matin, R., Skiadopoulou, G., 2021. Are climate change risks priced in the U.S. stock market? (No. 169). In: *Danmarks National Bank Working Papers*.
- Fahmy, H., 2022. The rise in investors' awareness of climate risks after the Paris agreement and the clean energy-oil-technology prices nexus. *Energy Econ.* 106, 105738. <https://doi.org/10.1016/j.eneco.2021.105738>.
- Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *J. Financ. Econ.* 33 (1), 3–56. [https://doi.org/10.1016/0304-405X\(93\)90023-5](https://doi.org/10.1016/0304-405X(93)90023-5).
- Fard, A., Javadi, S., Kim, I., 2020. Environmental regulation and the cost of bank loans: international evidence. *J. Financ. Stabil.* 51, 100797.
- Ferrer, R., Shahzad, S.J.H., López, R., Jareño, F., 2018. Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Econ.* 76, 1–20. <https://doi.org/10.1016/j.eneco.2018.09.022>.
- Fiorino, D.J., 2022. Climate change and right-wing populism in the United States. *Environ. Polit.* 1–19. <https://doi.org/10.1080/09644016.2021.2018854>.
- Fu, F., 2009. Idiosyncratic risk and the cross-section of expected stock returns. *J. Financ. Econ.* 91 (1), 24–37.
- Gabauer, D., Gupta, R., Marfatia, H., Miller, S.M., 2020. Estimating U.S. housing price network connectedness: Evidence from dynamic elastic net, lasso, and ridge vector autoregressive models. In: *Lasso, and Ridge Vector Autoregressive Models* (July 26, 2020).
- Garman, M.B., Klass, M.J., 1980. On the estimation of security price volatilities from historical data. *J. Bus.* 53 (1), 67–78. Retrieved from. <http://www.jstor.org/stable/2352358>.
- González-Urteaga, A., Rubio, G., 2022. Guarantee requirements by European central counterparties and international volatility spillovers. *Res. Int. Bus. Financ.* 101629.
- Grand, M.C., D'Elia, V.V., 2005. Environmental News and Stock Markets Performance: Further Evidence for Argentina. *Universidad del CEMA*.
- Hao, L.N., Umar, M., Khan, Z., Ali, W., 2021. Green growth and low carbon emission in G7 countries: how critical the network of environmental taxes, renewable energy and human capital is? *Sci. Total Environ.* 752, 141853.
- Jotzo, F., Depledge, J., Winkler, H., 2018. U.S. and international climate policy under President Trump. *Clim. Policy* 18 (7), 813–817. <https://doi.org/10.1080/14693062.2018.1490051>.
- Khalifaoui, R., Jabeur, S.B., Dogan, B., 2022. The spillover effects and connectedness among green commodities, Bitcoins, and U.S. stock markets: evidence from the quantile VAR network. *J. Environ. Manag.* 306, 114493.
- Kocaarslan, B., Soytaş, U., 2021. Reserve currency and the volatility of clean energy stocks: the role of uncertainty. *Energy Econ.* 104, 105645. <https://doi.org/10.1016/j.eneco.2021.105645>.
- Landsman, W.R., Maydew, E.L., 2002. Has the information content of quarterly earnings announcements declined in the past three decades? *J. Account. Res.* 40 (3), 797–808. <https://doi.org/10.1111/1475-679X.00071>.
- Landsman, W.R., Maydew, E.L., Thornock, J.R., 2012. The information content of annual earnings announcements and mandatory adoption of IFRS. *J. Account. Econ.* 53 (1), 34–54. <https://doi.org/10.1016/j.jacceco.2011.04.002>.
- Li, J., Dong, X., Dong, X., 2022. Green energy as a new determinant of green growth in China: the role of green technological innovation. *Energy Econ.* 114, 106260.
- Lv, X., Dong, X., Dong, W., 2021. Oil prices and stock prices of clean energy: New evidence from Chinese subsectoral data. *Emerg. Mark. Financ. Tr.* 57 (4), 1088–1102. <https://doi.org/10.1080/1540496X.2019.1689810>.
- Mamidi, V., Marisetty, V.B., Thomas, E.N., 2021. Clean energy transition and intertemporal socio-economic development: evidence from an emerging market. *Energy Econ.* 101, 105392.
- Mensi, W., Shafiqullah, M., Vo, X.V., Kang, S.H., 2022. Spillovers and connectedness between green bond and stock markets in bearish and bullish market scenarios. *Financ. Res. Lett.* 49, 103120.
- Meyer, M., Smyth, B., 2019. Exploiting re-voting in the Helios election system. *Inf. Process. Lett.* 143, 14–19. <https://doi.org/10.1016/j.ipl.2018.11.001>.
- Morse, D., 1981. Price and trading volume reaction surrounding earnings announcements: a closer examination. *J. Account. Res.* 19 (2), 374–383. <https://doi.org/10.2307/2490871>.
- Nadja, P., Livia, A.-R., Kendra, P.-L., 2020. The Trump administration is reversing nearly 100 environmental rules. Here's the full list. *New York Times*. May 6. (Nytimes.com).
- Neuger, G.-L., Huynh, T.L.D., Wang, M., 2021. Which industries benefited from Trump environmental policy news? Evidence from industrial stock market reactions. *Res. Int. Bus. Financ.* 57, 101418. <https://doi.org/10.1016/j.ribaf.2021.101418>.
- Nguyen, J.H., Phan, H.V., 2020. Carbon risk and corporate capital structure. *J. Corp. Financ.* 64, 101713.
- Palman, O., Sun, H.-L., Tang, A.P., 1994. The impact of publication of analysts' recommendations on returns and trading volume. *Financ. Rev.* 29 (3), 395–417. <https://doi.org/10.1111/j.1540-6288.1994.tb00403.x>.
- Pástor, L., Stambaugh, R.F., Taylor, L.A., 2022. Dissecting green returns. *J. Financ. Econ.* 146 (2), 403–424.
- Pham, L., 2019. Do all clean energy stocks respond homogeneously to oil price? *Energy Econ.* 81, 355–379.
- Pham, H., Nguyen, V., Ramiah, V., Mudalige, P., Moosa, I., 2019. The effects of environmental regulation on the Singapore stock market. *J. Risk Financ. Manag.* 12 (4), 175. Retrieved from. <https://www.mdpi.com/1911-8074/12/4/175>.
- Qadan, M., Shuval, K., 2022. Variance risk and the idiosyncratic volatility puzzle. *Financ. Res. Lett.* 45, 102176.
- 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. *Rev. Corp. Financ. Stud.* 10 (4), 748–787. <https://doi.org/10.1093/rcfs/cfab010>.
- Ramiah, V., Martin, B., Moosa, I., 2013. How does the stock market react to the announcement of green policies? *J. Bank. Financ.* 37 (5), 1747–1758. <https://doi.org/10.1016/j.jbankfin.2013.01.012>.
- Ramiah, V., Pichelli, J., Moosa, I., 2015a. The effects of environmental regulation on corporate performance: a Chinese perspective. *Rev. Pacific Basin Financ. Mark. Policies* 18 (04), 1550026. <https://doi.org/10.1142/s0219091515500265>.
- Ramiah, V., Pichelli, J., Moosa, I., 2015b. Environmental regulation, the Obama effect and the stock market: some empirical results. *Appl. Econ.* 47 (7), 725–738. <https://doi.org/10.1080/00036846.2014.980572>.
- Ramiah, V., Morris, T., Moosa, I., Gangemi, M., Puican, L., 2016. The effects of announcement of green policies on equity portfolios. *Manage. Auditing J.* 31 (2), 138–155. <https://doi.org/10.1108/MAJ-08-2014-1065>.
- Reboredo, J.C., 2015. Is there dependence and systemic risk between oil and renewable energy stock prices? *Energy Econ.* 48, 32–45. <https://doi.org/10.1016/j.eneco.2014.12.009>.
- Roy, P., Ahmad, W., Sadorsky, P., Phani, B.V., 2022. What do we know about the idiosyncratic risk of clean energy equities? *Energy Econ.* 112, 106167.
- Stambaugh, R.F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *J. Financ.* 70 (5), 1903–1948.
- Strong, A.L., 2022. 2020—a pivotal moment in America's climate change efforts. In: *The 2020 Presidential Election*. Springer, New York, NY, pp. 143–162.
- Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. *J. R. Stat. Soc. Series B (Methodological)* 58 (1), 267–288.
- Tiwari, A.K., Abakah, E.J.A., Karikari, N.K., Hammoudeh, S., 2022. Time-varying dependence dynamics between international commodity prices and Australian industry stock returns: a perspective for portfolio diversification. *Energy Econ.* 108, 105891. <https://doi.org/10.1016/j.eneco.2022.105891>.
- Ulucak, R., 2020. How do environmental technologies affect green growth? Evidence from BRICS economies. *Sci. Total Environ.* 712, 136504.
- Urom, C., Mzoughi, H., Ndubuisi, G., Guesmi, K., 2022. Directional predictability and time-frequency spillovers among clean energy sectors and oil price uncertainty. *Q. Rev. Econ. Financ.* 85, 326–341.