# Do Markets Trump Politics? Evidence from Fossil Market Reactions to the Paris Agreement and the US Election

**Samson Mukanjari**† and **Thomas Sterner**‡

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**Abstract**

The Paris Agreement was acclaimed as a milestone for climate negotiations. We evaluate its impact on the stock market value of energy sector firms. Using event study and impulse indicator saturation methods, we show the agreement had only moderate effects, perhaps because the result was anticipated. To evaluate the importance of surprise, we analyze the unexpected election of Donald Trump. Although he is on record in favor of fossil industries, we again find little effect. However, using the difference in performance of renewables versus coal as an indicator of climate adaptation, we find small but significant effects.

**Keywords:** Climate change; event study; impulse indicator saturation; Paris climate agreement.

**JEL codes:** G14, Q4, Q54

† Corresponding author. Samson Mukanjari, Department of Economics, University of Gothenburg, Box 640, SE-405 30 Gothenburg, Sweden. Email address: samson.mukanjari@economics.gu.se, Fax: +46 31 786 10 43, Telephone: +46 31 786 1367.

‡ Thomas Sterner, Department of Economics, University of Gothenburg, Box 640, SE-405 30 Gothenburg, Sweden. Email address: thomas.sterner@economics.gu.se, Fax: +46 31 786 1043, Telephone: +46 31 786 1377.

## 1. Introduction

Media focuses public attention on high-profile events such as political elections and international negotiations. Although important, their effect is sometimes exaggerated compared to the effects of gradual but fundamental shifts in the underlying trends in technology and societal preferences. The year 2016 was described as important to climate because of the Paris Agreement, while the election of Donald Trump as US president has been described as a disaster for the climate. Here, the importance of these events is evaluated using analytical techniques.

The recognition of anthropogenic climate change as an externality requiring global coordination led to the establishment of the UN Framework Convention on Climate Change at the 1992 Earth Summit in Rio de Janeiro. In 2009, the 15th session of the Conference of the Parties (COP 15) in Copenhagen ended without results and, until 2015, a global climate agreement proved elusive, mainly due to disagreements regarding how the burden of emissions reductions would be shared among countries. The run-up to Paris was filled with conflicts concerning the strategy to be followed. Various countries proposed conflicting schemes or instruments but other countries, including notably the large fossil producers, were openly skeptical of these suggestions. Many observers voiced concerns that the Paris COP would once more fail to reach an agreement. Nevertheless, on 12 December 2015, 195 nations signed the Paris climate agreement. After decades of negotiations, this agreement was acclaimed as a significant milestone for climate negotiations. It united all the world's countries behind one text and that text contained a goal that was deemed surprisingly radical: to keep warming well below 2°C above pre-industrial levels 'and to pursue efforts to limit the temperature increase even further to 1.5°C'. On the other hand, the treaty did not allocate reductions among countries nor stipulate the use of efficient policy instruments such as taxes or permit trading. Its main instrument is the required submission of

Intended Nationally Determined Contributions (INDCs). There is, however, no strong mechanism to ensure that these contributions add up to the stated goal of remaining below 2°C, nor are there any enforcement mechanisms. The Paris climate agreement has been reported as a 'success' in the media. However, evaluating the success of such an agreement is difficult because its results in terms of mitigating future climate change will only be witnessed many decades from now.

The Paris agreement also comes at a time of increasing concern by central banks that climate change risks affect financial stability (Batten, Sowerbutts, & Tanaka, 2016; Carney, 2015). In addition, stock markets may price climate risks inefficiently without full disclosure of corporate exposures (Hong, Li, & Xu, 2016). With this perspective, the shorter-term effect of the Paris climate agreement can be evaluated by looking at its impact on energy sector firms. In financial markets, information regarding environmental management is reflected by how market analysts assess the financial impact on a company's performance. In efficient markets, the effect of an unexpected announcement or development will be reflected immediately by changes in asset prices. Several studies have used event study analysis to assess the relationship between firm financial performance and the release of environment-related news (Cram & Koehler, 2000; Dasgupta, Laplante, & Mamingi, 2001; Fisher-Vanden & Thorburn, 2011; Griffin, Jaffe, Lont, & Dominguez-Faus, 2015; Hamilton, 1995; Khanna, Quimio, & Bojilova, 1998).

This paper assesses the 'success' of the recently signed Paris climate agreement in reducing future reliance on fossil fuels, as well as the impact of other climate-relevant political events on fossil markets. If the Paris climate agreement is judged a success, its announcement should spur sizeable negative abnormal returns across fossil fuel markets. There should be a similar increase if the election of President Trump is good news for coal and other fossil fuel industries. Here, we test these hypotheses by applying the standard event study approach (see for example Campbell, Lo, & MacKinlay, 1997) to measure the abnormal returns for a number of fossil fuel stocks in Asia, Australia, Europe, South Africa and North America. The shift from fossils toward cleaner energy should generate significantly negative abnormal returns to investors in the fossil fuel sector while delivering positive gains to renewable energy investors over time.

The rest of the paper is organized as follows. Section 2 presents our estimation strategy and data. Section 3 contains the main empirical results and a discussion of the results, while Section 4 concludes.

## 2. Empirical Strategy and Data

In this section, we present the two main methods of analysis used in the paper namely the event study analysis and impulse indicator saturation method.

### 2.1 Event Study Analysis

Stock market event studies assume an efficient stock market in which prices fully reflect all available information and future expectations. New information about the profitability in a particular industry should change stock prices of firms affected. Stock prices may be affected positively or negatively depending on the nature of the new information. In general, the event study methodology examines return behavior for a sample of firms experiencing a common event. The basic idea is that, because news is unexpected, we can determine the unexpected part of the change in asset prices. The event might take place on the same date or at different points in time for different firms (Kothari & Warner, 2007).

We use the standard methodology (i.e. Campbell et al., 1997; MacKinlay, 1997) to measure the abnormal returns, defined as the difference between the normal return predicted by the market model for the firm and the firm's actual return on a specific date. The market model is a statistical model relating the return of any given security to the return in the overall market. The model assumes a stable linear relation between the market return and the stock return based on the assumed joint normality of asset returns. For any security $i$, we have:

$$r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it} \qquad (1)$$

$$E[\epsilon_{it}] = 0 \text{ and } \mathrm{Var}[\epsilon_{it}] = \sigma_{\epsilon_i}^2$$

Equation 1 is based on the assumption that, in the absence of unexpected news (i.e., during the estimation period), the relationship between the returns to the firm and the returns on the market index should be unchanged; therefore, the expected value of the abnormal returns $\epsilon_{it}$ is zero. The firm-specific parameters of the market model are estimated using least squares and are denoted by $\alpha_i$, $\beta_i$ and $\sigma_{\epsilon_i}^2$.[3] Equation 1 usually is referred to as the single-factor model because it only controls for the market return. The abnormal return ($\epsilon_{it}$) for firm $i$ is generated on a given event-related day $t$ when unexpected news affects the return for the firm ($r_{it}$) without affecting the market return ($r_{mt}$). The abnormal return $\epsilon_{it}$ for the $i$th firm at time $t$ is then given as $\epsilon_{it} = r_{it} - (\hat{\alpha}_i + \hat{\beta}_i r_{mt})$. Normally, one can use several event windows – i.e., intervals around the event date over which markets are likely to have incorporated changing expectations. This is important because, if the event was partially expected, some of the abnormal return behavior should show up in the pre-event period. Likewise, some period post-event is included in the event window if markets are inefficient and respond with a lag.

[3] We also estimate Equation 1 using the GARCH(1,1) specification which represents the error term as a generalized autoregressive conditional heteroskedasticity model following Bollerslev (1986).

From the estimated residuals in Equation 1, the cumulative abnormal returns $(CAR_{it})$ are generated as $CAR_{i,(t_0,t_1)} = \sum_{t=t_0}^{t_1} \epsilon_{it}$, where $t_0$ is the first day of the event window. The cumulative average abnormal returns for a sample of $N$ stocks over the event window is given as $CAAR_{(t_0,t_1)} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,(t_0,t_1)}$. Given that more elaborate pricing models rarely add much difference to the results, especially for short event windows, (Campbell et al., 1997; MacKinlay, 1997), we prefer the standard one-factor market model.

We analyze different energy markets using equally weighted portfolios. The analysis is conducted at the global level for all energy sources as well as at country level for coal. The country-level analysis includes coal companies from North America, Asia, Africa, Australia and Europe. We assess whether the Paris climate agreement and the US election had any impact on fossil markets by formally testing the null hypothesis that the event has no impact on abnormal returns.

A common problem that often plagues event study analysis arises from event clustering, i.e., the event becomes news at the same time for all firms in the sample, leading to statistical errors.[4] Event clustering leads to contemporaneous correlation across firms (see for example Cram & Koehler, 2000) and the covariance between the abnormal returns will therefore differ from zero. The presence of event clustering means the abnormal returns and the cumulative abnormal returns are not independent across securities. We confront this problem at the global and country level by constructing and analyzing equally weighted portfolios. Given total clustering, we make

[4] Traditional event studies have tended to focus on things such as stock splits and earnings reports, which are firm-specific. A survey of the top four finance journals by Kolari and Pynnönen (2010) finds only 76 studies with potential event clustering for the period 1980 to mid-2007.

use of the test statistic presented in Brown and Warner (1985) which corrects for event clustering. The test statistic is constructed as the ratio of the event day abnormal returns to the estimated standard deviation of those abnormal returns. The standard deviation is estimated from the time series of sample (portfolio) mean returns from the pre-event period $\mathrm{t} = -235$ to $-11$. For any given day *t*, the test statistic is given as:

$$\bar{\epsilon}_t / \hat{S}(\bar{\epsilon}_t), \qquad (2)$$

where

$$\bar{\epsilon}_t = \frac{1}{N} \sum_{i=1}^{N} \epsilon_{it},$$

$$\hat{S}(\bar{\epsilon}_t) = \sqrt{\sum_{t=-235}^{-11} \frac{(\bar{\epsilon}_t - \bar{\bar{\epsilon}})^2}{224}},$$

$$\bar{\bar{\epsilon}} = \frac{1}{225} \sum_{t=235}^{-11} \bar{\epsilon}_t$$

where $N$ is the number of stocks. The test statistic presented in Equation 2 follows a Student-*t* distribution under the null hypothesis if the $\epsilon_t$ are independent, identically distributed and normal. The test statistic is assumed unit normal. For event windows greater than a single day, the test statistic is presented as $CAAR_{(t_0,t_1)} / \left( \sqrt{(t_1 - t_0)} \times \hat{S}(\bar{\epsilon}_t) \right)$. While a range of nonparametric tests have been employed in the literature, parametric tests work well with daily data, while nonparametric tests often perform poorly (Berry, Gallinger, & Henderson Jr, 1990; Brown & Warner, 1985; Dyckman, Philbrick, & Stephan, 1984).

## 2.2 Impulse Indicator Saturation

The event study approach outlined so far is based on imposing the event of interest from the onset. In this section, we present methods that can help detect significant political events, such as the announcement of the Paris climate agreement, ratification of the agreement by key countries, and other climate-related political events, such as the US election in November 2016. The recent US election can be argued to be positive for fossil fuels, especially coal, and presents us with a truly exogenous event affecting energy firms. To a large extent, evidence from prediction markets (see Figure 2) and opinion polls leading up to the announcement of the election results indicate the results were unexpected.[5] There has also been anticipation that the new administration may seek to reverse the US commitment to the global climate agreement. As such, the US presidential election results can be taken as positive news for the fossil sector, especially coal.

Visual analysis of Figure 1 fails to identify any significant changes in energy markets around the date that the Paris climate agreement was announced. A systematic approach using statistical techniques is necessary. Instead of including the event from the onset in a model, we propose also to search for breaks in our dependent variable and check whether any detected breaks coincide with the announcement of the Paris climate agreement and other significant climate news or to combine models that impose shocks and those that detect them automatically. There are several approaches to detecting structural breaks, including the Step- and Impulse Indicator Saturation

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[5] As late as Election Day, a *New York Times* feature entitled the 'The Upshot' reviewed polling data and gave Mr. Trump a 15% chance of winning. Katz, Josh, 'The Upshot: Who Will Be President?', *New York Times*, November 8, 2016, https://www.nytimes.com/interactive/2016/upshot/presidential-polls-forecast.html, archive accessed on January 30, 2017.

(SIS and IIS) methods and the Chow test (see Castle, Doornik, Hendry, & Pretis, 2015; Chow, 1960; Doornik, Hendry, & Pretis, 2013).

[INSERT FIGURE 1 HERE]

IIS treats every data point in the time series as a potential impulse shock. The technique saturates the sample period with a full set of impulse indicators and removes all but the significant ones at a selected level of significance $\alpha$ (set at 0.001). IIS treats the detection of impulses as a model selection exercise. While multiple breaks of different forms such as impulses and changing trends can also be identified by this technique, we seek to detect impulses because a climate agreement is unlikely to result in step shifts in stock returns. It is more likely that we would see a step in stock values – but this corresponds to an impulse in returns. IIS – a flexible and robust break detection technique – is thus suitable for this task, as it does not require prior knowledge of the location of the breaks and does not impose a limit on the number of breaks that can be identified or the length of such breaks. Breaks can also be allowed to occur at the beginning and/or end of the sample. This is an advantage over techniques that do not accommodate breaks at the start and/or end of the sample. To overcome the identification problem that is often attributable to insufficient observations (because of dates too near the start and/or the end of the sample), these techniques often recommend trimming the sample by 15% on either side (Andrews, 1993).

We consider an augmented market model of the following form under the null of no breaks:

$$r_{sct} = \beta_0 + \beta_1' x_t + u_t \qquad (3)$$

where $u_t$ follows an independent normal distribution with zero mean and variance $\delta_u^2$. $r_{sct}$ is the difference between the performance of renewables (proxied by solar indexes) and the performance of coal, (i.e., the difference in stock returns $r_t$ for these two sectors) and thus is an indicator of climate adaptation. $x_t$ is a vector of conditioning variables that include the market return ($r_{mt}$). As in Castle et al. (2015), we add a full set of impulse indicators to Equation 3 to get:

$$r_{sct} = \beta_0 + \beta_1' x_t + \sum_{j=1}^{T} \delta_j \, 1_{\{t=j\}} + u_t \tag{4}$$

Equation 4 is analyzed using IIS to identify outliers. On average, $\alpha T$ indicator variables are retained by chance for a significance level α and $T$ observations. We set α very low at $0.001$. While there are several specifications of impulse indicators, Castle et al. (2015) argue that this should have little impact on the detection of impulses. The period of analysis covers a total of $T = 503$ daily return observations from January 2015 to January 2017. The Paris agreement was announced on 12 December 2015 and the US presidential election results were announced on 9 November 2016. However, using IIS with additional conditioning variables means that we have more variables than the number of observations. IIS therefore applies a general-to-specific selection over the impulse functions. Nonetheless, even with such a large number of potential regressors, only a few are retained for the analysis, demonstrating the power of IIS to control for the false positive rate using a low enough value of $\alpha$. This, according to Doornik et al. (2013), suggests that over-fitting is not a major issue with IIS.

### 2.3 Sample Selection and Data Description

The analysis is conducted using daily financial data from January 2015 collected from the Thompson Reuters Eikon and Bloomberg databases. The daily prices of securities and exchange-traded funds (ETFs) used here are ‘closing’ prices – i.e., prices at which the last transaction in each of the securities occurred during the trading day. Although the global energy industry is composed of many firms, some of the firms are privately held institutions and thus have no active equity trading. We therefore limit our analysis to those stocks and funds for which daily stock prices are publicly available and which trade continuously during the sample period and have non-missing estimation period returns data for at least 100 trading days. This restricts our analysis to a sample in which bankruptcy events have no influence given that a number of firms in the US filed for bankruptcy during the period under analysis. The sampling interval is set to one day because we are using daily stock returns. Because the agreement was announced on 12 December 2015, a non-trading day, the next trading day – 14 December 2015 – is chosen as the event day. For our event study analysis, we make use of several event windows and also report results for the $[-10, +2]$ event window, which coincides with the onset of the COP 21 climate negotiations in Paris. For the announcement, we make use of the 225-trading-day period prior to the event window as the estimation window. Our choice of the estimation window is meant to coincide with about two weeks after the 20th session of the Conference of the Parties (COP 20) in Lima, Peru. The Lima Call for Climate Action paved the way for a new global climate agreement in Paris. Our sample includes firms that are part of major energy indexes and ETFs composed of firms operating in countries responsible for significant global carbon emissions (Tables A1 and A2 in Appendix).

Our ETFs are based on equities and follow a particular index composed of a number of stocks.[6] We therefore exclude commodity-based ETFs or those based on futures contracts, as they are less

[6] Our choice of using ETFs is motivated by the fact that ETFs trade like an individual stock on major stock exchanges and can therefore be bought or sold throughout the trading day. In addition, ETFs provide an efficient way to analyze a wide variety of securities listed in different countries and also allow us to detect effects that are likely to have affected stock prices of all companies in the same direction. Also, for

likely to accurately capture events similar to the one under consideration. In addition, movements in commodity prices are likely largely driven by current demand and supply forces. We also exclude exchange-traded notes on similar grounds.

### 2.4 Timeline of Events

Table 1 sets out the timeline of events leading up to the Paris climate agreement and afterward. Prior to the climate negotiations in Paris, countries had to submit Intended Nationally Determined Contributions (INDCs). Negotiations started on 30 November 2015 and culminated with an agreement on 12 December 2015. The agreement was signed by 195 parties in April 2016. After signing, parties had to individually ratify the agreement after consultations in their respective countries. At the time of ratification, governments could submit their first Nationally Determined Contribution (NDC); otherwise, the INDC submitted ahead of Paris became their first NDC and the first emissions target under the Paris agreement. The agreement was designed to go into effect one month after two thresholds were satisfied: (*i*) ratification by at least 55 countries and (*ii*) the 55 countries should be responsible for at least 55 percent of global emissions of greenhouse gases – the 'double threshold'. The first threshold was met on 21 September 2016, while the second was fulfilled on 5 October 2016, setting the agreement to take effect on 4 November.

[INSERT TABLE 1 HERE]

## 3. Results and Discussion

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nuclear and renewable energy, there are no obvious commodity markets to study. Even for coal and oil, there are many different types of oil and coal; therefore, we prefer to analyze stock prices.

In this section, we firstly present results from the event study analysis using different event windows. We also run the market model using the GARCH(1,1) specification and the results are presented in the appendix. Results for the US 2016 election using the impulse indicator saturation method are then presented and discussed.

### 3.1 Abnormal Returns Related to Announcement

While having the expected signs, with fossils reacting negatively, we do not detect any statistically significant negative mean abnormal returns on the announcement day except for solar energy (Table 2). For solar energy, the significance of the mean CARs persists even as the event window is lengthened to include the entire negotiations. For coal, where we expect the strongest effect, we find no significant effect for the event windows including the post announcement period. In order to capture *ex ante* reactions as a result of market expectations, we also include days prior to the announcement date in the calculation of the abnormal returns. We do find some significant mean cumulative abnormal stock returns but only for coal when we extend the event window to consider the pre-announcement period. An analysis of the mean cumulative abnormal returns over the announcement and post announcement period shows they are largely indistinguishable from zero. These results are in line with the Bank of England results for a limited subsample of energy firms in France, Germany, the UK and the US (Batten et al., 2016).

[INSERT TABLE 2 HERE]

We also do not find any effect at the aggregate industry level (Table 3) for coal. While we do not find any strong post announcement effects for a range of renewable and non-renewable energy stocks except for solar energy, the Paris climate agreement really ought to depress coal stocks given coal's large contribution to carbon emissions (even compared to other fossil fuels).

[INSERT TABLE 3 HERE]

We therefore repeat the analysis of the coal sector using country-level equally weighted portfolios covering all major coal-producing countries. For this analysis, our portfolios include firms that satisfy the following criteria: (*i*) listed in one of the major markets and (*ii*) continuously traded over the sample period and have not filed for bankruptcy during this period and have non-missing estimation period returns data for at least 100 trading days. Criterion (*ii*) therefore restricts the analysis to a sample in which bankruptcy or listing events have no influence on the results.[7] These criteria leave us with a sample of 137 companies in 14 different stock markets (Table A2 in Appendix). Most of these companies are constituents of major global coal indexes and exchange traded funds.

[INSERT TABLE 4 AND 5 HERE]

For most nations, the Paris accord has no effect on domestic coal markets (Table 4 and 5). There is however, a negative statistically significant effect in Australia and South Africa around announcement time. Their reliance on coal exports may expose them to other countries' climate policies that may affect future exports. Globally, the coal industry has been struggling due to a combination of deteriorating prices and weak demand (due to increased energy efficiency, slowing economic growth in major coal-consuming countries and increasing environmental regulations). There has already been substantial disinvestment from coal, even in the absence of a global climate agreement. Companies operating in more mature economies in North America and Europe therefore face increasing pressure. The Paris climate agreement comes at a time when the

[7] Including firms that go bankrupt is not feasible because they have no market values. We note that, because of this exclusion, our methodology may somewhat understate how badly a given sector is faring.

coal industry is in decline and has been for several years. It is within this context, already quite negative for coal and other fossil fuels, that we should interpret the lack of further, statistically significant, negative effects of the accord itself.

The results described above need to be seen within the context of the global push to reduce carbon emissions. Global efforts have largely focused on reducing reliance on coal for three reasons. Firstly, coal emits more carbon per unit of energy. Secondly, the rents from coal are small compared to oil, which has large rents due to very low extraction costs and market power. Policies to subsidize renewable energy or introduce a carbon tax can therefore eliminate coal rents and lead to its substitution by cleaner energy. The discovery of coal resources does not make countries rich in the same way as oil discoveries. By contrast, the marginal cost of oil extraction is generally so low that a carbon tax cannot completely erode rents. Even with an oil price below $40/barrel in 2015, oil-exporting countries continued to bring more oil to the market. Many oil producers actually welcomed the Paris climate agreement. Thirdly, remaining coal reserves are sizeable compared to oil and the supply of coal can be thought of as perfectly elastic. If exploited, this would result in significant carbon emissions. Bauer et al. (2016) present evidence showing that any ambitious climate target will have a drastic impact on coal, resulting in a large part of the reserve remaining unused.[8] The fact that we do not find major effects on coal shares might be interpreted as meaning that investors either predicted the Paris agreement or doubt its credibility. Indeed, investor skepticism regarding the practicality of scaling back fossil

[8] A related idea is that of unburnable carbon and stranded assets, defined as assets that cannot maintain their value or that turn into liabilities well ahead of the end of their expected economic life (see Griffin et al., 2015).

fuel demand within an economically meaningful horizon might contribute to a weak market response (Griffin et al., 2015).

In interpreting our results, there are two keywords: *surprising* and *strong*. It is only when both these words apply simultaneously that we expect to see a strong reaction in the fossil markets.[9] The 'surprise' noted by the media and commentators alike can be explained by the fact that the agreement probably exceeded expectations, given that previous climate change negotiations failed to achieve common ground. Nevertheless, surprise alone is not sufficient – the agreement needs to be strong, i.e., it should provide solutions for anthropogenic climate change. However, current commitments in the INDCs on which the Paris climate agreement is anchored are not consistent with temperature increases below the 2°C and 1.5°C stipulated in the Paris agreement.[10]

Given that these commitments were public knowledge leading up to the Paris climate agreement, markets might already have formed expectations in anticipation of an agreement based on the INDCs. In the presence of partial anticipation by investors, Malatesta and Thompson (1985) argue that the standard event study approach may underestimate the abnormal stock returns, because the announcement of the event only captures the change in the firm's value due to the resolution of the uncertainty regarding the timing of the event. Indeed, this uncertainty has been

[9] It can be said that it is necessary but not sufficient that the announcement of the agreement be *surprising* for markets to react in the first place. For a large reaction to be realized, the agreement has to be *strong* as well.

[10] The shortcomings of voluntary contributions toward optimal provision of a public good have been studied elsewhere in the literature (see Marwell & Ames, 1981).

significant when it comes to climate change negotiations because, despite huge expectations, previous COP meetings such as COP 15 in Copenhagen failed to deliver a global climate agreement. We have tried to incorporate this aspect by considering a longer event window for the analysis of the Paris climate agreement. It is also important to note that market response may tend to be weak in the presence of the uncertainty that often characterizes climate change negotiations.

### 3.2. The US Election and Fossil Markets

The US climate change debate has been characterized by a lack of political consensus. The disagreements in the US climate debate have been intense. Politicians such as Mr. Trump and many other Republicans are significantly more aligned with coal industry interests than are their Democratic counterparts. The recent presidential election produced a result that was not expected by opinion polls or prediction markets (see Figure 2) and therefore presents us with a natural experiment to test the impact of broader political events on fossil markets. Again, we note that globally, fossil fuels do not appear to have benefitted from the election of Mr. Trump, despite his express desire to promote fossils such as coal (Table 6 and 7). We do, however, see that renewables and clean energy experienced statistically significant negative abnormal returns on the announcement day.

[INSERT TABLE 6 AND 7 HERE]

At country-level, the US election appears to have benefited US coal companies (Table 8 – 10). We also report significant positive abnormal returns for South Africa and Thailand around the announcement of the US election results (Table 8).

[INSERT TABLE 8 – 10 HERE]

The lack of a significant reaction to the Paris agreement especially for coal is surprising and we seek therefore to refine them. In Table 11, we present results for several specifications using the Impulse Indicator Saturation (IIS) method. For the purposes of this analysis, we create an index of climate (or conversely coal) sensitivity. It is measured as the *difference* in stock returns in the renewable industries and coal. We are thus using the fact that the timing of these shocks is expected to coincide but the signs are opposite. By looking at the difference in stock returns, we create a more sensitive indicator of policy and maximize the chance of finding some evidence. In addition, given that we are working with daily data, which can be noisy, taking the difference in stock returns can help in getting greater precision in the model estimation. We use the *gets* package in R (Pretis, Reade, & Sucarrat, Forthcoming).

Specification I is an augmented market model which includes a dummy variable *Paris* equal to 1 on the day the Paris climate agreement was announced and zero otherwise. The variable *US Election* is equal to 1 on the day the US 2016 presidential election results were announced. From specification I, we note that both coefficients are statistically significant and have the expected signs. Specification II adds dynamics by allowing for an autoregressive term. In specification III, we allow IIS to search for additional impulses in addition to the ones we have indicated in our baseline regression. Five additional dates are picked up and, when an autoregressive term is added in specification IV, we can detect up to four of these additional impulses. In specifications V and VI, we allow IIS to detect the relevant events on its own; again, the two most important climate-related political events during the two-year period are retained, namely the Paris climate agreement and the US election. Through the above empirical model discovery exercise, IIS allows us to learn from the data. While embedding theory in a broader model can result in chance retention of some residuals from selection, this should not be a major issue provided one chooses a reasonably low level of significance for selection. In our case, we set $\alpha = 0.001$. This gives us a fairly negligible number of false positives.

[INSERT TABLE 11 HERE]

From Table 11, the most striking result is the robustness of our estimates. All specifications tested show a similar pattern, with a positive shock from Paris and a negative shock from the US election for the difference between renewables and coal.

### 3.3 Other Dates of Interest: What More Can We Learn from Indicator Saturation?

The IIS identifies a number of dates, all in 2015, when our simple index of climate compatibility picks up significant impacts. In this section, we elaborate further on these dates. We find positive impacts on 4 and 5 March 2015 as well as 16 December 2015 (Figure 3 and Table 11). On 20 May and 19 June 2015, there was an impact of the opposite sign – good for coal and/or bad for renewables (Figure 3 and Table 11). These dates do not correspond to any very obvious events such as those we have summarized in the negotiation timeline in Table 1. We have searched systematically for explanations by reading the relevant news telegrams from a news service, Retriever[11], using the search words 'climate', 'renewables', 'coal' and 'solar'. A fairly large number of news articles are returned and it is, of course, a matter of judgment what might be of interest. We know, however, that we are looking for large and unexpected events of international significance.

[INSERT FIGURE 3 HERE]

[11] http://web.retriever-info.com.ezproxy.ub.gu.se/services/archive

As a start, we note the absence of dates otherwise considered to be significant climate-related events, such as ratification by various countries and the Paris climate agreement's entry into force on 4 November 2016. These dates do not appear to matter much for stock markets, as they are not detected by IIS. Given that the Paris climate agreement was reached unanimously, one might argue ratification was anticipated. Evidence from the history of international climate agreements such as the 1997 Kyoto Protocol suggests ratification almost always follows the signing of the agreements. In addition, ratification was largely based on the INDCs already submitted before the climate negotiations in Paris.

We turn now to the dates identified by the IIS. For 4 and 5 March 2015, we find several interesting and quite plausible news items that could be contributing elements. The most striking of these is that China's government released plans for further restricting its consumption of coal. At the opening session of the National People's Congress, Premier Li Keqiang said Beijing would move forward with a proposal to reduce energy intensity and hold down coal consumption growth in 'key areas' (*Herald Sun*, 5 March 2015 23:36). This news is also corroborated by other news on the same day, in which the National Development and Reform Commission of China announced, in its just-published annual report, that it would implement policies aimed at further promoting solar as well as wind investments, reducing coal consumption, and controlling the number of energy-intensive projects in polluted regions (*World Coal*, 5 March 2015). On 5 March 2015, Bloomberg also reported that energy storage in the US will more than triple in 2015 as regulators allow use of the technology by utilities and homeowners. Analysts were quoted as saying that this would strengthen Tesla with its 'Giga-factory' for batteries that can store solar energy from day to night.

On 16 December 2015, the other date with an impact that was positive for solar and negative for coal, there are news articles on how global temperatures are at a record high, as well as articles on solar energy, but nothing that was obviously of a magnitude that sticks out as an important factor. Considering the proximity to the Paris agreement, the impact we see might be a delayed result of the negotiations. We note that this date is not picked up in the models that allow for autoregressive terms.

For the two remaining dates, we find quite strong evidence of concern for the climate on 20 May. President Hollande gave an important speech at UNESCO voicing concern for how difficult the Paris negotiations would be and how urgent the process was (AFP, 20 May 2015). On the same day, big losses were reported for two large solar panel producers in Hong Kong (*The Telegraph*, 21 May 2015). On 19 June, negative returns for renewables could be explained by several pieces of bad news for wind power in the UK, with large protests against investments and, simultaneously, news of important reductions in UK subsidies (*The Scotsman*, 20 June 2015, and *Herald*, 20 June 2015).

## 4. Conclusion

This paper presents some evidence of the reaction of firms in the fossil fuel markets to the announcement of the Paris climate agreement and other climate-related political events. If the Paris climate agreement is good for the climate, then we would expect significant negative abnormal returns for fossil fuel stocks across the major markets on the announcement date. We fail to find sizeable and significant effects notably for coal. The lack of a stronger reaction might be due to the Paris agreement being either anticipated or considered weak. Turning to the results of the recent US presidential election, we know that we have an event that is unexpected and positive for coal and other fossil fuels. With carefully designed methods, we are able to find some results, particularly for renewables, but they are smaller than expected – particularly for coal. In this case, a careful analysis is required to evaluate competing explanations. The IIS technique is promising because it allows the researcher to learn from the data. The surprising lack of reaction by global coal markets may be a sign that major events have somewhat less importance than generally believed in the media. More important may be underlying fundamentals such as technical developments making renewables and natural gas cheaper in relation to coal. Thanks to the IIS technique, we found that an important event – the Chinese decision to reduce coal – had important effects on the global market.

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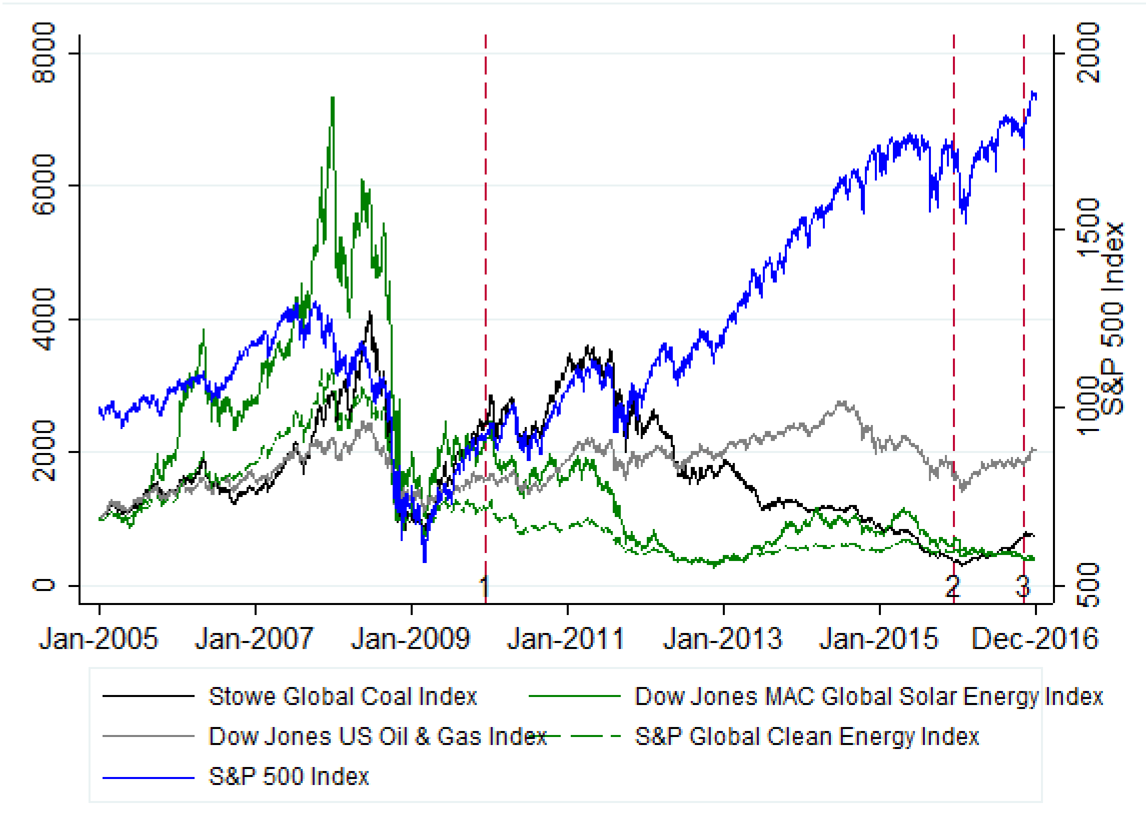
**Figure 1: Energy indexes vs. global benchmarks**

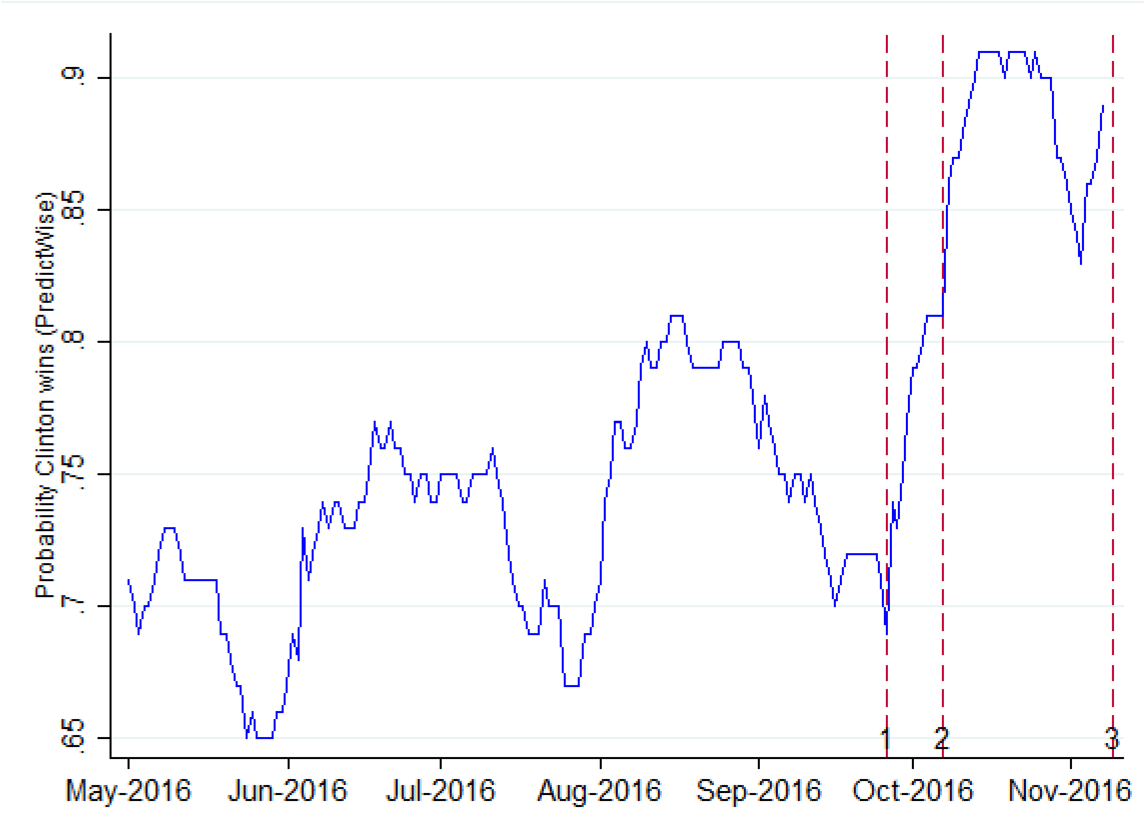



*Notes*: Figure 1 shows the performance of several energy indexes against the S&P 500. The red dashed lines marks days with significant climate related political events. (1) 18/12/2009: The Copenhagen Climate Change Conference comes to an end. (2) 12/12/2015: The Paris Climate Accord is announced. (3) 09/11/2016: Donald Trump wins the US presidential election.

**Table 1: Timeline of Paris Agreement**

| Date | Event |
|---|---|
| 12 December 2014 | COP 20 in Lima ends |
| 31 March 2015 | Countries start submitting INDCs |
| 01 October 2015 | Deadline for submitting INDCs |
| 30 November 2015 | Climate negotiation start in Paris |
| 12 December 2015 | Agreement reached by 195 countries |
| 22 April 2016 | Paris Agreement opened for signature on Earth Day |
| 22 April 2016 | 15 countries submit their instruments of ratification |
| 3 September 2016 | US and China ratify |
| 21 September 2016 | 55 countries ratify the agreement (first threshold passed) |
| 2 October 2016 | India ratifies |
| 4 October 2016 | EU ratifies (second threshold passed) |
| 4 November 2016 | Agreement enters into force |
| 8 November 2016 | COP 22 begins in Marrakech |
| 9 November 2016 | US presidential results announced |

**Figure 2: US Election PredictWise market prices**




*Notes*: The red dashed lines mark days with significant election related events. (1) 26/08/2016: First presidential debate which is won by Hillary Clinton. (2) 07/10/2016: The Washington Post releases a video of an outtake from "Access Hollywood". (3) 09/11/2016: Donald Trump wins the US presidential election.

**Table 2: Paris climate agreement announcement mean cumulative abnormal returns for renewable and non-renewable energy**

| | Coal | Oil | Natural Gas | Solar | Wind | Alternative Energy | Nuclear |
|---|---|---|---|---|---|---|---|
| $CAAR_{-2,0}$ | -4.23% | -1.74% | -3.86% | 3.63% | -1.14% | -0.22% | -1.37% |
| | (-2.013)** | (-0.612) | (-1.233) | (1.201) | (-0.746) | (-0.177) | (-1.014) |
| $CAAR_{-1,0}$ | -3.09% | -2.55% | -4.91% | 3.74% | -0.26% | 0.55% | -0.56% |
| | (-1.802)* | (-1.095) | (-1.919)* | (1.512) | (-0.210) | (0.535) | (-0.507) |
| $CAAR_{0}$ | -1.48% | -0.39% | -2.13% | 4.45% | 0.79% | 0.76% | -0.55% |
| | (-1.219) | (-0.235) | (-1.175) | (2.545)** | (0.896) | (1.035) | (-0.700) |
| $CAAR_{0,+1}$ | -1.88% | 1.74% | -0.82% | 7.06% | 0.39% | 1.28% | 0.34% |
| | (-1.095) | (0.748) | (-0.319) | (2.858)*** | (0.317) | (1.236) | (0.310) |
| $CAAR_{0,+2}$ | -0.35% | -1.90% | -4.68% | 12.91% | 2.15% | 4.20% | 1.10% |
| | (-0.165) | (-0.668) | (-1.493) | (4.264)*** | (1.410) | (3.311)*** | (0.813) |
| $CAAR_{-1,+1}$ | -3.49% | -0.42% | -3.60% | 6.35% | -0.66% | 1.08% | 0.33% |
| | (-1.662)* | (-0.147) | (-1.149) | (2.099)** | (-0.430) | (0.84) | (0.244) |
| $CAAR_{-2,+2}$ | -3.10% | -3.26% | -6.42% | 12.09% | 0.22% | 3.22% | 0.28% |
| | (-1.142) | (-0.886) | (-1.587) | (3.095)*** | (0.113) | (1.965)** | (0.157) |
| $CAAR_{-10,+2}$ | -8.36% | -11.32% | -15.96% | 16.86% | 1.94% | 4.74% | 0.79% |
| | (-1.914)* | (-1.908)* | (-2.446)** | (2.676)*** | (0.612) | (1.793)* | (0.280) |
| Number of stocks | 1 | 4 | 3 | 2 | 1 | 7 | 1 |

This table reports mean cumulative abnormal returns for equally weighted renewable and non-renewable energy ETF portfolios for the Paris climate agreement announcement. The market model is estimated using OLS and the market index is the S&P 500. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 3: Paris agreement announcement mean cumulative abnormal returns using energy indexes**

| | Coal | Oil and Gas | Solar | Alternative Energy |
|---|---|---|---|---|
| $CAAR_{-2,0}$ | -3.06% | -0.50% | 3.40% | -0.48% |
| | (-1.246) | (-0.275) | (1.197) | ( -0.265) |
| $CAAR_{-1,0}$ | -2.05% | -1.00% | 4.11% | 1.07% |
| | (-1.021) | (-0.673) | (1.770)* | (0.717) |
| $CAAR_{0}$ | -1.97% | 0.16% | 3.92% | 1.53% |
| | (-1.389) | (0.153) | (2.387)** | (1.458) |
| $CAAR_{0,+1}$ | -2.77% | 1.82% | 5.51% | 2.33% |
| | (-1.381) | (1.221) | (2.372)** | (1.567) |
| $CAAR_{0,+2}$ | -1.44% | -0.35% | 11.70% | 5.84% |
| | (-0.588) | (-0.190) | (4.115)*** | (3.208)*** |
| $CAAR_{-1,+1}$ | -2.84% | 0.65% | 5.70% | 1.86% |
| | (-1.159) | (0.359) | (2.003)** | (1.024) |
| $CAAR_{-2,+2}$ | -2.53% | -1.01% | 11.18% | 3.82% |
| | (-0.800) | (-0.428) | (3.047)*** | (1.628) |
| $CAAR_{-10,+2}$ | -7.47% | -6.74% | 18.76% | 6.09% |
| | (-1.464) | (-1.777)* | (3.170)*** | (1.608) |

This table reports the mean cumulative abnormal returns for the widely followed global energy indexes. Coal is made up of an equally weighted average of the two main coal indexes namely the Dow Jones US Coal Index (DJUSCL) and the Stowe Global Coal Index (COAL). Oil and Gas is represented by the Dow Jones US Oil and Gas Index (DJUSEN) while Solar is made up of two indexes namely the MAC Global Solar Energy Index (SUNIDX) and the Ardour Solar Energy Index (SOLRX). Alternative Energy is represented by the S&P Global Clean Energy Index (SPGTCED). The market model is estimated using OLS and the market index is the S&P 500. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Figure 3: Paris climate agreement announcement cumulative abnormal returns for renewable and non-renewable energy**

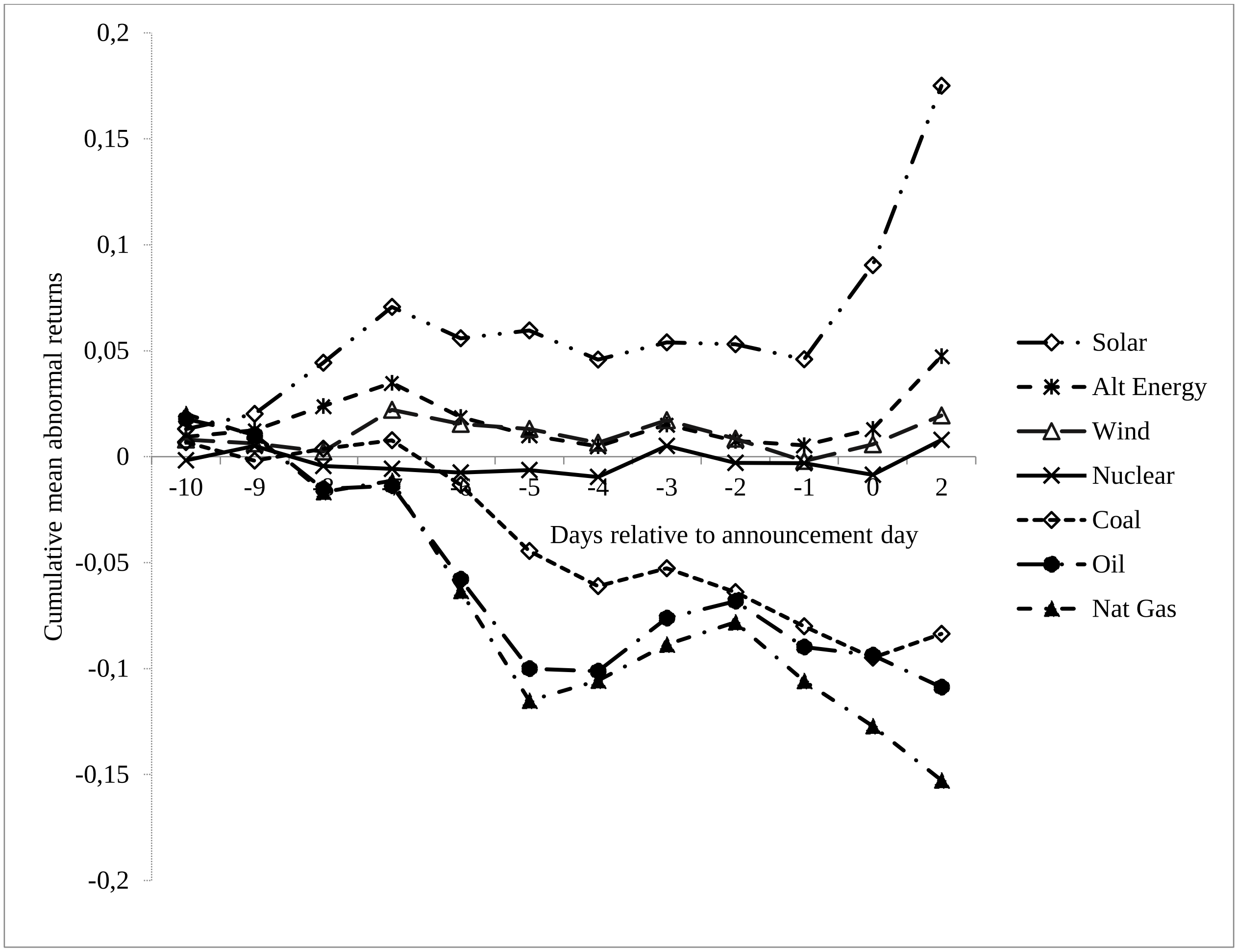


**Table 4: Paris climate agreement country-level announcement mean cumulative abnormal returns for coal†**

| | | China | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Australia | Hong Kong | Shanghai | Shenzhen | India | Indonesia | Japan | Philippines | Poland | Russia | Thailand | South Africa |
| $CAAR_{-2,0}$ | -3.87% | 1.77% | 1.53% | 1.51% | 5.37% | -2.08% | -0.33% | -3.24% | 3.47% | 0.24% | -2.43% | -3.25% |
| | (-1.225) | (0.367) | (0.567) | (0.455) | (1.689)* | (-1.274) | (-0.236) | (-0.960) | (0.708) | (0.070) | (-0.888) | (-1.033) |
| $CAAR_{-1,0}$ | -3.41% | 0.60% | 1.32% | 2.09% | 5.17% | -0.24% | 0.10% | -3.80% | 2.03% | -0.44% | -0.14% | -5.81% |
| | (-1.322) | (0.153) | (0.596) | (0.773) | (1.990)** | (-0.183) | (0.087) | (-1.377) | (0.509) | (-0.160) | (-0.063) | (-2.264)** |
| $CAAR_{0}$ | -2.55% | 1.19% | 0.63% | 1.37% | 2.81% | -0.04% | 0.82% | -2.29% | 1.79% | -0.28% | -1.25% | -3.68% |
| | (-1.400) | (0.430) | (0.402) | (0.715) | (1.530) | (-0.040) | (1.017) | (-1.177) | (0.633) | (-0.146) | (-0.790) | (-2.030)** |
| $CAAR_{0,+1}$ | -5.94% | 2.06% | -0.23% | 0.02% | 1.28% | 1.09% | 0.28% | -1.61% | -0.47% | -0.57% | -2.49% | -2.44% |
| | (-2.305)** | (0.525) | (-0.103) | (0.008) | (0.492) | (0.821) | (0.248) | (-0.583) | (-0.117) | (-0.208) | (-1.115) | (-0.952) |
| $CAAR_{0,+2}$ | -5.19% | -2.45% | -0.39% | 0.17% | -0.89% | -0.08% | -0.27% | -5.35% | -1.53% | -0.33% | -2.81% | 2.86% |
| | (-1.645)* | (-0.510) | (-0.143) | (0.051) | (-0.278) | (-0.050) | (-0.195) | (-1.585) | (-0.313) | (-0.097) | (-1.025) | (0.910) |
| $CAAR_{-1,+1}$ | -6.76% | 1.47% | 0.46% | 0.75% | 3.64% | 0.89% | -0.44% | -3.11% | -0.22% | -0.73% | -1.39% | -4.57% |
| | (-2.141)** | (0.305) | (0.170) | (0.225) | (1.14) | (0.544) | (-0.313) | (-0.921) | (-0.045) | (-0.216) | (-0.506) | (-1.454) |
| $CAAR_{-2,+2}$ | -6.39% | -1.91% | 0.52% | 0.31% | 1.68% | -2.12% | -1.41% | -6.30% | 0.14% | 0.19% | -3.99% | 3.30% |
| | (-1.568) | (-0.307) | (0.149) | (0.072) | (0.408) | (-1.009) | (-0.789) | (-1.445) | (0.023) | (0.044) | (-1.128) | (0.813) |
| $CAAR_{-10,+2}$ | -9.63% | -5.24% | -2.27% | -1.08% | -0.33% | -7.37% | 0.54% | -1.67% | -6.64% | -1.18% | -4.38% | -6.02% |
| | (-1.466) | (-0.523) | (-0.403) | (-0.157) | (-0.050) | (-2.171)** | (0.186) | (-0.237) | (-0.652) | (-0.168) | (-0.769) | (-0.921) |
| Number of stocks | 23 | 21 | 22 | 7 | 5 | 16 | 4 | 3 | 2 | 4 | 5 | 9 |

This table reports country-level mean cumulative abnormal returns for the major coal-producing and exporting countries using equally weighted portfolios. The market model is estimated using OLS and the market is proxied by the local market index. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

[†]We make use of the Thompson Reuters Business Classification (TRBC) to construct our country level portfolios and focus on primary quotes. The TRBC is a market-based classification system in which companies are assigned an industry based on the end market they serve rather than the products or services they offer. Market-based classification emphasizes the usage of a product rather than the materials used for the manufacturing process. The TRBC recognizes that the market served is a key determinant of firm performance and thus groups together firms that share similar market characteristics.

**Table 5: Paris climate agreement country-level announcement mean cumulative abnormal returns for coal**

| | United States | | |
|---|---|---|---|
| | Full Sample | NYSE | NASDAQ |
| $CAAR_{-2,0}$ | -4.63% | -5.02% | -4.47% |
| | (-0.912) | (-0.982) | (-0.584) |
| $CAAR_{-1,0}$ | -5.00% | -6.20% | -2.93% |
| | (-1.206) | (-1.488) | (-0.469) |
| $CAAR_{0}$ | -3.76% | -5.06% | -1.30% |
| | (-1.281) | (-1.715)* | (-0.294) |
| $CAAR_{0,+1}$ | -3.84% | -3.95% | -3.63% |
| | (-0.927) | (-0.946) | (-0.580) |
| $CAAR_{0,+2}$ | -3.72% | -2.05% | -6.90% |
| | (-0.733) | (-0.401) | (-0.901) |
| $CAAR_{-1,+1}$ | -5.09% | -5.09% | -5.26% |
| | (-1.002) | (-0.997) | (-0.687) |
| $CAAR_{-2,+2}$ | -4.60% | -2.01% | -10.07% |
| | (-0.702) | (-0.305) | (-1.019) |
| $CAAR_{-10,+2}$ | -14.39% | -11.79% | -20.26% |
| | (-1.361) | (-1.109) | (-1.271) |
| Number of stocks | 15 | 10 | 5 |

This table reports mean cumulative abnormal returns for the major US coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using OLS and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ sample. We use the S&P 500 for the full sample. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 6: Announcement mean cumulative abnormal returns for renewable and non-renewable energy portfolios (US election)**

| | Coal | Oil | Natural Gas | Solar | Wind | Alternative Energy | Nuclear |
|---|---|---|---|---|---|---|---|
| $CAAR_{-5,-1}$ | -2.81% | -1.79% | -3.49% | -1.33% | -2.88% | -0.76% | 0.27% |
| | (-0.829) | (-0.482) | (-0.444) | (-0.414) | (-1.523) | (-0.504) | (0.174) |
| $CAAR_{0}$ | 0.45% | 0.84% | 1.02% | -6.44% | -4.38% | -2.83% | -4.49% |
| | (0.294) | (0.502) | (0.291) | (-4.483)*** | (-5.174)*** | (-4.175)*** | (-6.412)*** |
| $CAAR_{0,+1}$ | -1.71% | 0.98% | 0.45% | -6.76% | -7.46% | -3.55% | -3.73% |
| | (-0.801) | (0.415) | (0.092) | (-3.329)*** | (-6.228)*** | (-3.713)*** | (-3.772)*** |
| $CAAR_{0,+2}$ | -2.50% | -1.19% | -2.26% | -8.17% | -8.00% | -2.88% | -5.06% |
| | (-0.953) | (-0.411) | (-0.371) | (-3.284)*** | (-5.455)*** | (-2.459)** | (-4.173)*** |
| $CAAR_{0,+5}$ | -6.26% | 1.93% | 2.22% | -6.10% | -10.88% | -2.77% | -4.42% |
| | (-1.688)* | (0.474) | (0.258) | (-1.735)* | (-5.247)*** | (-1.668)* | (-2.582)*** |
| Number of stocks | 1 | 4 | 4 | 2 | 1 | 7 | 1 |

This table reports mean cumulative abnormal returns for equally weighted energy ETF portfolios for the US presidential election. The market model is estimated using OLS and the market index is the S&P 500. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 7: Announcement mean cumulative abnormal returns for energy indexes (US election)**

| | Coal | Oil and Gas | Solar | Alternative Energy |
|---|---|---|---|---|
| $CAAR_{-5,-1}$ | -0.39%<br>(-0.107) | -1.08%<br>(-0.443) | -1.26%<br>(-0.400) | -2.35%<br>(-1.047) |
| $CAAR_{0}$ | -0.42%<br>(-0.259) | 0.25%<br>(0.230) | -6.12%<br>(-4.332)*** | -5.88%<br>(-5.865)*** |
| $CAAR_{0,+1}$ | 1.92%<br>(0.840) | 0.21%<br>(0.137) | -6.06%<br>(-3.032)*** | -7.97%<br>(-5.622)*** |
| $CAAR_{0,+2}$ | 2.01%<br>(0.719) | -1.27%<br>(-0.672) | -7.22%<br>(-2.950)*** | -8.81%<br>(-5.075)*** |
| $CAAR_{0,+5}$ | -3.78%<br>(-0.956) | 0.23%<br>(0.086) | -7.04%<br>(-2.032)** | -9.16%<br>(-3.730)*** |

This table reports the mean cumulative abnormal returns for the widely followed global energy indexes. Coal is made up of an equally weighted average of the two main coal indexes namely the Dow Jones US Coal Index (DJUSCL) and the Stowe Global Coal Index (COAL). Oil and Gas is represented by the Dow Jones US Oil and Gas Index (DJUSEN) while for Solar we use two indexes namely the MAC Global Solar Energy Index (SUNIDX) and the Ardour Solar Energy Index (SOLRX). Alternative Energy is represented by the S&P Global Clean Energy Index (SPGTCED). The market model is estimated using OLS and the market index is the S&P 500. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 8: US election country-level announcement mean cumulative abnormal returns for coal**

| | Australia[1] | China: Hong Kong | China: Shanghai | China: Shenzhen | India | Indonesia | Japan | Philippines | Poland | Russia | Thailand | South Africa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $CAAR_{-5,-1}$ | -2.65% | -1.36% | 0.17% | -0.52% | -3.20% | 6.70% | -1.48% | 0.19% | 0.77% | -1.01% | 1.16% | -1.37% |
| | (-0.787) | (-0.366) | (0.058) | (-0.120) | (-0.930) | (1.534) | (-0.629) | (0.040) | (0.118) | (-0.250) | (0.339) | (-0.389) |
| $CAAR_{0}$ | -4.34% | -0.63% | 1.20% | 1.39% | 1.68% | 0.48% | -0.47% | -0.22% | -1.42% | -0.52% | 3.58% | 1.52% |
| | (-2.878)*** | (-0.382) | (0.904) | (0.710) | (1.095) | (0.246) | (-0.443) | (-0.102) | (-0.486) | (-0.286) | (2.337)** | (0.964) |
| $CAAR_{0,+1}$ | -1.39% | 0.71% | -0.05% | 0.52% | 1.50% | 4.66% | 0.04% | 2.18% | 2.55% | 1.42% | 3.39% | 4.64% |
| | (-0.653) | (0.301) | (-0.026) | (0.189) | (0.688) | (1.686)* | (0.028) | (0.710) | (0.617) | (0.554) | (1.564) | (2.081)** |
| $CAAR_{0,+2}$ | -0.73% | 1.56% | 1.19% | 3.78% | 2.43% | 6.16% | -1.24% | 3.12% | 4.33% | 2.15% | 4.05% | 6.46% |
| | (-0.278) | (0.543) | (0.517) | (1.117) | (0.912) | (1.821)* | (-0.681) | (0.830) | (0.856) | (0.684) | (1.528) | (2.367)** |
| $CAAR_{0,+5}$ | -3.51% | 1.80% | 0.64% | 4.38% | -3.55% | 0.46% | 0.16% | 3.88% | 4.54% | 3.20% | 0.18% | 1.56% |
| | (-0.951) | (0.443) | (0.196) | (0.916) | (-0.943) | (0.095) | (0.063) | (0.728) | (0.635) | (0.722) | (0.048) | (0.405) |
| Number of stocks | 24 | 20 | 23 | 5 | 4 | 15 | 4 | 3 | 2 | 4 | 5 | 8 |

This table reports country-level mean cumulative abnormal returns for the major coal-producing and exporting countries using equally weighted portfolios. The market model is estimated using OLS and the market is proxied by the local market index. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

[1] On 9 November 2016, the Queensland Parliament passed the Environmental Protection (Underground Water Management) and Other Legislation Amendment Act that seeks to tighten groundwater license requirements for mines.

**Table 9: US election country-level announcement mean cumulative abnormal returns for coal**

| | United States | | | | |
|---|---|---|---|---|---|
| | Full Sample | | NYSE | | NASDAQ |
| | I | II† | III | IV† | V |
| $CAAR_{-5,-1}$ | -2.84% | -2.91% | -3.50% | -3.69% | -1.36% |
| | (-0.509) | (-0.572) | (-0.540) | (-0.650) | (-0.268) |
| $CAAR_{0}$ | 10.74% | 7.72% | 10.07% | 5.46% | 12.24% |
| | (4.303)*** | (3.390)*** | (3.478)*** | (2.149)** | (5.406)*** |
| $CAAR_{0,+1}$ | 11.92% | 7.82% | 11.28% | 5.05% | 13.36% |
| | (3.377)*** | (2.428)** | (2.754)*** | (1.405) | (4.171)*** |
| $CAAR_{0,+2}$ | 12.17% | 9.47% | 10.44% | 6.17% | 16.07% |
| | (2.816)*** | (2.401)** | (2.081)** | (1.403) | (4.097)*** |
| $CAAR_{0,+5}$ | 10.03% | 6.42% | 9.83% | 4.39% | 10.48% |
| | (1.640) | (1.151) | (1.385) | (0.706) | (1.889)* |
| Number of stocks | 13 | 12 | 9 | 8 | 4 |

This table reports mean cumulative abnormal returns for the major US coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using OLS and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ subsample. We use the S&P 500 Index for the full sample. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

†Column II and IV represent results excluding Peabody Energy.

**Table 10: US election country-level announcement mean abnormal returns for coal**

| | United States | | | | |
|---|---|---|---|---|---|
| | Full Sample | | NYSE | | NASDAQ |
| | I | II† | III | IV† | V |
| -5 | -0.91% | -0.88% | -0.94% | -0.90% | -0.83% |
| | (-0.364) | (-0.385) | (-0.325) | (-0.354) | (-0.367) |
| -4 | 1.96% | 2.00% | 2.23% | 2.33% | 1.33% |
| | (0.784) | (0.876) | (0.772) | (0.916) | (0.589) |
| -3 | 0.80% | 0.88% | -0.16% | -0.15% | 2.95% |
| | (0.320) | (0.388) | (-0.054) | (-0.059) | (1.302) |
| -2 | -3.62% | -3.99% | -3.15% | -3.66% | -4.66% |
| | (-1.449) | (-1.752)* | (-1.089) | (-1.439) | (-2.056)** |
| -1 | -1.07% | -0.92% | -1.48% | -1.31% | -0.15% |
| | (-0.429) | (-0.406) | (-0.512) | (-0.516) | (-0.066) |
| 0 | 10.74% | 7.72% | 10.07% | 5.46% | 12.24% |
| | (4.303)*** | (3.390)*** | (3.478)*** | (2.149)* | (5.406)*** |
| +1 | 1.18% | 0.10% | 1.21% | -0.41% | 1.12% |
| | (0.472) | (0.043) | (0.416) | (-0.162) | (0.494) |
| +2 | 0.25% | 1.65% | -0.84% | 1.12% | 2.71% |
| | (0.102) | (0.726) | (-0.289) | (0.442) | (1.196) |
| +3 | 2.28% | 1.55% | 3.01% | 2.01% | 0.63% |
| | (0.913) | (0.681) | (1.040) | (0.792) | (0.278) |
| +4 | -3.77% | -3.96% | -2.88% | -3.06% | -5.78% |
| | (-1.511) | (-1.741)* | (-0.994) | (-1.203) | (-2.551)** |
| +5 | -0.65% | -0.64% | -0.75% | -0.74% | -0.44% |
| | (-0.262) | (-0.280) | (-0.258) | (-0.290) | (-0.195) |
| Number of stocks | 13 | 12 | 9 | 8 | 4 |

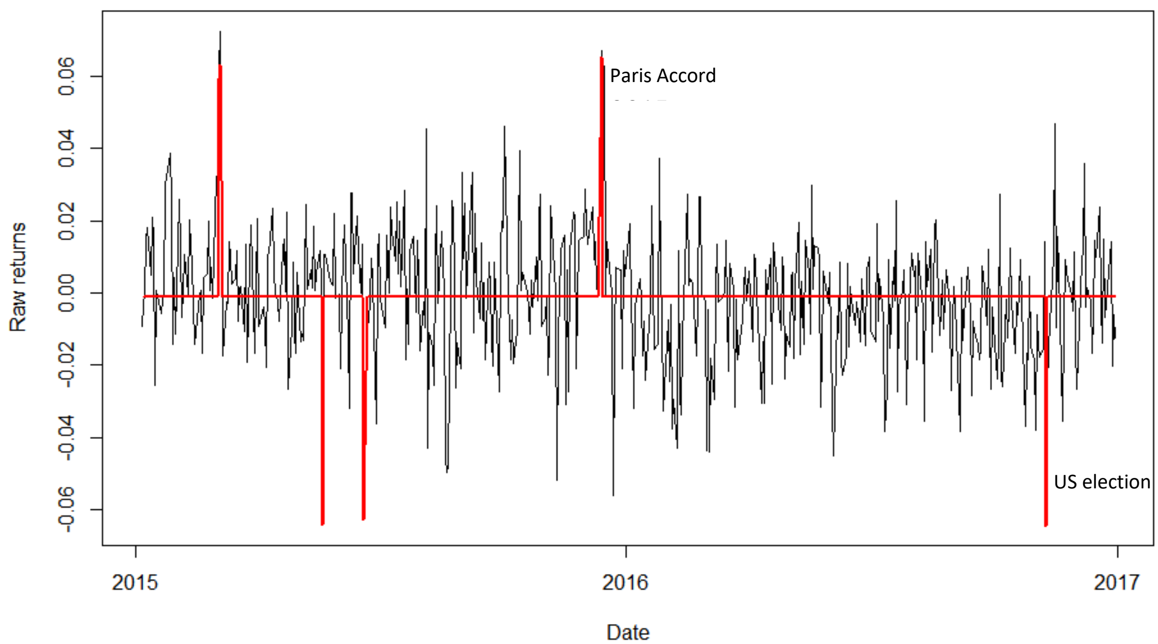
This table reports mean abnormal returns for the major US coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using OLS and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ subsample. We use the S&P 500 Index for the full sample. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.
†Column II and IV represent results excluding Peabody Energy.

**Table 11: Output from impulse indicator saturation to detect relevant climate-related political and market events between January 2015 and 2017**

| | I | II | III | IV | V | VI |
|---|---|---|---|---|---|---|
| Market Returns | 0.3375***<br>(0.0889) | 0.3220***<br>(0.0881) | 0.3123***<br>(0.0837) | 0.3194***<br>(0.0840) | 0.3332***<br>(0.0844) | 0.3194***<br>(0.0840) |
| Paris | 0.0665***<br>(0.0180) | 0.0663***<br>(0.0177) | 0.0668***<br>(0.0169) | 0.0664***<br>(0.0169) | 0.0666***<br>(0.0171) | 0.0664***<br>(0.0169) |
| US Election | -0.0615***<br>(0.0180) | -0.0640***<br>(0.0178) | -0.0611***<br>(0.0169) | -0.0635***<br>(0.0169) | -0.0615***<br>(0.0171) | -0.0635***<br>(0.0169) |
| $r_{sc(t-1)}$ | | 0.1693***<br>(0.0426) | | 0.1419***<br>(0.0412) | | 0.1419***<br>(0.0412) |
| 04 March 2015 | | | 0.0648***<br>(0.0169) | 0.0604***<br>(0.0170) | 0.0648***<br>(0.0171) | 0.0604***<br>(0.0170) |
| 05 March 2015 | | | 0.0736***<br>(0.0169) | 0.0644***<br>(0.0171) | 0.0734***<br>(0.0171) | 0.0644***<br>(0.0171) |
| 20 May 2015 | | | -0.0628***<br>(0.0169) | -0.0634***<br>(0.0169) | -0.0629***<br>(0.0171) | -0.0634***<br>(0.0169) |
| 19 June 2015 | | | -0.0597***<br>(0.0169) | -0.0619***<br>(0.0169) | -0.0597***<br>(0.0171) | -0.0619***<br>(0.0169) |
| 16 December 2015 | | | 0.0596***<br>(0.0169) | | | |
| constant | -0.0012<br>(0.0008) | -0.0010<br>(0.0008) | -0.0013*<br>(0.0008) | -0.0010<br>(0.0008) | -0.0012<br>(0.0008) | -0.0010<br>(0.0008) |
| Ljung-Box AR(2) | 15.2672<br>[0.0001]† | 0.2395<br>[0.8872] | 11.5635<br>[0.0007] | 0.2920<br>[0.8642] | 13.2523<br>[0.0003] | 0.2920<br>[0.8642] |
| Ljung-Box ARCH(1) | 8.7764<br>[0.0031] | 2.6176<br>[0.1057] | 0.5828<br>[0.4452] | 0.0365<br>[0.8484] | 0.7776<br>[0.3779] | 0.0365<br>[0.8484] |
| Jarque-Bera | 34.3861<br>[0.0000] | 26.1072<br>[0.0000] | 7.5473<br>[0.0230] | 7.9635<br>[0.0187] | 7.9783<br>[0.0185] | 7.9635<br>[0.0187] |
| Log-likelihood | 1309.95 | 1314.70 | 1344.38 | 1340.95 | 1338.15 | 1340.95 |

This table presents results from several specifications using Impulse Indicator Saturation (IIS) with $\alpha = 0.001$. The baseline regression in specification I includes a dummy variable *Paris* equal to 1 on the day the Paris agreement was announced and zero otherwise. The variable *US Election* is equal to 1 on the day the US 2016 presidential election results were announced. Specification II adds some dynamics by allowing for an autoregressive term. Specification III uses the IIS to search for outliers in addition to the ones included in the baseline model, while specification IV adds an autoregressive term to III. In specification V, no outliers are imposed on the model in advance and no autoregressive term is included, while specification VI includes an additional autoregressive term not included in V. The dependent variable used is the stock return differential between solar and coal. Standard errors are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ denote significance at 10%, 5% and 1% respectively. †$p$-values in square brackets.

**Figure 3: Impulse indicator saturation detected climate-related political and market events between January 2015 and December 2017**



## Technical Appendix

This section provides some technical definitions which complement the analysis in the main paper.

### Exchange Traded Funds

Exchange Traded Funds (ETFs) are portfolios or baskets of securities traded on a stock exchange analogous to individual company stocks. They are similar to mutual funds but unlike mutual funds – bought and sold only at the end of the day through a mutual fund company – ETFs trade all day and investors transact through brokerage firms similar to individual stocks. ETFs are usually designed to replicate well-known market indexes such as the S&P 500 but others also track customized indexes. Customized indexes are not market indexes as their intention is not to measure the value or performance of financial markets or sectors. To this extend, customized indexes can be considered investment strategies designed for a specific task.

While the supply and demand for ETF shares is driven by the values of the underlying securities in the index they track, Ferri (2011) also points out that other factors can and do affect ETF market prices. Since ETF shares are based on an underlying portfolio of securities, when their prices deviate from those of the underlying securities, authorized participants step in and drive ETF prices higher through arbitrage. Because of this process, short sellers are unable to manipulate ETF prices.

ETFs can be actively managed in which case they may not necessarily follow a particular index but rather invest in a portfolio of securities that is chosen at the discretion of the fund manager. The idea is that better performance can be attained through active management than following a particular index. Since actively managed ETFs invest in a portfolio with securities directly selected by the fund manager, the composition of the portfolio therefore changes more frequently than that of other ETFs tracking an index. Actively managed fund's holdings are therefore required to be disclosed daily.

***Leveraged and Short ETFs***

Short/bear/inverse ETFs move in the opposite direction of the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. For example, in our sample, the ProShares Short Oil and Gas ETF (DDG) is a short ETF that 'seeks daily results, before fees and expenses, that correspond to the inverse (-1x) of the daily performance of the Dow Jones U.S. Oil and Gas Index.' Short ETFs can also be leveraged in which case they are designed to magnify the inverse of an index's performance. For example, the ProShares UltraShort Oil and Gas ETF (DUG) in our sample is a leveraged short ETF designed to produce results two times the inverse (-2x) of the Dow Jones U.S. Oil and Gas Index's daily performance.

The Direxion Daily Natural Gas Related Bull 3x Shares (GASL) is a leveraged ETF that seek returns that are three times (3x) the ISE-Reserve Natural Gas Index's daily performance. The target index in this case turns out to be a customized index.

It is important to note that leveraged and short ETFs are actively managed and therefore seek to rebalance their investment strategies on a daily basis. In our sample, we have three actively managed ETFs confined to the oil and natural gas sectors. Movements in the stock prices of these ETFs can thus to some extend reflect the active management by the fund managers behind them. We however, feel this should not significantly affect our results since actively managed ETFs make up just 50% of our natural gas portfolio and 33% of the oil sector sample. Our event study analysis makes adjustment for short ETFs. We do not make any distinction whether an ETF follows a customized index or a traditional market index.

***Thin trading***

Thin trading arises when stocks do not trade every day and presents problems of its own. While this is not a major problem with the US listed ETFs we analyze, it is a potential problem with some of our country level analysis (Canada and UK). It is standard for most data sets to treat non-trading days by repeating the last realized transaction price from the previous day. Calculating daily returns from the recorded price series therefore gives zero returns for non-trading days. In addition, when trading takes place, the absolute value of realized returns tends to be relatively large.

When requesting data from Thompson Reuters Eikon, one can choose how missing prices have to be treated when downloading the data. When one chooses the price on non-trading days to be reported as missing, any remaining zero raw returns are assumed to be a result of unchanging prices on two consecutive days. Alternatively, if some of the non-missing prices are a result of using the average of bid and ask quotes on days with no trade, a zero return can arise when market makers do not adjust their bid and ask quotes on two consecutive days. Treating missing prices by repeating the last realized price generates zero returns often called lumped returns. The presence of numerous zeros in the return series however results in the underestimation of the variance of returns and may lead to incorrect inference regarding abnormal performance.

Other methods used include the ‘uniform returns’ procedure in which lumped returns are first computed and thereafter the average daily return is allocated to each day within the multi-period interval between two subsequent trades. This however, leads to some smoothing of returns and ultimately leads to the same issues with lumped returns. A third alternative, the trade-to-trade procedure, involves first calculating the returns over periods with non-missing price. Trade-to-trade returns are then calculated for the market index over the same interval. These two sets of return series are then used to estimate the market model before computing the abnormal returns. Trade-to-trade returns yield better results than the other methods of treating missing returns and are therefore used in this paper. In terms of estimating the benchmark model, when an estimation period contains one or more missing values, we do not use the first succeeding non-missing return. This is because it is a multi-period return whose inclusion can lead to unexpected consequences in estimating parameters of the benchmark model. We therefore treat the first non-missing return following a sequence of missing estimation period returns as a missing value. In cases where the non-missing return occurs in the event window, we adjust the abnormal returns to account for the multi-period character of the first post-missing return.

## Online Appendix: Additional Tables

**Table 1: Paris climate agreement announcement mean cumulative abnormal returns for renewable and non-renewable energy**

| | Coal | Oil | Natural Gas | Solar | Wind | Alternative Energy | Nuclear |
|---|---|---|---|---|---|---|---|
| $CAAR_{-2,0}$ | -4.21% | -1.72% | -3.89% | 3.64% | -1.17% | -0.19% | -1.37% |
| | (-2.005)** | (-0.605) | (-1.242) | (1.204) | (-0.769) | (-0.153) | (-1.014) |
| $CAAR_{-1,0}$ | -3.09% | -2.56% | -4.97% | 3.75% | -0.29% | 0.59% | -0.56% |
| | (-1.804)* | (-1.099) | (-1.941)* | (1.517) | (-0.236) | (0.565) | (-0.507) |
| $CAAR_{0}$ | -1.45% | -0.35% | -2.08% | 4.44% | 0.79% | 0.75% | -0.55% |
| | (-1.199) | (-0.212) | (-1.149) | (2.544)** | (0.897) | (1.025) | (-0.700) |
| $CAAR_{0,+1}$ | -1.82% | 1.84% | -0.69% | 7.05% | 0.40% | 1.26% | 0.34% |
| | (-1.060) | (0.790) | (-0.269) | (2.854)*** | (0.325) | (1.21) | (0.310) |
| $CAAR_{0,+2}$ | -0.24% | -1.73% | -4.45% | 12.89% | 2.17% | 4.15% | 1.10% |
| | (-0.115) | (-0.607) | (-1.419) | (4.258)*** | (1.426) | (3.272)*** | (0.813) |
| $CAAR_{-1,+1}$ | -3.46% | -0.37% | -3.58% | 6.36% | -0.68% | 1.09% | 0.33% |
| | (-1.646)* | (-0.129) | (-1.141) | (2.101)** | (-0.445) | (0.860) | (0.244) |
| $CAAR_{-2,+2}$ | -3.00% | -3.11% | -6.26% | 12.08% | 0.21% | 3.21% | 0.28% |
| | (-1.106) | (-0.844) | (-1.547) | (3.093)*** | (0.108) | (1.957)* | (0.157) |
| $CAAR_{-10,+2}$ | -8.20% | -11.07% | -15.81% | 16.88% | 1.85% | 4.78% | 0.79% |
| | (-1.876)* | (-1.866)* | (-2.422)** | (2.679)*** | (0.585) | (1.809)* | (0.280) |
| Number of stocks | 1 | 4 | 3 | 2 | 1 | 7 | 1 |

This table reports mean cumulative abnormal returns for equally weighted renewable and non-renewable energy ETF portfolios for the Paris climate agreement announcement. The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

## Table 2: Paris climate agreement announcement mean abnormal returns for renewable and non-renewable energy

| Day relative to event date (Day 0 = December 14, 2015) | Coal | | Oil | | Natural Gas | | Solar | | Wind | | Alternative Energy | | Nuclear | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -10 | 0.69% | 0.69% | 1.78% | 1.77% | 2.01% | 1.97% | 1.30% | 1.33% | 0.80% | 0.79% | 0.93% | 0.95% | -0.17% | -0.17% |
| | (0.568) | (0.571) | (1.083) | (1.078) | (1.112) | (1.088) | (0.746) | (0.763) | (0.910) | (0.895) | (1.275) | (1.290) | (-0.221) | (-0.221) |
| -9 | -0.88% | -0.85% | -0.74% | -0.68% | -1.01% | -0.93% | 0.71% | 0.71% | -0.17% | -0.16% | 0.31% | 0.30% | 0.67% | 0.67% |
| | (-0.727) | (-0.697) | (-0.447) | (-0.411) | (-0.559) | (-0.514) | (0.409) | (0.404) | (-0.191) | (-0.180) | (0.429) | (0.405) | (0.859) | (0.859) |
| -8 | 0.57% | 0.56% | -2.56% | -2.57% | -2.67% | -2.73% | 2.42% | 2.43% | -0.39% | -0.41% | 1.14% | 1.16% | -0.94% | -0.94% |
| | (0.469) | (0.462) | (-1.554) | (-1.564) | (-1.478) | (-1.506) | (1.385) | (1.390) | (-0.445) | (-0.470) | (1.552) | (1.582) | (-1.204) | (-1.204) |
| -7 | 0.39% | 0.37% | 0.14% | 0.11% | 0.53% | 0.46% | 2.64% | 2.65% | 1.97% | 1.94% | 1.11% | 1.14% | -0.13% | -0.13% |
| | (0.322) | (0.308) | (0.085) | (0.067) | (0.293) | (0.253) | (1.513) | (1.519) | (2.241)** | (2.211)** | (1.512) | (1.551) | (-0.161) | (-0.161) |
| -6 | -2.10% | -2.05% | -4.40% | -4.31% | -5.19% | -5.05% | -1.48% | -1.50% | -0.67% | -0.64% | -1.62% | -1.65% | -0.18% | -0.18% |
| | (-1.736)* | (-1.689)* | (-2.677)*** | (-2.618)*** | (-2.870)*** | (-2.790)*** | (-0.848) | (-0.856) | (-0.759) | (-0.732) | (-2.207)** | (-2.255)** | (-0.233) | (-0.233) |
| -5 | -3.12% | -3.12% | -4.22% | -4.22% | -5.19% | -5.21% | 0.37% | 0.38% | -0.24% | -0.26% | -0.86% | -0.85% | 0.12% | 0.12% |
| | (-2.575)** | (-2.575)** | (-2.567)** | (-2.568)** | (-2.866)*** | (-2.879)*** | (0.214) | (0.217) | (-0.275) | (-0.293) | (-1.180) | (-1.159) | (0.153) | ( 0.153) |
| -4 | -1.66% | -1.66% | -0.13% | -0.13% | 0.95% | 0.92% | -1.38% | -1.37% | -0.65% | -0.67% | -0.52% | -0.50% | -0.33% | -0.33% |
| | (-1.372) | (-1.371) | (-0.078) | (-0.078) | (0.524) | (0.511) | (-0.789) | (-0.786) | (-0.741) | (-0.758) | (-0.709) | (-0.689) | (-0.417) | (-0.417) |
| -3 | 0.85% | 0.85% | 2.51% | 2.50% | 1.71% | 1.68% | 0.82% | 0.83% | 1.07% | 1.05% | 1.03% | 1.04% | 1.47% | 1.47% |
| | (0.704) | (0.702) | (1.526) | (1.523) | (0.944) | (0.926) | (0.471) | (0.474) | (1.213) | (1.194) | (1.400) | (1.422) | (1.883)* | (1.883* |
| -2 | -1.14% | -1.12% | 0.80% | 0.83% | 1.05% | 1.08% | -0.10% | -0.11% | -0.88% | -0.88% | -0.78% | -0.78% | -0.81% | -0.81% |
| | (-0.938) | (-0.923) | (0.488) | (0.506) | (0.578) | (0.594) | (-0.059) | (-0.060) | (-0.995) | (-0.998) | (-1.062) | (-1.064) | (-1.040) | (-1.040) |
| -1 | -1.61% | -1.64% | -2.16% | -2.21% | -2.78% | -2.89% | -0.71% | -0.70% | -1.05% | -1.08% | -0.20% | -0.17% | -0.01% | -0.01% |
| | (-1.329) | (-1.35) | (-1.314) | (-1.342) | (-1.539) | (-1.595) | (-0.406) | (-0.398) | (-1.194) | (-1.231) | (-0.279) | (-0.226) | (-0.016) | (-0.016) |
| 0 | -1.48% | -1.45% | -0.39% | -0.35% | -2.13% | -2.08% | 4.45% | 4.44% | 0.79% | 0.79% | 0.76% | 0.75% | -0.55% | -0.55% |
| | (-1.219) | (-1.199) | (-0.235) | (-0.212) | (-1.175) | (-1.149) | (2.545)** | (2.544)** | (0.896) | (0.897) | (1.035) | (1.025) | (-0.700) | (-0.700) |
| +1 | -0.40% | -0.36% | 2.13% | 2.19% | 1.31% | 1.39% | 2.62% | 2.61% | -0.39% | -0.38% | 0.52% | 0.51% | 0.89% | 0.89% |
| | (-0.330) | (-0.300) | (1.294) | (1.330) | (0.724) | (0.768) | (1.497) | (1.493) | (-0.448) | (-0.437) | (0.714) | (0.690) | (1.139) | (1.139) |
| +2 | 1.53% | 1.58% | -3.64% | -3.57% | -3.86% | -3.76% | 5.84% | 5.83% | 1.75% | 1.77% | 2.92% | 2.90% | 0.76% | 0.76% |
| | (1.263) | (1.300) | (-2.215)** | (-2.170)** | (-2.136)** | (-2.077)** | (3.344)*** | (3.339)*** | (1.994)** | (2.011)** | (3.987)*** | (3.952)*** | (0.970) | (0.970) |
| Number of stocks | 1 | 1 | 4 | 4 | 3 | 3 | 2 | 2 | 1 | 1 | 7 | 7 | 1 | 1 |
| GARCH error | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

This table reports mean abnormal returns for equally weighted renewable and non-renewable energy ETF portfolios for a thirteen-day period surrounding announcement of the Paris climate agreement. The market model is estimated using OLS and the GARCH(1,1) specification and the market index is the S&P

500. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively

**Table 3: Announcement mean cumulative abnormal returns for renewable and non-renewable energy portfolios (US election)**

| | Coal | Oil | Natural Gas | Solar | Wind | Alternative Energy | Nuclear |
|---|---|---|---|---|---|---|---|
| $CAAR_{-5,-1}$ | -2.85% | -1.56% | -2.80% | -1.58% | -2.84% | -0.82% | 0.24% |
| | (-0.843) | (-0.418) | (-0.356) | (-0.491) | (-1.502) | (-0.539) | (0.153) |
| $CAAR_{0}$ | 0.48% | 0.89% | 1.40% | -6.58% | -4.37% | -2.86% | -4.51% |
| | (0.320) | (0.534) | (0.397) | (-4.572)*** | (-5.163)*** | (-4.217)*** | (-6.441)*** |
| $CAAR_{0,+1}$ | -1.69% | 1.08% | 0.95% | -6.95% | -7.44% | -3.59% | -3.75% |
| | (-0.789) | (0.458) | (0.191) | (-3.415)*** | (-6.214)*** | (-3.751)*** | (-3.793)*** |
| $CAAR_{0,+2}$ | -2.50% | -1.04% | -1.75% | -8.37% | -7.97% | -2.92% | -5.08% |
| | (-0.955) | (-0.361) | (-0.286) | (-3.361)*** | (-5.438)*** | (-2.492)** | (-4.191)*** |
| $CAAR_{0,+5}$ | -6.30% | 2.22% | 3.09% | -6.45% | -10.83% | -2.83% | -4.47% |
| | (-1.700)* | (0.544) | (0.358) | (-1.830)* | (-5.224)*** | (-1.708)* | (-2.606)*** |
| Number of stocks | 1 | 4 | 4 | 2 | 1 | 7 | 1 |

This table reports mean cumulative abnormal returns for equally weighted energy ETF portfolios for the US presidential election. The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 4: Announcement mean abnormal returns for energy portfolios (US election)**

| Day relative to event date (Day 0 = November 9, 2016) | Coal | | Oil | | Natural Gas | | Solar | | Wind | | Alternative Energy | | Nuclear | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -1 | -1.59% | -1.59% | -0.79% | -0.74% | -1.90% | -1.73% | 0.81% | 0.72% | -1.47% | -1.46% | -0.08% | -0.10% | -0.17% | -0.18% |
| | (-1.051) | (-1.053) | (-0.472) | (-0.443) | (-0.540) | (-0.491) | (0.568) | (0.504) | (-1.732)* | (-1.723)* | (-0.124) | (-0.143) | (-0.244) | (-0.254) |
| 0 | 0.45% | 0.48% | 0.84% | 0.89% | 1.02% | 1.40% | -6.44% | -6.58% | -4.38% | -4.37% | -2.83% | -2.86% | –† | –† |
| | (0.294) | (0.320) | (0.502) | (0.534) | (0.291) | (0.397) | (-4.483)*** | (-4.572)*** | (-5.174)*** | (-5.163)*** | (-4.175)*** | (-4.217)*** | | |
| 1 | -2.16% | -2.17% | 0.14% | 0.19% | -0.57% | -0.45% | -0.32% | -0.37% | -3.08% | -3.07% | -0.73% | -0.74% | -4.49% | -4.51% |
| | (-1.428) | (-1.436) | (0.085) | (0.114) | (-0.162) | (-0.128) | (-0.225) | (-0.257) | (-3.634)*** | (-3.625)*** | (-1.076) | (-1.089) | (-6.412)*** | (-6.441)*** |
| 2 | -0.78% | -0.82% | -2.16% | -2.12% | -2.72% | -2.69% | -1.41% | -1.43% | -0.54% | -0.53% | 0.67% | 0.67% | 0.75% | 0.75% |
| | (-0.517) | (-0.539) | (-1.300) | (-1.273) | (-0.773) | (-0.765) | (-0.980) | (-0.992) | (-0.640) | (-0.632) | (0.992) | (0.989) | (1.077) | (1.077) |
| 3 | -0.84% | -0.86% | 0.96% | 1.00% | 1.73% | 1.79% | 0.98% | 0.95% | -0.89% | -0.88% | 0.33% | 0.33% | -1.32% | -1.33% |
| | (-0.555) | (-0.571) | (0.575) | (0.602) | (0.491) | (0.507) | (0.683) | (0.661) | (-1.046) | (-1.038) | (0.489) | (0.482) | (-1.893)* | (-1.895)* |
| 4 | -3.58% | -3.56% | 2.66% | 2.71% | 3.68% | 3.95% | -0.40% | -0.49% | -0.77% | -0.77% | 0.07% | 0.04% | 0.63% | 0.62% |
| | (-2.367)** | (-2.354)** | (1.597) | (1.628) | (1.046) | (1.122) | (-0.279) | (-0.343) | (-0.915) | (-0.905) | (0.097) | (0.065) | (0.902) | (0.885) |
| 5 | 0.66% | 0.63% | -0.50% | -0.45% | -0.92% | -0.91% | 1.49% | 1.47% | -1.22% | -1.21% | -0.28% | -0.28% | -0.34% | -0.34% |
| | (0.437) | (0.415) | (-0.299) | (-0.273) | (-0.263) | (-0.257) | (1.035) | (1.021) | (-1.443) | (-1.435) | (-0.412) | (-0.414) | (-0.489) | (-0.489) |
| Number of stocks | 1 | 1 | 4 | 4 | 4 | 4 | 2 | 2 | 1 | 1 | 7 | 7 | 1 | 1 |
| GARCH error | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes | No | Yes |

This table reports mean abnormal returns for a seven-day period around the US election using equally weighted renewable and non-renewable energy ETF portfolios. The market model is estimated using OLS and GARCH(1,1) specification and the market index is the S&P 500. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

†Denotes a day in the event window with missing returns.

**Table 5: Paris agreement announcement mean cumulative abnormal returns using energy indexes**

| | Coal | Oil | Solar | Alternative Energy |
|---|---|---|---|---|
| $CAAR_{-2,0}$ | -2.92% | -0.53% | 3.40% | -0.37% |
| | (-1.192) | (-0.289) | (1.195) | (-0.202) |
| $CAAR_{-1,0}$ | -1.97% | -1.04% | 4.11% | 1.13% |
| | (-0.982) | (-0.702) | (1.770)* | (0.761) |
| $CAAR_{0}$ | -1.91% | 0.19% | 3.91% | 1.58% |
| | (-1.348) | (0.178) | (2.383)** | (1.509) |
| $CAAR_{0,+1}$ | -2.64% | 1.89% | 5.49% | 2.45% |
| | (-1.320) | (1.272) | (2.365)** | (1.647)* |
| $CAAR_{0,+2}$ | -1.25% | -0.20% | 11.67% | 6.02% |
| | (-0.510) | (-0.112) | (4.105)*** | (3.312)*** |
| $CAAR_{-1,+1}$ | -2.70% | 0.66% | 5.69% | 1.99% |
| | (-1.101) | (0.362) | (2.000)** | (1.095) |
| $CAAR_{-2,+2}$ | -2.27% | -0.92% | 11.16% | 4.07% |
| | (-0.715) | (-0.390) | (3.040)*** | (1.734)* |
| $CAAR_{-10,+2}$ | -6.84% | -6.67% | 18.71% | 6.67% |
| | (-1.339) | (-1.757)* | (3.162)*** | (1.760)* |

This table reports the mean cumulative abnormal returns for the widely followed global energy indexes. Coal is made up of an equally weighted average of the two main coal indexes namely the Dow Jones US Coal Index (DJUSCL) and the Stowe Global Coal Index (COAL). Oil and Gas is represented by the Dow Jones US Oil and Gas Index (DJUSEN) while Solar is made up of two indexes namely the MAC Global Solar Energy Index (SUNIDX) and the Ardour Solar Energy Index (SOLRX). Alternative Energy is represented by the S&P Global Clean Energy Index (SPGTCED). The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 6: Announcement mean cumulative abnormal returns for energy indexes (US election)**

| | Coal | Oil | Solar | Alternative Energy |
|---|---|---|---|---|
| $CAAR_{-5,-1}$ | -0.50% | -0.90% | -1.67% | -2.52% |
| | (-0.139) | (-0.369) | (-0.529) | (-1.122) |
| $CAAR_{0}$ | -0.42% | 0.32% | -6.29% | -5.94% |
| | (-0.258) | (0.293) | (-4.440)*** | (-5.928)*** |
| $CAAR_{0,+1}$ | 1.89% | 0.31% | -6.30% | -8.07% |
| | (0.829) | (0.203) | (-3.146)** | (-5.688)*** |
| $CAAR_{0,+2}$ | 1.95% | -1.15% | -7.50% | -8.93% |
| | (0.698) | (-0.606) | (-3.059)** | (-5.139)*** |
| $CAAR_{0,+5}$ | -3.92% | 0.45% | -7.54% | -9.37% |
| | (-0.991) | (0.169) | (-2.174)* | (-3.813)*** |

This table reports the mean cumulative abnormal returns for the widely followed global energy indexes. Coal is made up of an equally weighted average of the two main coal indexes namely the Dow Jones US Coal Index (DJUSCL) and the Stowe Global Coal Index (COAL). Oil and Gas is represented by the Dow Jones US Oil and Gas Index (DJUSEN) while for Solar we use two indexes namely the MAC Global Solar Energy Index (SUNIDX) and the Ardour Solar Energy Index (SOLRX). Alternative Energy is represented by the S&P Global Clean Energy Index (SPGTCED). The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 7: Paris climate agreement country-level announcement mean cumulative abnormal returns for coal†**

| | | China | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Australia | Hong Kong | Shanghai | Shenzhen | India | Indonesia | Japan | Philippines | Poland | Russia | Thailand | South Africa |
| $CAAR_{-2,0}$ | -3.23% | 1.01% | 1.66% | 1.62% | 5.26% | -2.26% | -0.48% | -3.13% | 2.93% | 0.09% | -2.39% | -3.61% |
| | (-1.024) | (0.205) | (0.611) | (0.482) | (1.652)* | (-1.379) | (-0.343) | (-0.928) | (0.591) | (0.027) | (-0.872) | (-1.146) |
| $CAAR_{-1,0}$ | -2.95% | -0.06% | 1.44% | 2.21% | 5.10% | -0.51% | 0.03% | -3.71% | 0.92% | -0.64% | -0.11% | -6.04% |
| | (-1.146) | (-0.014) | (0.650) | (0.807) | (1.963)** | (-0.379) | (0.023) | (-1.346) | (0.227) | (-0.232) | (-0.051) | (-2.352)** |
| $CAAR_{0}$ | -2.14% | 0.96% | 0.76% | 1.54% | 2.77% | -0.28% | 0.72% | -2.33% | 1.52% | -0.38% | -1.23% | -3.72% |
| | (-1.173) | (0.337) | (0.484) | (0.798) | (1.507) | (-0.291) | (0.889) | (-1.193) | (0.533) | (-0.195) | (-0.780) | (-2.049)** |
| $CAAR_{0,+1}$ | -5.40% | 1.88% | -0.09% | 0.29% | 1.20% | 0.90% | 0.09% | -1.59% | -0.16% | -0.47% | -2.45% | -2.46% |
| | (-2.094)** | (0.464) | (-0.039) | (0.107) | (0.460) | (0.671) | (0.076) | (-0.576) | (-0.039) | (-0.172) | (-1.097) | (-0.960) |
| $CAAR_{0,+2}$ | -4.90% | -1.57% | -0.22% | 0.50% | -1.01% | -0.12% | -0.36% | -5.52% | -0.46% | -0.17% | -2.75% | 3.01% |
| | (-1.553) | (-0.317) | (-0.080) | (0.149) | (-0.317) | (-0.071) | (-0.260) | (-1.633) | (-0.094) | (-0.051) | (-1.004) | (0.956) |
| $CAAR_{-1,+1}$ | -6.16% | 0.86% | 0.60% | 0.96% | 3.53% | 0.67% | -0.60% | -2.97% | -0.76% | -0.73% | -1.33% | -4.78% |
| | (-1.952)* | (0.173) | (0.219) | (0.285) | (1.108) | (0.406) | (-0.432) | (-0.880) | (-0.154) | (-0.217) | (-0.487) | (-1.521) |
| $CAAR_{-2,+2}$ | -5.85% | -1.52% | 0.68% | 0.57% | 1.48% | -2.12% | -1.56% | -6.32% | 0.94% | 0.30% | -3.90% | 3.12% |
| | (-1.435) | (-0.238) | (0.195) | (0.132) | (0.361) | (-1.001) | (-0.865) | (-1.449) | (0.147) | (0.068) | (-1.104) | (0.769) |
| $CAAR_{-10,+2}$ | -8.15% | -4.44% | -1.92% | -0.69% | -0.77% | -7.71% | 0.13% | -1.63% | -8.52% | -1.52% | -4.17% | -6.86% |
| | (-1.240) | (-0.431) | (-0.339) | (-0.099) | (-0.116) | (-2.259)** | (0.044) | (-0.232) | (-0.826) | (-0.217) | (-0.732) | (-1.048) |
| Number of stocks | 23 | 21 | 23 | 7 | 5 | 16 | 4 | 3 | 2 | 4 | 5 | 9 |

This table reports country-level mean cumulative abnormal returns for the major coal-producing and exporting countries using equally weighted portfolios. The market model is estimated using a GARCH(1,1) specification and the market is proxied by the local market index. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

†We make use of the Thompson Reuters Business Classification (TRBC) to construct our country level portfolios and focus on primary quotes. The TRBC is a market-based classification system in which companies are assigned an industry based on the end market they serve rather than the products or services they offer. Market-based classification emphasizes the usage of a product rather than the materials used for the manufacturing process. The TRBC recognizes that the market served is a key determinant of firm performance and thus groups together firms that share similar market characteristics.

**Table 8: US election country-level announcement mean cumulative abnormal returns for coal**

| | | China | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Australia[13] | Hong Kong | Shanghai | Shenzhen | India | Indonesia | Japan | Philippines | Poland | Russia | Thailand | South Africa |
| $CAAR_{-5,-1}$ | -2.52% | -0.81% | 0.41% | 0.09% | -3.06% | 8.18% | -1.42% | 0.61% | 0.99% | -1.06% | 1.66% | -1.23% |
| | (-0.743) | (-0.219) | (0.139) | (0.021) | (-0.889) | (1.870)* | (-0.601) | (0.125) | (0.151) | (-0.261) | (0.486) | (-0.346) |
| $CAAR_{0}$ | -4.03% | -0.55% | 1.28% | 1.54% | 1.68% | 0.69% | -0.57% | -0.79% | -1.38% | -0.55% | 3.68% | 1.63% |
| | (-2.662)*** | (-0.335) | (0.960) | (0.788) | (1.091) | (0.354) | (-0.543) | (-0.360) | (-0.473) | (-0.306) | (2.402)** | (1.032) |
| $CAAR_{0,+1}$ | -1.45% | 0.93% | 0.03% | 0.73% | 1.56% | 5.25% | 0.11% | 1.96% | 2.63% | 1.36% | 3.59% | 4.92% |
| | (-0.676) | (0.395) | (0.017) | (0.265) | (0.716) | (1.897)* | (0.076) | (0.632) | (0.636) | (0.529) | (1.660)* | (2.201)** |
| $CAAR_{0,+2}$ | -0.82% | 1.87% | 1.30% | 4.09% | 2.44% | 6.83% | -1.15% | 2.53% | 4.46% | 2.08% | 4.33% | 6.49% |
| | (-0.313) | (0.650) | (0.565) | (1.208) | (0.917) | (2.013)** | (-0.628) | (0.667) | (0.881) | (0.662) | (1.630) | (2.369)** |
| $CAAR_{0,+5}$ | -3.24% | 2.43% | 0.90% | 5.04% | -3.51% | 1.85% | 0.38% | 3.32% | 4.80% | 3.10% | 0.71% | 1.65% |
| | (-0.873) | (0.598) | (0.276) | (1.051) | (-0.933) | (0.386) | (0.148) | (0.619) | (0.671) | (0.699) | (0.190) | (0.427) |
| Number of stocks | 24 | 20 | 23 | 5 | 4 | 15 | 4 | 3 | 2 | 4 | 5 | 8 |

This table reports country-level mean cumulative abnormal returns for the major coal-producing and exporting countries using equally weighted portfolios. The market model is estimated using a GARCH(1,1) specification and the market is proxied by the local market index. The estimation period includes trading days

[13] On 9 November 2016, the Queensland Parliament passed the Environmental Protection (Underground Water Management) and Other Legislation Amendment Act that seeks to tighten groundwater license requirements for mines.

-6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 9: Paris climate agreement country-level announcement mean cumulative abnormal returns for coal**

| | United States | | |
|---|---|---|---|
| | Full Sample | NYSE | NASDAQ |
| $CAAR_{-2,0}$ | -4.34% | -4.87% | -3.29% |
| | (-0.854) | (-0.953) | (-0.430) |
| $CAAR_{-1,0}$ | -4.73% | -6.05% | -2.10% |
| | (-1.140) | (-1.451) | (-0.335) |
| $CAAR_{0}$ | -3.76% | -5.08% | -1.13% |
| | (-1.281) | (-1.722)* | (-0.255) |
| $CAAR_{0,+1}$ | -3.92% | -4.04% | -3.69% |
| | (-0.945) | (-0.968) | (-0.589) |
| $CAAR_{0,+2}$ | -3.92% | -2.24% | -7.27% |
| | (-0.770) | (-0.439) | (-0.948) |
| $CAAR_{-1,+1}$ | -4.89% | -5.01% | -4.66% |
| | (-0.963) | (-0.981) | (-0.608) |
| $CAAR_{-2,+2}$ | -4.50% | -2.03% | -9.44% |
| | (-0.685) | (-0.308) | (-0.953) |
| $CAAR_{-10,+2}$ | -13.66% | -11.52% | -17.94% |
| | (-1.291) | (-1.084) | (-1.124) |
| Number of stocks | 15 | 10 | 5 |

This table reports mean cumulative abnormal returns for the major US coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ sample. We use the S&P 500 for the full sample. The estimation period includes trading days -11 to -235 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 14 December 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, 12 December 2015. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

**Table 10: US election country-level announcement mean cumulative abnormal returns for coal**

| | United States | | | | |
|---|---|---|---|---|---|
| | Full Sample | | NYSE | | NASDAQ |
| | I | II† | III | IV† | V |
| $CAAR_{-5,-1}$ | -2.16% | -2.91% | -2.51% | -3.68% | -1.38% |
| | (-0.387) | (-0.572) | (-0.387) | (-0.647) | (-0.273) |
| $CAAR_0$ | 10.99% | 7.78% | 10.42% | 5.54% | 12.26% |
| | (4.399)*** | (3.413)*** | (3.595)*** | (2.178)** | (5.412)*** |
| $CAAR_{0,+1}$ | 12.29% | 7.87% | 11.81% | 5.12% | 13.37% |
| | (3.480)*** | (2.443)** | (2.881)*** | (1.424) | (4.174)*** |
| $CAAR_{0,+2}$ | 12.63% | 9.50% | 11.10% | 6.21% | 16.06% |
| | (2.919)*** | (2.406)** | (2.211)** | (1.411) | (4.095)*** |
| $CAAR_{0,+5}$ | 10.86% | 6.43% | 11.04% | 4.42% | 10.45% |
| | (1.775)* | (1.152) | (1.555) | (0.710) | (1.884)* |
| Number of stocks | 13 | 12 | 9 | 8 | 4 |

This table reports mean cumulative abnormal returns for the major US coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ subsample. We use the S&P 500 Index for the full sample. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series *t*-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

†Column II and IV represent results excluding Peabody Energy.

**Table 11: US election country-level announcement mean abnormal returns for coal**

| Day relative to event date | United States | | | | |
|---|---|---|---|---|---|
| (Day 0 = November 9, 2016) | Full Sample | | NYSE | | NASDAQ |
| | I | II† | III | IV† | V |
| -5 | -0.89% | -0.94% | -0.90% | -0.98% | -0.86% |
| | (-0.357) | (-0.411) | (-0.312) | (-0.384) | (-0.380) |
| -4 | 2.00% | 1.95% | 2.31% | 2.27% | 1.31% |
| | (0.802) | (0.855) | (0.796) | (0.892) | (0.579) |
| -3 | 0.88% | 0.85% | -0.03% | -0.18% | 2.93% |
| | (0.352) | (0.375) | (-0.012) | (-0.073) | (1.295) |
| -2 | -3.23% | -3.86% | -2.61% | -3.49% | -4.61% |
| | (-1.293) | (-1.695)* | (-0.902) | (-1.371) | (-2.037)** |
| -1 | -0.92% | -0.92% | -1.26% | -1.30% | -0.15% |
| | (-0.369) | (-0.403) | (-0.436) | (-0.511) | (-0.067) |
| 0 | 10.99% | 7.78% | 10.42% | 5.54% | 12.26% |
| | (4.399)*** | (3.413)*** | (3.595)*** | (2.178)** | (5.412)*** |
| +1 | 1.30% | 0.09% | 1.39% | -0.42% | 1.11% |
| | (0.523) | (0.041) | (0.480) | (-0.163) | (0.491) |
| +2 | 0.34% | 1.63% | -0.71% | 1.09% | 2.69% |
| | (0.135) | (0.714) | (-0.245) | (0.429) | (1.190) |
| +3 | 2.38% | 1.53% | 3.16% | 1.99% | 0.62% |
| | (0.952) | (0.673) | (1.090) | (0.783) | (0.273) |
| +4 | -3.57% | -3.93% | -2.60% | -3.01% | -5.77% |
| | (-1.431) | (-1.726)* | (-0.896) | (-1.186) | (-2.548)** |
| +5 | -0.57% | -0.67% | -0.62% | -0.77% | -0.46% |
| | (-0.229) | (-0.292) | (-0.215) | (-0.303) | (-0.202) |
| Number of stocks | 13 | 12 | 9 | 8 | 4 |

This table reports mean abnormal returns for the major US coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using a GARCH(1,1) specification and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ subsample. We use the S&P 500 Index for the full sample. The estimation period includes trading days -6 to -220 relative to the event. The null hypothesis is that the mean cumulative abnormal returns on day zero is zero. The announcement date ($t = 0$) is taken as 9 November 2016. Portfolio time-series $t$-statistics are shown in parentheses. The symbols *, **, and *** denote statistical significance at the 10%, 5% and 1% respectively.

†Column II and IV represent results excluding Peabody Energy.

**Table A1: List of Exchange-Traded Funds[1]**

| | Energy Sector | Co.s | Index Tracked |
|---|---|---|---|
| | Natural Gas | | |
| DDG | ProShares Short Oil and Gas | 72 | Dow Jones U.S. Oil & Gas Index |
| FCG | First Trust ISE-Revere Natural Gas | 35 | ISE-REVERE Natural Gas Index |
| FRAK | VanEck Vectors Unconventional Oil & Gas | 45 | MVIS Global Unconventional Oil & Gas Index |
| GASL | Direxion Daily Natural Gas Related Bull 3x Shares | 46 | ISE-REVERE Natural Gas Index |
| | Coal | | |
| KOL | VanEck Vectors Coal | 31 | Market Vectors Global Coal Index |
| | Oil | | |
| OIH | VanEck Vectors Oil Services | 26 | MVIS U.S. Listed Oil Services 25 Index |
| DDG | ProShares Short Oil and Gas | 72 | Dow Jones U.S. Oil & Gas Index |
| DUG | ProShares UltraShort Oil & Gas | 72 | Dow Jones U.S. Oil & Gas Index |
| FRAK | VanEck Vectors Unconventional Oil & Gas | 45 | MVIS Global Unconventional Oil & Gas Index |
| | Nuclear Energy | | |
| NLR | VanEck Vectors Uranium and Nuclear Energy | 51 | Market Vectors Global Uranium & Nuclear Energy Index |
| | Clean and Alternative Energy | | |
| GEX | VanEck Vectors Global Alternative Energy | 31 | Ardour Global Index |

[1] The ETFs DDG and DUG are sold short. Prior to including them in the analysis, we reverse the sign of each estimation-period and event-period security return for the security event. After the sign reversal, we make no further distinction between securities sold short or long. The event study calculations thus proceed by treating the sample as an equally weighted portfolio of securities held long. The negative weights of shorted securities are implied by the sign reversal.

| | | | |
|---|---|---|---|
| PBD | PowerShares Global Clean Energy Portfolio | 94 | WilderHill New Energy Global Innovation Index |
| PZD | PowerShares Cleantech Portfolio | 54 | The Cleantech Index |
| PBW | PowerShares WilderHill Clean Energy | 36 | WilderHill Clean Energy Index |
| QCLN | First Trust NASDAQ Clean Edge Green Energy | 35 | NASDAQ Clean Edge Green Energy Index |
| PUW | PowerShares WilderHill Progressive Energy Portfolio | 52 | WilderHill Progressive Energy Index |
| ICLN | iShares Global Clean Energy | 30 | S&P Global Clean Energy Index |
| | Solar Energy | | |
| TAN | Guggenheim Solar | 29 | MAC Global Solar Energy Index |
| KWT | VanEck Vectors Solar Energy | 32 | Market Vectors Global Solar Energy Index |
| | Wind Energy | | |
| FAN | First Trust ISE Global Wind Energy Index Fund | 46 | ISE Global Wind Energy Index |

Table A1 shows the equity-based exchange-traded funds (ETF) that form our portfolios. Our clean and alternative energy portfolio is made up of firms involved in conservation, energy efficiency and advancing renewable energy. This includes developers, distributors, and installers in one of the following: advanced materials that enable clean energy or reduce the need for petroleum products; energy intelligence, storage and conversion; and renewable electricity generation (solar, wind, geothermal, etc.). The remaining portfolios comprise companies involved in direct operations (production, mining and drilling), transportation, production of mining or drilling equipment and provision of energy as a final output. For a firm to be included in an ETF, these activities should account for a large proportion of the firm’s revenues and assets.

## Table A2: List of Global Coal Stocks

| Name | Market Capitalization ($Bn) |
|---|---|
| **Australia** | |
| Aspire Mining Ltd | 0,015 |
| Atrum Coal NL | 0,048 |
| Australian Pacific Coal Ltd | 0,036 |
| Carbon Energy Ltd | 0,017 |
| Citation Resources Ltd | 0,011 |
| Mastermyne Group Ltd | 0,022 |
| Metro Mining Ltd | 0,100 |
| New Age Exploration Ltd | 0,005 |
| New Hope Corporation Ltd | 1,059 |
| NSL Consolidated Ltd | 0,052 |
| Nucoal Resources Ltd | 0,003 |
| Prairie Mining Ltd | 0,060 |
| Resource Generation Ltd | 0,032 |
| Rey Resources Ltd | 0,020 |
| Salt Lake Potash Ltd | 0,045 |
| Stanmore Coal Ltd | 0,061 |
| Terracom Ltd | 0,060 |
| Washington H Soul Pattinson and Company Ltd | 3,279 |
| White Energy Company Ltd | 0,008 |
| Whitehaven Coal Ltd | 1,976 |
| Volt Resources Ltd | 0,023 |
| BHP Billiton Ltd | 56,262 |
| Rio Tinto Ltd | 18,710 |
| Wesfarmers Ltd | 36,781 |
| **Japan** | |
| Mitsui Matsushima Co Ltd | 0,179 |
| Nippon Coke & Engineering Co Ltd | 0,272 |
| Taiheiyo Kouhatsu Inc | 0,070 |
| Sumiseki Holdings Inc | 0,050 |
| **India** | |
| Coal India Ltd | 26,928 |
| Mercator Ltd | 0,194 |
| NLC India Ltd | 2,435 |
| Hemang Resources Ltd | 0,002 |
| Chandra Prabhu International Ltd | 0,001 |

| South Africa | |
|---|---|
| Exxaro Resources Ltd | 2,407 |
| Petmin Ltd | 0,064 |
| Wescoal Holdings Ltd | 0,061 |
| Keaton Energy Holdings Ltd | 0,035 |
| Sentula Mining Ltd | 0,026 |
| Mine Restoration Investments Ltd | 0,002 |
| Anglo American PLC | 19,459 |
| Glencore Plc | 54,564 |
| Sasol | 20,274 |

| Thailand | |
|---|---|
| Banpu PCL | 2,803 |
| Energy Earth PCL | 0,429 |
| Asia Green Energy PCL | 0,075 |
| Lanna Resources PCL | 0,195 |
| Unique Mining Services PCL | 0,034 |

| Poland | |
|---|---|
| Jastrzebska Spolka Weglowa SA | 2,264 |
| Lubelski Wegiel Bogdanka SA | 0,622 |

| Philippines | |
|---|---|
| Semirara Mining and Power Corporation | 3,408 |
| Coal Asia Holdings Inc | 0,034 |
| Forum Pacific Inc | 0,007 |

| Russia | |
|---|---|
| Raspadskaya PAO | 0,851 |
| Belon OAO | 0,054 |
| Kuzbasskaya Toplivnaya Kompaniya PAO | 0,199 |
| UK Yuzhnyi Kuzbass PAO | 0,470 |

| Indonesia | |
|---|---|
| Indika Energy Tbk PT | 0,457 |
| Bumi Resources Tbk PT | 1,094 |
| United Tractors Tbk PT | 7,249 |
| Delta Dunia Makmur Tbk PT | 0,572 |
| Adaro Energy Tbk PT | 3,876 |
| Indo Tambangraya Megah Tbk PT | 1,560 |
| Bukit Asam (Persero) Tbk PT | 2,014 |
| Harum Energy Tbk PT | 0,487 |
| Petrosea Tbk PT | 0,082 |

| | |
|---|---|
| Golden Eagle Energy Tbk PT | 0,031 |
| Resource Alam Indonesia Tbk PT | 0,154 |
| Toba Bara Sejahtra Tbk PT | 0,233 |
| Bayan Resources Tbk PT | 1,701 |
| Perdana Karya Perkasa Tbk PT | 0,004 |
| SMR Utama Tbk PT | 0,356 |
| Exploitasi Energi Indonesia Tbk PT | 0,034 |
| Mitrabara Adiperdana Tbk PT | 0,221 |

| **United States** | |
|---|---|
| Arch Coal Inc | 1,799 |
| Cloud Peak Energy Inc | 0,254 |
| CONSOL Energy Inc | 3,609 |
| New Wei Inc | 0,005 |
| Peabody Energy Corp | 2,364 |
| Westmoreland Coal Co | 0,180 |
| Hallador Energy Co | 0,225 |
| James River Coal Co | 0,000 |
| Freightcar America Inc | 0,220 |
| Aliance Resources Partners. L.P | 1,705 |
| Komatsu Mining Corp | 2,818 |
| Headwaters Inc | 1,817 |
| Suncoke Energy Inc | 0,513 |
| Nacco Industries Inc | 0,458 |
| Foresight Energy LP | 0,685 |

| **China – Shanghai** | |
|---|---|
| China Shenhua Energy Co Ltd | 55,093 |
| Shaanxi Coal Industry Co Ltd | 8,005 |
| Shanxi LuAn Environmental Energy Development Co Ltd | 3,089 |
| Yanzhou Coal Mining Co Ltd | 6,376 |
| Yang Quan Coal Industry Group Co Ltd | 2,176 |
| Anhui Hengyuan Coal Industry and Electricity Power Co Ltd | 1,017 |
| Shanxi Lanhua Sci-Tech Venture Co Ltd | 1,186 |
| Kailuan Energy Chemical Co Ltd | 1,349 |
| Pingdingshan Tianan Coal Mining Co Ltd | 1,661 |
| China Coal Energy Co Ltd | 9,037 |
| China Coal Xinji Energy Co Ltd | 1,555 |
| Qinghai Spring Medicinal Resources Technology Co Ltd | 1,343 |
| Beijing Haohua Energy Resource Co Ltd | 1,199 |
| CCS Supply Chain Management Co Ltd | 2,030 |
| Datong Coal Industry Co Ltd | 1,206 |
| Guizhou Panjiang Refined Coal Co Ltd | 1,666 |

| | |
|---|---|
| Shanghai Datun Energy Resources Co Ltd | 1,136 |
| Wintime Energy Co Ltd | 6,523 |
| Zhengzhou Coal Industry & Electric Power Co Ltd | 0,716 |
| Qinghai Jinrui Mineral Development Co Ltd | 0,470 |
| Inner Mongolia Yitai Coal Co Ltd | 3,236 |
| Anyuan Coal Industry Group Co Ltd | 0,620 |
| Xinjiang Bai Hua Cun Co Ltd | 0,851 |
| Henan Dayou Energy Co Ltd | 1,675 |
| Hidili Industry International Development Ltd | 0,084 |
| China Qinfa Group Ltd | 0,070 |
| China Unienergy Group Ltd | 0,544 |
| Kinetic Mines and Energy Ltd | 0,357 |
| China Leon Inspection Holding Ltd | 0,080 |
| Feishang Anthracite Resources Ltd | 0,227 |

| **China – Hong Kong** | |
|---|---|
| Skyway Securities Group Ltd | 0,895 |
| Agritrade Resources Ltd | 0,289 |
| Huscoke Resources Holdings Ltd | 0,066 |
| CITIC Resources Holdings Ltd | 0,959 |
| King Stone Energy Group Ltd | 0,174 |
| Elife Holdings Ltd | 0,135 |
| Loudong General Nice Resources China Holdings Ltd | 0,219 |
| Ares Asia Ltd | 0,058 |
| Mongolia Energy Corp Ltd | 0,054 |
| Asia Coal Ltd | 0,111 |
| China CBM Group Co Ltd | 0,025 |
| Grand Ocean Advanced Resources Co Ltd | 0,019 |
| Union Asia Enterprise Holdings Ltd | 0,012 |
| Nan Nan Resources Enterprise Ltd | 0,044 |
| Siberian Mining Group Co Ltd | 0,028 |
| Kaisun Energy Group Ltd | 0,031 |
| Capital Finance Holdings Ltd | 0,030 |
| Rosan Resources Holdings Ltd | 0,015 |
| Bel Global Resources Holdings Ltd | |
| Superb Summit International Group Ltd | |

| **China – Shenzhen** | |
|---|---|
| Jizhong Energy Resources Co Ltd | 3,279 |
| Shanxi Xishan Coal and Electricity Power Co Ltd | 3,523 |
| Huolinhe Opencut Coal Industry Corp Ltd of Inner Mongolia | 2,133 |
| Taiyuan Coal Gasification Co Ltd | 2,166 |
| Sundiro Holding Co Ltd | 0,891 |

| | |
|---|---|
| Gansu Jingyuan Coal Industry and Electricity Power Co Ltd | 1,177 |
| Inner Mongolia PingZhuang Energy Resources Co Ltd | 0,635 |