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Abstract

The Paris Agreement was acclaimed as a milestone for climate negotiations. It has also been criticized – as too soft by environmentalists and too constraining by the current U.S. administration, which has decided to leave. The election of President Trump was itself widely interpreted as unexpected, good news for the fossil industry (and less good for the climate). We seek to evaluate the impact of global climate policy making by studying its effect on the stock market value of energy sector firms. In particular, we study the signing of the Paris Agreement and the latest U.S. presidential election. Using event study and impulse indicator saturation methods, we show that both events had only moderate effects.

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

JEL Codes: G14, Q40, Q54

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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 underlying effects of gradual but fundamental shifts in technology trends and societal preferences. The year 2016 was described as important to climate because of the Paris Agreement, while the election of Donald Trump as U.S. president has been described as a disaster for the climate.[1] Here, the importance of these events to energy sector firms and climate change 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, partly 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 while 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'. These facts speak in favor of Paris being a success. 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, furthermore, 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. This would speak against Paris being a major climate policy. On the other hand, the fact that Trump wants to leave the Paris

[1] See: 'Breaking the habit: The future of oil', The Economist, November 26, 2016, https://www.economist.com/news/special-report/21710628-worlds-use-oil-approaching-tipping-point-writes-henry-tricks-dont-expect?fsrc=scn/fb/te/bl/ed/thefutureofoil, archive accessed on January 20, 2018.

agreement can again be interpreted as a sign that the policy was a relatively ambitious climate policy.[2]

Turning to the media, the Paris climate agreement was reported as a 'success'. 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 purpose of this paper is to seek more firm evidence by studying market effects of the Paris climate agreement as well as the U.S. 2016 election.

The Paris agreement 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 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 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. We expect the impact on coal stocks to be significantly larger than that on oil and natural gas stocks given that coal results in significantly more emissions per unit energy produced compared to oil which in turn results in higher emissions per unit of energy produced than natural gas. We evaluate the agreement's 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. It is important to recognize that economic theory would

[2] See: 'Statement by President Trump on the Paris Climate Accord', The White House, June 1, 2017, https://www.whitehouse.gov/the-press-office/2017/06/01/statement-president-trump-paris-climate-accord, archive accessed on November 08, 2017.

require two factors as decisive for a stock market effect: First of all that the event is beneficial or detrimental to the industry concerned and secondly an element of surprise. If the event is expected then its positive or negative effect will already be discounted by the market.

One may have legitimate arguments about both the efficacy of the Paris climate agreement and about whether or not it was ‘surprising’. Hence the presence or absence of effects must take both these factors into account. A moderate effect may be because the agreement was anticipated. To investigate this, we conduct a media content analysis of articles published in one of the leading financial newspapers, The Financial Times (FT), during the two months leading up to the climate negotiations and the period afterwards until the end of 2015. To further evaluate the importance of *surprise* as a factor, we analyze the election of Donald Trump. Here there is little doubt that the event was unexpected and little doubt that he is a candidate in favor of fossil industries.

Following the forgoing discussion, there should be a positive effect on fossil stocks following the election of President Trump and a negative one on for example renewable energy stocks. 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

A visual analysis of Figure 1 shows big movements but fails to identify any significant changes in energy markets around the particular dates that the Paris climate agreement and the U.S. presidential results were announced. A systematic approach using statistical techniques is therefore necessary. 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.

[INSERT FIGURE 1 HERE]

2.1. Event Study Analysis Method

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 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 (r_{it}) to the return in the overall market (r_{mt}). The model assumes a stable linear relation between the market return and the stock return. For any security i, we have:

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

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

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 $\hat{\epsilon}_{it}$ is zero. The firm-specific parameters of the market model are estimated using least squares and are denoted by $\hat{\alpha}_i$, $\hat{\beta}_i$ and $\hat{\sigma}^2_{\epsilon_i}$.[3] Equation 1 is usually referred to as the single-factor model because it only controls for the market return. The abnormal return ($\hat{\epsilon}_{it}$) 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

[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). The GARCH model has been suggested by Pynnonen (2005) as a partial remedy to shifts in the level of volatility within the event window. (See also Corhay and Rad (1996) for an earlier application of the GARCH model in event studies). Often the GARCH(1,1) specification has been found to sufficiently capture stock return volatility.

(r_{mt}).[4] The abnormal return $\hat{\epsilon}_{it}$ for the ith firm at time *t* is then given as $\hat{\epsilon}_{it} = r_{it} - (\hat{\alpha}_i + \hat{\beta}_i r_{mt})$. 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.

From the estimated residuals in Equation 1, the cumulative abnormal returns (CAR_{it}) are generated as $CAR_{i,(t_0,t_1)} = \sum_{t=t_0}^{t_1} \hat{\epsilon}_{it}$, 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 $CAAR_{(t_0,t_1)} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,(t_0,t_1)}$. More elaborate models such as multifactor models and the Capital Asset Pricing model (CAPM) are available but in the context of event studies, experience has seldom shown these models to be superior, especially for short event windows (Campbell et al., 1997; MacKinlay, 1997). In this paper we therefore prefer the standard one-factor market model.

We assess whether a) the Paris climate agreement and b) the U.S. election had any impact on fossil markets by formally testing the null hypothesis that the events had no impact on abnormal returns. We want to be ambitious in terms of details. It is possible that there would be differential effects in different countries depending on details of the political or market landscape. The analysis is therefore conducted at the global level for all energy sources as well as in greater detail at the country level for coal. The country-level analysis includes coal companies from North America, Asia, Africa, Australia and Europe.

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.[5] 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 address this problem at the global and country level by constructing and

[4] In the next section, we consider instead $r_{it} - r_{jt}$ as the dependent variable, with r_{it} taken as the return on solar stocks and r_{jt} the return on coal stocks.

[5] 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.

analyzing equally weighted portfolios. Given total clustering, we make 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 for notational convenience, $\bar{\epsilon}_t = \overline{\hat{\epsilon}_t}$ and

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

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

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

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 $\hat{\epsilon}_t$ are assumed to be independent and identically distributed (iid) as normal (see Brown & Warner, 1985). According to Brown and Warner (1985), this test statistic is assumed unit normal when the degrees of freedom exceed 200. 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 Method

The event study approach outlined so far is based on imposing the event of interest from the onset. In this section, we enhance the event study approach by introducing a more powerful and flexible method 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 November 2016 U.S. election as well as other not a priori identified effects. The evidence of an effect is then stronger if the dates of interest are identified without being imposed a priori. The returns to holding fossil stocks can be influenced by any number of random events such as oil spills, wars, and business news. If these other shocks are not identified and dealt with, they may bias the overall analysis.

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

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 α. 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 is a random error term with zero mean and variance δ_u^2.[6] r_{sct} is the difference between the performance of renewables (proxied by the MAC Global Solar Energy Index) and the performance of coal (proxied by the Stowe Global Coal Index), (i.e., the difference in stock returns ($r_{st} - r_{ct}$) for these two sectors where r_{st} is the index return for solar at time *t* and r_{st} is the index return for coal at time *t*). r_{sct} can be interpreted as an index of climate (or conversely coal) sensitivity. We are thus using the fact that the timing of the 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, taking the difference in stock returns can help in getting greater precision in the model estimation. 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:

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

Equation 4 is analyzed using IIS to identify outliers. We use the *gets* package in R (Pretis, Reade, & Sucarrat, Forthcoming). On average, αT indicator variables are retained by chance for a significance level α and T observations. We set α very low at 0.001 and 0.0005. The period of analysis covers a total of $T = 503$ daily return observations from January 2015 to January 2017. Therefore, under the null hypothesis that no indicators are needed, 0.5 (or 0.25 with $\alpha = 0.0005$) of an indicator will be significant by chance on average. 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 Paris agreement was announced on 12 December 2015 and Donald Trump was elected as the 45th U.S. president on 8 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 α. This, according to Doornik et al. (2013), suggests that over-fitting is not a major issue with IIS.

[6] The error term is likely to be non-normal, heteroskedastic and only a martingale difference sequence rather than an independent sequence. The simplest case is when the error term is assumed to be iid normal.

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. ETFs are portfolios or baskets of securities traded on a stock exchange analogous to individual company stocks.[7] They are usually designed to replicate well-known market indices such as the S&P 500 but others also track customized indices (see Technical Appendix for a detailed discussion on ETFs).

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 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 U.S. 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 Paris 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. For the Paris agreement event study, we also report results for the $[-10, +2]$ event window, which coincides with the onset of the COP 21 climate negotiations in Paris. We use the 225-trading-day period prior to the event window as the estimation window. Our choice of the estimation window for the Paris agreement event study 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.

We use two samples in our analysis – the first sample is made up of ETFs (see Table 1) composed of firms operating in countries responsible for significant global carbon emissions. The

[7] 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 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.

second sample includes individual firms in the coal industry across a number of countries (see Table 2) that account for significant global carbon emissions.

[INSERT TABLE 1 AND 2 HERE]

Our ETFs are based on equities and follow a particular index composed of a number of stocks. We therefore exclude commodity-based ETFs or those based on futures contracts, as they are less likely to accurately capture events similar to the ones under consideration. In addition, movements in commodity prices are largely driven by many short-term factors. We also exclude exchange-traded notes since their value is at times influenced by the credit rating of the issuer.

2.4. Timeline of Events

Table 3 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. We are treating 12 December 2015 as the decision day, but the agreement required the fulfillment of a number of conditions before coming into force. The agreement was signed by 195 UNFCCC members 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, and the second on 5 October 2016, setting the agreement to take effect on 4 November 2016. Turning to the U.S. election, Donald Trump won the U.S. presidential election on 8 November 2016. On 1 June 2017, President Trump announced his intention to withdraw the U.S. from the Paris climate agreement citing that the accord would undermine the U.S. economy.

[INSERT TABLE 3 HERE]

3. Market effects of the Paris Agreement and the U.S. Election

In this section, we firstly present results from the event study analysis. We also estimate the market model using the GARCH(1,1) specification and the results are presented in the Appendix. Results for the Paris Agreement and the U.S. 2016 election using the impulse indicator saturation method are then presented and discussed.

3.1. Abnormal Returns Related to the Paris Announcement

Table 4 shows the results for all the sectors studied and for different event windows. We find no statistically significant negative mean abnormal returns for fossil fuel industries on the Paris Agreement announcement day. When we look at solar energy, the results are however significant on the event day and 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 for fossil stocks 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 U.S. (Batten et al., 2016).

[INSERT TABLE 4 HERE]

To corroborate our results and deepen the analysis, we also look at various energy indices (Table 5). 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 5 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.[8] These criteria leave us with a sample of 140 companies in 14 different stock markets (Table 2). Most of these companies are constituents of major global coal indices and exchange traded funds.

[INSERT TABLE 6a AND 6b HERE]

For most nations, the Paris accord has no effect on domestic coal markets (Table 6a and 6b). 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 coal industry is in decline and has been for several years (see Figure 1). Tightening environmental regulations have slowed future investments in coal while reducing the economic viability of existing ones. At the same time, increasing environmental awareness concerning global warming has led to a general preference for renewable energy. This coincides with the significant fall in the cost of solar energy in recent years largely driven by technological change (see Kåberger, 2018; Wagner, Kåberger, Olai, Oppenheimer, & Sterner, 2015). 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.

[8] Including firms that go bankrupt is not feasible because they have no market values. We note that, because of this exclusion, our methodology may understate how badly a given sector is faring. In Table 9b, as part of robustness tests, we include Peabody Energy Corp which filed for Chapter 11 bankruptcy in April 2016 but continued trading on the over-the-counter markets. Indeed it appears that it is more of an outlier compared to how other firms responded to the two major events analyzed.

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. One interpretation of this is that they understand these kind of climate policies will be more detrimental to coal and thus may even benefit oil (and gas). 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.[9] The fact that we do not find major effects on coal stocks 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 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 on any particular day.[10] Our detailed media content analysis of 200 FT articles collected from Factiva using the search strings "Paris" and "climate" and published between 1 October 2015 and 31 December 2015 turned only a handful of articles that framed the announcement of the Paris agreement as surprising. The 'surprise' noted by other media and commentators alike can be explained by the fact that the agreement probably exceeded expectations, at least when it comes to

[9] 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).

[10] 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.

its ambitions and given that previous climate change negotiations failed to achieve any 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.[11]

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 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.

3.2. Abnormal Returns Related to the U.S. Election

The U.S. climate change debate has been characterized by a lack of political consensus. The disagreements in the U.S. climate debate have been intense. Politicians such as Mr. Trump and many other Republicans are significantly more aligned with coal (and other fossil) industry interests than are their Democratic counterparts. The 2016 presidential election produced a result that was not expected by opinion polls or prediction markets (see Figure 2) and therefore presents us with a perfect case where there is a strong element of surprise as well as an unambiguous event in favor of fossil fuels.[12] Again, we note that globally, fossil fuels do not appear to have benefitted

[11] The shortcomings of voluntary contributions toward optimal provision of a public good have been studied elsewhere in the literature (see Marwell & Ames, 1981). We do not necessarily mean, in this context, to be disparaging concerning the power of the bottom-up approach. The optimists will argue that this was the best approach available and that it is the political dynamics created that will eventually lead to new rounds of ratcheting up the commitments.

[12] 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.

from the election of Mr. Trump, despite his express desire to promote fossils such as coal (Table 7 and 8). We could interpret this as indicating the U.S.'s limited power to disrupt global climate policies. On the other hand, our results also suggest that a change in U.S. climate policy in favor of its domestic fossil industry in response to the Paris agreement, might indirectly hurt coal companies in *other* countries. We do, however, see that renewables and clean energy experienced statistically significant negative abnormal returns on the announcement day.

[INSERT TABLE 7 AND 8 HERE]

At the country-level, the election of Donald Trump as the 45th U.S. president benefited U.S. coal companies (Table 9b – 9c). We also report significant positive abnormal returns for South Africa and Thailand around the announcement of the U.S. election results (Table 9a).

[INSERT TABLE 9a – 9c HERE]

3.3. Impulse Indicator Saturation Results

The lack of a significant reaction to the Paris agreement and U.S. election especially for coal is surprising and we seek therefore to refine the results and put them in a unified framework with an analysis of both the Paris meeting and the U.S. election. In Table 10, we present results for several specifications using the Impulse Indicator Saturation (IIS) method. 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 U.S. 2016 presidential election results were announced. From specification I, we note that both the dummy variables' coefficients are statistically significant and show a strong positive reaction by U.S. coal stocks. Specification I uses IIS to search for additional impulses in addition to the ones we have included without selection. Five additional dates are picked up and, when an autoregressive term is added in specification II, we can detect up to four of these additional impulses. In specifications III and IV, we allow IIS to detect the relevant events on its own (i.e. no variables are retained in the model without selection); again, the two most important climate-related political events during the two-year period are retained, namely the Paris climate agreement and the U.S. election. Specification V is similar to IV but selection is carried out at an even tighter level of significance ($\alpha = 0.0005$). All but one of the previously retained dates are retained in this last specification. 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 $\alpha = 0.001$ and 0.0005. This gives us a fairly negligible number of false positives.

[INSERT TABLE 10 HERE]

From Table 10, 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 U.S. 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. We find positive impacts on 4 and 5 March 2015 as well as 16 December 2015 (Figure 3 and Table 10). 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 10). We have searched systematically for explanations by reading the relevant news telegrams from a news service, Retriever[13], 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]

As a start, we note the absence of some dates considered significant, such as ratification by various countries or the Paris climate agreement’s entry into force on 4 November 2016. These are not detected by IIS. Given that the Paris climate agreement was unanimous, 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.

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

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 U.S. 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, the U.S. 2016 presidential election 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 do find some effect but moderate compared to the acclaimed importance of the Paris Accord. The lack of a stronger reaction might be due to the agreement being either anticipated or considered weak. Turning to the results of the recent U.S. 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, again, moderate and perhaps 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. Thanks to the IIS technique, we found that an important event – the Chinese decision to reduce coal – had important effects on the global market. 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 the underlying fundamentals such as technical developments which have systematically been making renewables and natural gas cheaper in relation to coal over the past decades (see Kåberger, 2018; Wagner et al., 2015). A natural conclusion for both media and policy makers is to turn more of their attention to watching – and influencing – long run changes in technology and maybe other parameters such as tastes or resource availability.

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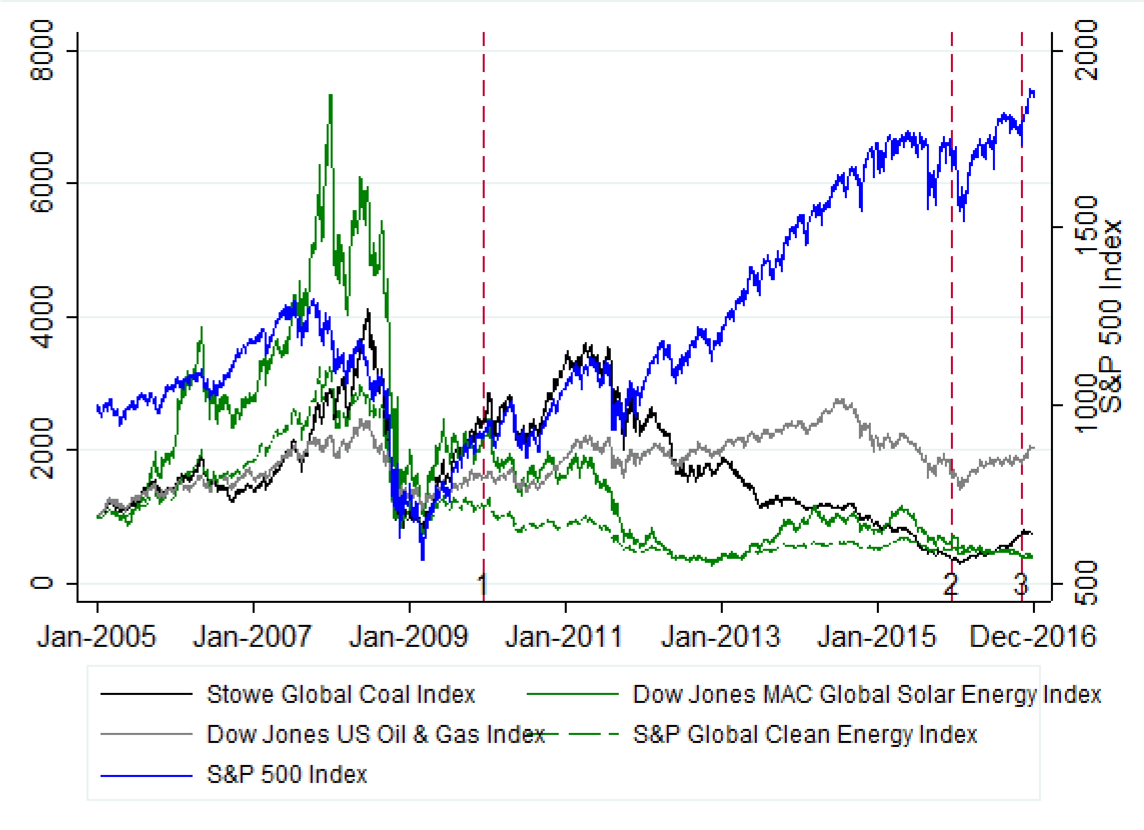
Figure 1: Energy indices vs. global benchmarks



Notes: Figure 1 shows the performance of several energy indices 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 U.S. presidential election.

Table 1: Descriptive Statistics for Exchange-Traded Funds[14]

	Number of ETFs	Average # of Stocks	Mean ETF Size (Millions USD)	Average # of Countries
Natural Gas	4	51	94	3
Coal	1	31	102	12
Oil	4	57	325	3
Nuclear Energy	1	51	34	9
Clean and Alternative Energy	7	47	61	12
Solar Energy	2	31	89	9
Wind Energy	1	46	75	17

Table 1 shows the equity-based exchange-traded funds (ETFs) 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.

[14] Some of our ETFs are sold short. Short 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. 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.

Table 2: Descriptive Statistics for Coal Stocks by Country

Number	Country	Number of stocks	Mean Firm Size (Millions USD)
1	China	52	
	Shanghai	24	4717
	Hong Kong	21	172
	Shenzhen	7	1972
2	Australia	24	4945
3	Indonesia	17	1184
4	United States	15	1170
5	South Africa	9	3646
6	India	5	5912
7	Thailand	5	707
8	Japan	4	142
9	Russia	4	394
10	Philippines	3	1150
11	Poland	2	1443

This table reports the summary statistics of our country-level sample for coal.

Table 3: Timeline of Paris Agreement and recent climate policy events

Date	Event
12 December 2014	COP 20 in Lima ends
31 March 2015	Countries start submitting INDCs
1 October 2015	Deadline for submitting INDCs
30 November 2015	Climate negotiation start in Paris (COP 21)
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	U.S. 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
7 November 2016	COP 22 begins in Marrakech
8 November 2016	Donald Trump elected U.S. president
1 June 2017	President Trump announces intention to withdraw from Paris Agreement

Figure 2: U.S. Election Clinton Victory Probability

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) 08/11/2016: Donald Trump wins the U.S. presidential election. Source: https://predictwise.com/politics/2016-president-winner

Table 4: Effects of Paris climate agreement on energy sector using ETFs

	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%
	(-2.01)**	(-0.61)	(-1.23)	(1.20)	(-0.75)	(-0.18)	(-1.01)
$CAAR_{-1,0}$	-3.09%	-2.55%	-4.91%	3.74%	-0.26%	0.55%	-0.56%
	(-1.80)*	(-1.10)	(-1.92)*	(1.51)	(-0.21)	(0.54)	(-0.51)
$CAAR_{0}$	-1.48%	-0.39%	-2.13%	4.45%	0.79%	0.76%	-0.55%
	(-1.22)	(-0.24)	(-1.18)	(2.55)**	(0.90)	(1.04)	(-0.70)
$CAAR_{0,+1}$	-1.88%	1.74%	-0.82%	7.06%	0.39%	1.28%	0.34%
	(-1.10)	(0.75)	(-0.32)	(2.86)***	(0.32)	(1.24)	(0.31)
$CAAR_{0,+2}$	-0.35%	-1.90%	-4.68%	12.91%	2.15%	4.20%	1.10%
	(-0.17)	(-0.67)	(-1.49)	(4.26)***	(1.41)	(3.31)***	(0.81)
$CAAR_{-1,+1}$	-3.49%	-0.42%	-3.60%	6.35%	-0.66%	1.08%	0.33%
	(-1.66)*	(-0.15)	(-1.15)	(2.10)**	(-0.43)	(0.84)	(0.24)
$CAAR_{-2,+2}$	-3.10%	-3.26%	-6.42%	12.09%	0.22%	3.22%	0.28%
	(-1.14)	(-0.89)	(-1.59)	(3.10)***	(0.11)	(1.97)**	(0.16)
$CAAR_{-10,+2}$	-8.36%	-11.32%	-15.96%	16.86%	1.94%	4.74%	0.79%
	(-1.91)*	(-1.91)*	(-2.45)**	(2.68)***	(0.61)	(1.79)*	(0.28)
Number of ETFs	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 5: Effects of Paris climate agreement on energy sector using energy indices

	Coal	Oil and Gas	Solar	Alternative Energy
$CAAR_{-2,0}$	-3.06%	-0.50%	3.40%	-0.48%
	(-1.25)	(-0.28)	(1.20)	(-0.27)
$CAAR_{-1,0}$	-2.05%	-1.00%	4.11%	1.07%
	(-1.02)	(-0.67)	(1.77)*	(0.72)
$CAAR_{0}$	-1.97%	0.16%	3.92%	1.53%
	(-1.39)	(0.15)	(2.39)**	(1.46)
$CAAR_{0,+1}$	-2.77%	1.82%	5.51%	2.33%
	(-1.38)	(1.22)	(2.37)**	(1.57)
$CAAR_{0,+2}$	-1.44%	-0.35%	11.70%	5.84%
	(-0.59)	(-0.19)	(4.12)***	(3.21)***
$CAAR_{-1,+1}$	-2.84%	0.65%	5.70%	1.86%
	(-1.16)	(0.36)	(2.00)**	(1.02)
$CAAR_{-2,+2}$	-2.53%	-1.01%	11.18%	3.82%
	(-0.80)	(-0.43)	(3.05)***	(1.63)
$CAAR_{-10,+2}$	-7.47%	-6.74%	18.76%	6.09%
	(-1.46)	(-1.78)*	(3.17)***	(1.61)

In this table, we corroborate our results in Table 4 by reporting the mean cumulative abnormal returns for the widely followed global energy indices. Coal is made up of an equally weighted average of the two main coal indices 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 indices 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

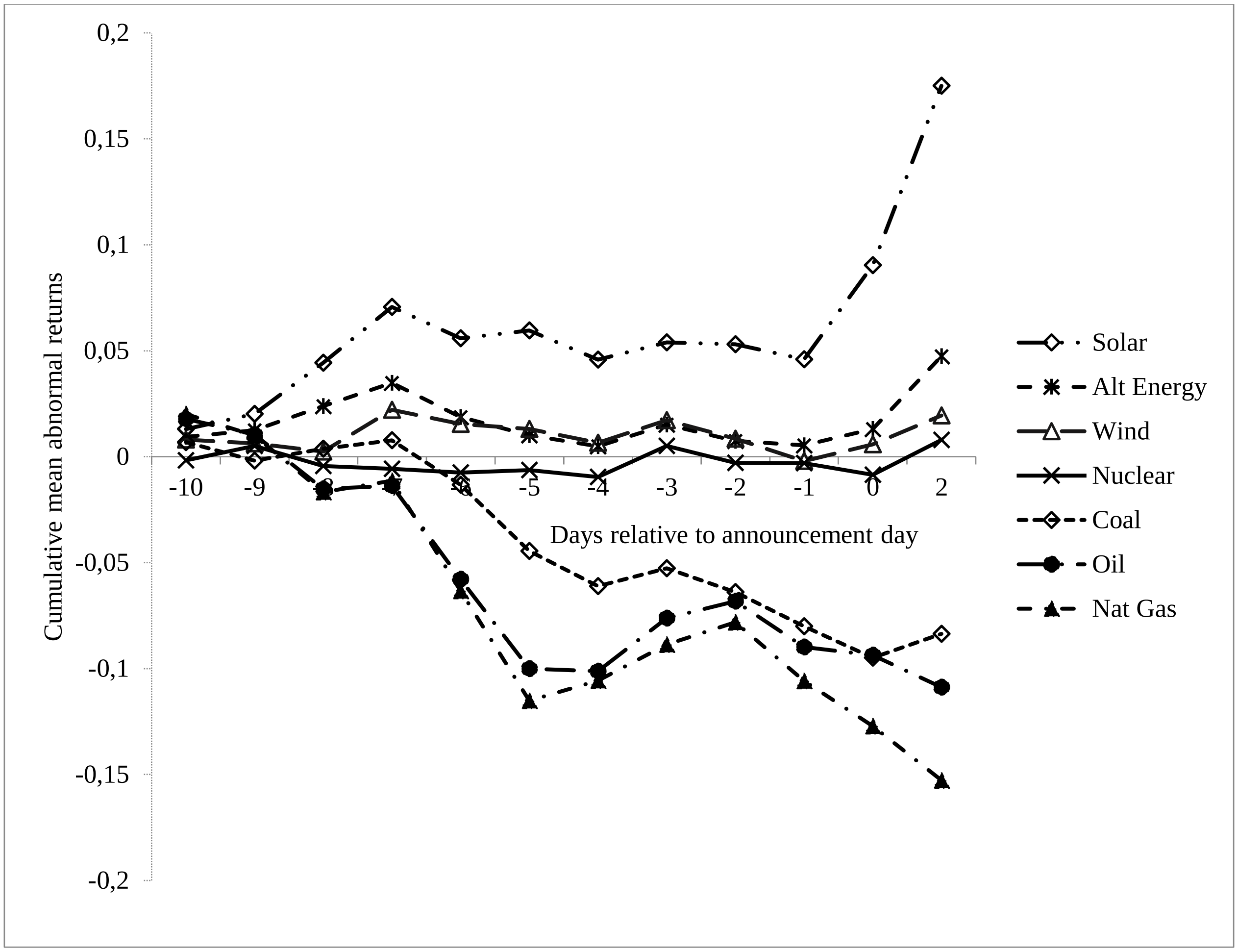


Table 6a: Effects of Paris climate agreement on coal stocks†

		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%
	(-1.23)	(0.37)	(0.57)	(0.46)	(1.69)*	(-1.27)	(-0.24)	(-0.96)	(0.71)	(0.07)	(-0.89)	(-1.03)
$CAAR_{-1,0}$	-3.41%	0.60%	1.32%	2.09%	5.17%	-0.24%	0.10%	-3.80%	2.03%	-0.44%	-0.14%	-5.81%
	(-1.32)	(0.15)	(0.60)	(0.77)	(1.99)**	(-0.18)	(0.09)	(-1.38)	(0.51)	(-0.16)	(-0.06)	(-2.26)**
$CAAR_{0}$	-2.55%	1.19%	0.63%	1.37%	2.81%	-0.04%	0.82%	-2.29%	1.79%	-0.28%	-1.25%	-3.68%
	(-1.40)	(0.43)	(0.40)	(0.72)	(1.53)	(-0.04)	(1.02)	(-1.18)	(0.63)	(-0.15)	(-0.79)	(-2.03)**
$CAAR_{0,+1}$	-5.94%	2.06%	-0.23%	0.02%	1.28%	1.09%	0.28%	-1.61%	-0.47%	-0.57%	-2.49%	-2.44%
	(-2.31)**	(0.53)	(-0.10)	(0.01)	(0.49)	(0.82)	(0.25)	(-0.58)	(-0.12)	(-0.21)	(-1.12)	(-0.95)
$CAAR_{0,+2}$	-5.19%	-2.45%	-0.39%	0.17%	-0.89%	-0.08%	-0.27%	-5.35%	-1.53%	-0.33%	-2.81%	2.86%
	(-1.65)*	(-0.51)	(-0.14)	(0.05)	(-0.28)	(-0.05)	(-0.20)	(-1.59)	(-0.31)	(-0.10)	(-1.03)	(0.91)
$CAAR_{-1,+1}$	-6.76%	1.47%	0.46%	0.75%	3.64%	0.89%	-0.44%	-3.11%	-0.22%	-0.73%	-1.39%	-4.57%
	(-2.14)**	(0.31)	(0.17)	(0.23)	(1.14)	(0.54)	(-0.31)	(-0.92)	(-0.05)	(-0.22)	(-0.51)	(-1.45)
$CAAR_{-2,+2}$	-6.39%	-1.91%	0.52%	0.31%	1.68%	-2.12%	-1.41%	-6.30%	0.14%	0.19%	-3.99%	3.30%
	(-1.57)	(-0.31)	(0.15)	(0.07)	(0.41)	(-1.01)	(-0.79)	(-1.45)	(0.02)	(0.04)	(-1.13)	(0.81)
$CAAR_{-10,+2}$	-9.63%	-5.24%	-2.27%	-1.08%	-0.33%	-7.37%	0.54%	-1.67%	-6.64%	-1.18%	-4.38%	-6.02%
	(-1.47)	(-0.52)	(-0.40)	(-0.16)	(-0.05)	(-2.17)**	(0.19)	(-0.24)	(-0.65)	(-0.17)	(-0.77)	(-0.92)
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 we 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 6b: Effects of Paris climate agreement on U.S. listed coal stocks

	United States Full Sample	NYSE	NASDAQ
$CAAR_{-2,0}$	-4.63%	-5.02%	-4.47%
	(-0.91)	(-0.98)	(-0.58)
$CAAR_{-1,0}$	-5.00%	-6.20%	-2.93%
	(-1.21)	(-1.49)	(-0.47)
$CAAR_{0}$	-3.76%	-5.06%	-1.30%
	(-1.28)	(-1.72)*	(-0.29)
$CAAR_{0,+1}$	-3.84%	-3.95%	-3.63%
	(-0.93)	(-0.95)	(-0.58)
$CAAR_{0,+2}$	-3.72%	-2.05%	-6.90%
	(-0.73)	(-0.40)	(-0.90)
$CAAR_{-1,+1}$	-5.09%	-5.09%	-5.26%
	(-1.00)	(-1.00)	(-0.69)
$CAAR_{-2,+2}$	-4.60%	-2.01%	-10.07%
	(-0.70)	(-0.31)	(-1.02)
$CAAR_{-10,+2}$	-14.39%	-11.79%	-20.26%
	(-1.36)	(-1.11)	(-1.27)
Number of stocks	15	10	5

This table reports mean cumulative abnormal returns for the major U.S. 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 7: Effects of U.S. election on energy sector using energy ETFs

	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%
	(-0.83)	(-0.48)	(-0.44)	(-0.41)	(-1.52)	(-0.50)	(0.17)
$CAAR_0$	0.45%	0.84%	1.02%	-6.44%	-4.38%	-2.83%	-4.49%
	(0.29)	(0.50)	(0.29)	(-4.48)***	(-5.17)***	(-4.18)***	(-6.41)***
$CAAR_{0,+1}$	-1.71%	0.98%	0.45%	-6.76%	-7.46%	-3.55%	-3.73%
	(-0.80)	(0.42)	(0.09)	(-3.33)***	(-6.23)***	(-3.71)***	(-3.77)***
$CAAR_{0,+2}$	-2.50%	-1.19%	-2.26%	-8.17%	-8.00%	-2.88%	-5.06%
	(-0.95)	(-0.41)	(-0.37)	(-3.28)***	(-5.46)***	(-2.46)**	(-4.17)***
$CAAR_{0,+5}$	-6.26%	1.93%	2.22%	-6.10%	-10.88%	-2.77%	-4.42%
	(-1.69)*	(0.47)	(0.26)	(-1.74)*	(-5.25)***	(-1.67)*	(-2.58)***
Number of ETFs	1	4	4	2	1	7	1

This table reports mean cumulative abnormal returns for equally weighted energy ETF portfolios for the U.S. 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 8: Effects of U.S. election on energy sector using energy indices

	Coal	Oil and Gas	Solar	Alternative Energy
$CAAR_{-5,-1}$	-0.39%	-1.08%	-1.26%	-2.35%
	(-0.11)	(-0.44)	(-0.40)	(-1.05)
$CAAR_{0}$	-0.42%	0.25%	-6.12%	-5.88%
	(-0.26)	(0.23)	(-4.33)***	(-5.87)***
$CAAR_{0,+1}$	1.92%	0.21%	-6.06%	-7.97%
	(0.84)	(0.14)	(-3.03)***	(-5.62)***
$CAAR_{0,+2}$	2.01%	-1.27%	-7.22%	-8.81%
	(0.72)	(-0.67)	(-2.95)***	(-5.08)***
$CAAR_{0,+5}$	-3.78%	0.23%	-7.04%	-9.16%
	(-0.96)	(0.09)	(-2.03)**	(-3.73)***

In this table, we corroborate the results in Table 7 by reporting the mean cumulative abnormal returns for the widely followed global energy indices. Coal is made up of an equally weighted average of the two main coal indices 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 indices 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 9a: Effects of U.S. election on coal stocks

		China										
	Australia[†]	Hong Kong	Shanghai	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%
	(-0.79)	(-0.37)	(0.06)	(-0.12)	(-0.93)	(1.53)	(-0.629)	(0.04)	(0.12)	(-0.25)	(0.34)	(-0.39)
$CAAR_{0}$	-4.34%	-0.63%	1.20%	1.39%	1.68%	0.48%	-0.47%	-0.22%	-1.42%	-0.52%	3.58%	1.52%
	(-2.88)***	(-0.38)	(0.90)	(0.71)	(1.10)	(0.25)	(-0.443)	(-0.10)	(-0.49)	(-0.29)	(2.34)**	(0.96)
$CAAR_{0,+1}$	-1.39%	0.71%	-0.05%	0.52%	1.50%	4.66%	0.04%	2.18%	2.55%	1.42%	3.39%	4.64%
	(-0.65)	(0.30)	(-0.03)	(0.19)	(0.69)	(1.69)*	(0.028)	(0.71)	(0.62)	(0.55)	(1.56)	(2.08)**
$CAAR_{0,+2}$	-0.73%	1.56%	1.19%	3.78%	2.43%	6.16%	-1.24%	3.12%	4.33%	2.15%	4.05%	6.46%
	(-0.28)	(0.54)	(0.52)	(1.12)	(0.91)	(1.82)*	(-0.681)	(0.83)	(0.86)	(0.68)	(1.53)	(2.37)**
$CAAR_{0,+5}$	-3.51%	1.80%	0.64%	4.38%	-3.55%	0.46%	0.16%	3.88%	4.54%	3.20%	0.18%	1.56%
	(-0.95)	(0.44)	(0.20)	(0.92)	(-0.94)	(0.10)	(0.063)	(0.73)	(0.64)	(0.72)	(0.05)	(0.41)
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.

[†]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 9b: Effects of U.S. election on U.S. listed coal stocks

	United States				
	Full Sample		NYSE		NASDAQ
	I	II†	III	IV†	V
$CAAR_{-5,-1}$	-2.84%	-2.91%	-3.50%	-3.69%	-1.36%
	(-0.51)	(-0.57)	(-0.54)	(-0.65)	(-0.27)
$CAAR_0$	10.74%	7.72%	10.07%	5.46%	12.24%
	(4.30)***	(3.39)***	(3.48)***	(2.15)**	(5.41)***
$CAAR_{0,+1}$	11.92%	7.82%	11.28%	5.05%	13.36%
	(3.38)***	(2.43)**	(2.75)***	(1.41)	(4.17)***
$CAAR_{0,+2}$	12.17%	9.47%	10.44%	6.17%	16.07%
	(2.82)***	(2.40)**	(2.08)**	(1.40)	(4.10)***
$CAAR_{0,+5}$	10.03%	6.42%	9.83%	4.39%	10.48%
	(1.64)	(1.15)	(1.39)	(0.71)	(1.89)*
Number of stocks	13	12	9	8	4

This table reports mean cumulative abnormal returns for the major U.S. 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 Corp which filed for Chapter 11 bankruptcy in April 2016 but whose stocks continued trading on the over-the-counter market. Its stock price increased by 50% on the announcement of the U.S. 2016 presidential election results. We feel it is more of an outlier than the norm for U.S. listed coal stocks and our results show a much higher abnormal return when it is included in the sample.

Table 9c: Effects of U.S. election on U.S. listed coal stocks (mean abnormal returns)

	United States				
	Full Sample		NYSE		NASDAQ
	I	II†	III	IV†	V
-5	-0.91%	-0.88%	-0.94%	-0.90%	-0.83%
	(-0.36)	(-0.39)	(-0.33)	(-0.35)	(-0.37)
-4	1.96%	2.00%	2.23%	2.33%	1.33%
	(0.78)	(0.88)	(0.77)	(0.92)	(0.59)
-3	0.80%	0.88%	-0.16%	-0.15%	2.95%
	(0.32)	(0.39)	(-0.05)	(-0.06)	(1.30)
-2	-3.62%	-3.99%	-3.15%	-3.66%	-4.66%
	(-1.45)	(-1.75)*	(-1.09)	(-1.44)	(-2.06)**
-1	-1.07%	-0.92%	-1.48%	-1.31%	-0.15%
	(-0.43)	(-0.41)	(-0.51)	(-0.52)	(-0.07)
0	10.74%	7.72%	10.07%	5.46%	12.24%
	(4.30)***	(3.39)***	(3.48)***	(2.15)*	(5.41)***
+1	1.18%	0.10%	1.21%	-0.41%	1.12%
	(0.47)	(0.04)	(0.42)	(-0.16)	(0.49)
+2	0.25%	1.65%	-0.84%	1.12%	2.71%
	(0.10)	(0.73)	(-0.29)	(0.44)	(1.20)
+3	2.28%	1.55%	3.01%	2.01%	0.63%
	(0.91)	(0.68)	(1.04)	(0.79)	(0.28)
+4	-3.77%	-3.96%	-2.88%	-3.06%	-5.78%
	(-1.51)	(-1.74)*	(-0.99)	(-1.20)	(-2.55)**
+5	-0.65%	-0.64%	-0.75%	-0.74%	-0.44%
	(-0.26)	(-0.28)	(-0.26)	(-0.29)	(-0.20)
Number of stocks	13	12	9	8	4

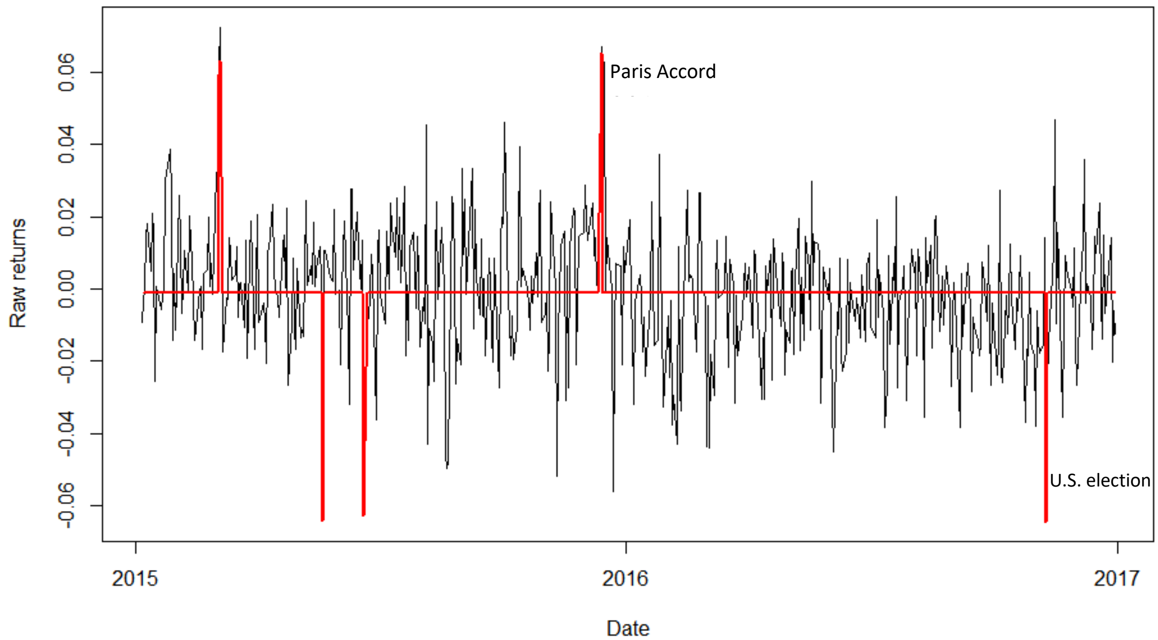
This table reports mean abnormal returns for the major U.S. coal-producing and exporting companies using equally weighted portfolios. The market model is estimated using OLS and the market index is the S&P 500 Index for the NYSE subsample and Dow Jones Industrial Average for the NASDAQ subsample. We 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 Corp.

Table 10: Output from impulse indicator saturation to detect relevant climate-related political and market events between January 2015 and 2017

	I	II	III	IV	V
Market Returns	0.3123***	0.3194***	0.3332***	0.3194***	0.3116***
	(0.0837)	(0.0840)	(0.0844)	(0.0840)	(0.0850)
Paris	0.0668***	0.0664***	0.0666***	0.0664***	0.0663***
	(0.0169)	(0.0169)	(0.0171)	(0.0169)	(0.0171)
US Election	-0.0611***	-0.0635***	-0.0615***	-0.0635***	-0.0637***
	(0.0169)	(0.0169)	(0.0171)	(0.0169)	(0.0171)
$r_{\mathrm{sc(t-1)}}$		0.1419***		0.1419***	0.1528***
		(0.0412)		(0.0412)	(0.0416)
04 March 2015	0.0648***	0.0604***	0.0648***	0.0604***	
	(0.0169)	(0.0170)	(0.0171)	(0.0170)	
05 March 2015	0.0736***	0.0644***	0.0734***	0.0644***	0.0636***
	(0.0169)	(0.0171)	(0.0171)	(0.0171)	(0.0173)
20 May 2015	-0.0628***	-0.0634***	-0.0629***	-0.0634***	-0.0636***
	(0.0169)	(0.0169)	(0.0171)	(0.0169)	(0.0171)
19 June 2015	-0.0597***	-0.0619***	-0.0597***	-0.0619***	-0.0622***
	(0.0169)	(0.0169)	(0.0171)	(0.0169)	(0.0171)
16-dec-15	0.0596***				
	(0.0169)				
Constant	-0.0013*	-0.0010	-0.0012	-0.0010	-0.0009
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Ljung-Box AR(2)	11.5635	0.2920	13.2523	0.2920	0.3335
	[0.0007]	[0.8642]	[0.0003]	[0.8642]	[0.8464]
Ljung-Box ARCH(1)	0.5828	0.0365	0.7776	0.0365	0.0114
	[0.4452]	[0.8484]	[0.3779]	[0.8484]	[0.9148]
Jarque-Bera	7.5473	7.9635	7.9783	7.9635	9.4766
	[0.0230]	[0.0187]	[0.0185]	[0.0187]	[0.0088]
Log-likelihood	1344.38	1340.95	1338.15	1340.95	1334.58

This table presents results from several specifications using Impulse Indicator Saturation (IIS). Specification I and II includes two regressors *Paris* and *US Election* retained without selection. The dummy variable *Paris* equals 1 on the day the Paris agreement was announced and zero otherwise. The variable *US Election* equals 1 on the day the U.S. 2016 presidential election results were announced. Specification II adds some dynamics to I by allowing for an autoregressive term. In specification III, no outliers are imposed on the model in advance and no autoregressive term is included, while specification IV includes an additional autoregressive term not included in III. Selection in specifications I – IV is carried out at the significance level $\alpha = 0.001$. Specification V is similar to IV but selection is carried out at a very tight significance level $\alpha = 0.0005$. All the selected regressors in specification I – IV are retained without selection in specification VI except the date 04 March 2015. 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 indices such as the S&P 500 but others also track customized indices. Customized indices are not market indices as their intention is not to measure the value or performance of financial markets or sectors. To this extend, customized indices 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 (Ferri, 2011).

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 extent 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 U.S. listed ETFs we analyze, it is a potential problem with some of our country level analysis (e.g. 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 (Bartholdy, Olson, & Peare, 2007) 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: Effects of Paris climate agreement on energy sector using ETFs

	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%
	(-2.01)**	(-0.61)	(-1.24)	(1.20)	(-0.77)	(-0.15)	(-1.01)
$CAAR_{-1,0}$	-3.09%	-2.56%	-4.97%	3.75%	-0.29%	0.59%	-0.56%
	(-1.80)*	(-1.10)	(-1.94)*	(1.52)	(-0.24)	(0.57)	(-0.51)
$CAAR_{0}$	-1.45%	-0.35%	-2.08%	4.44%	0.79%	0.75%	-0.55%
	(-1.20)	(-0.21)	(-1.15)	(2.54)**	(0.90)	(1.03)	(-0.70)
$CAAR_{0,+1}$	-1.82%	1.84%	-0.69%	7.05%	0.40%	1.26%	0.34%
	(-1.06)	(0.79)	(-0.27)	(2.85)***	(0.33)	(1.21)	(0.31)
$CAAR_{0,+2}$	-0.24%	-1.73%	-4.45%	12.89%	2.17%	4.15%	1.10%
	(-0.12)	(-0.61)	(-1.42)	(4.26)***	(1.43)	(3.27)***	(0.81)
$CAAR_{-1,+1}$	-3.46%	-0.37%	-3.58%	6.36%	-0.68%	1.09%	0.33%
	(-1.65)*	(-0.13)	(-1.14)	(2.10)**	(-0.45)	(0.86)	(0.24)
$CAAR_{-2,+2}$	-3.00%	-3.11%	-6.26%	12.08%	0.21%	3.21%	0.28%
	(-1.11)	(-0.84)	(-1.55)	(3.09)***	(0.11)	(1.96)*	(0.16)
$CAAR_{-10,+2}$	-8.20%	-11.07%	-15.81%	16.88%	1.85%	4.78%	0.79%
	(-1.88)*	(-1.87)*	(-2.42)**	(2.68)***	(0.59)	(1.81)*	(0.28)
Number of ETFs	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: Effects of Paris climate agreement on energy sector using ETFs (mean abnormal returns)

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%
	(0.57)	(0.57)	(1.08)	(1.08)	(1.11)	(1.09)	(0.75)	(0.76)	(0.91)	(0.90)	(1.28)	(1.29)	(-0.22)	(-0.22)
-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%
	(-0.73)	(-0.70)	(-0.45)	(-0.41)	(-0.56)	(-0.51)	(0.41)	(0.40)	(-0.19)	(-0.18)	(0.43)	(0.41)	(0.86)	(0.86)
-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%
	(0.47)	(0.46)	(-1.55)	(-1.56)	(-1.48)	(-1.51)	(1.39)	(1.39)	(-0.45)	(-0.47)	(1.55)	(1.58)	(-1.20)	(-1.20)
-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%
	(0.32)	(0.31)	(0.09)	(0.07)	(0.29)	(0.25)	(1.51)	(1.52)	(2.24)**	(2.21)**	(1.51)	(1.55)	(-0.16)	(-0.16)
-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%
	(-1.74)*	(-1.69)*	(-2.68)***	(-2.62)***	(-2.87)***	(-2.79)***	(-0.85)	(-0.86)	(-0.76)	(-0.73)	(-2.21)**	(-2.26)**	(-0.23)	(-0.23)
-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%
	(-2.58)**	(-2.58)**	(-2.57)**	(-2.57)**	(-2.87)***	(-2.88)***	(0.21)	(0.22)	(-0.28)	(-0.29)	(-1.18)	(-1.16)	(0.15)	(0.15)
-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%
	(-1.37)	(-1.37)	(-0.08)	(-0.08)	(0.52)	(0.51)	(-0.79)	(-0.79)	(-0.74)	(-0.76)	(-0.71)	(-0.69)	(-0.42)	(-0.42)
-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%
	(0.70)	(0.70)	(1.53)	(1.52)	(0.94)	(0.93)	(0.47)	(0.47)	(1.21)	(1.19)	(1.40)	(1.42)	(1.88)*	(1.88)*
-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%
	(-0.94)	(-0.92)	(0.49)	(0.52)	(0.58)	(0.59)	(-0.06)	(-0.06)	(-1.00)	(-1.00)	(-1.06)	(-1.06)	(-1.04)	(-1.04)
-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%
	(-1.33)	(-1.35)	(-1.31)	(-1.34)	(-1.54)	(-1.60)	(-0.41)	(-0.40)	(-1.19)	(-1.23)	(-0.28)	(-0.23)	(-0.02)	(-0.02)
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%
	(-1.22)	(-1.20)	(-0.24)	(-0.21)	(-1.18)	(-1.15)	(2.55)**	(2.54)**	(0.90)	(0.90)	(1.04)	(1.025)	(-0.70)	(-0.70)
+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%
	(-0.33)	(-0.30)	(1.29)	(1.33)	(0.72)	(0.77)	(1.50)	(1.49)	(-0.45)	(-0.44)	(0.71)	(0.69)	(1.14)	(1.14)
+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%
	(1.26)	(1.30)	(-2.22)**	(-2.17)**	(-2.14)**	(-2.08)**	(3.34)***	(3.34)***	(1.99)**	(2.01)**	(3.99)***	(3.95)***	(0.97)	(0.97)
Number of ETFs	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: Effects of U.S. election on energy sector using energy ETFs

	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%
	(-0.84)	(-0.42)	(-0.36)	(-0.49)	(-1.50)	(-0.54)	(0.15)
$CAAR_{0}$	0.48%	0.89%	1.40%	-6.58%	-4.37%	-2.86%	-4.51%
	(0.32)	(0.53)	(0.40)	(-4.57)***	(-5.16)***	(-4.22)***	(-6.44)***
$CAAR_{0,+1}$	-1.69%	1.08%	0.95%	-6.95%	-7.44%	-3.59%	-3.75%
	(-0.79)	(0.46)	(0.19)	(-3.42)***	(-6.21)***	(-3.75)***	(-3.79)***
$CAAR_{0,+2}$	-2.50%	-1.04%	-1.75%	-8.37%	-7.97%	-2.92%	-5.08%
	(-0.96)	(-0.36)	(-0.29)	(-3.36)***	(-5.44)***	(-2.49)**	(-4.19)***
$CAAR_{0,+5}$	-6.30%	2.22%	3.09%	-6.45%	-10.83%	-2.83%	-4.47%
	(-1.70)*	(0.54)	(0.36)	(-1.83)*	(-5.22)***	(-1.71)*	(-2.61)***
Number of ETFs	1	4	4	2	1	7	1

This table reports mean cumulative abnormal returns for equally weighted energy ETF portfolios for the U.S. 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: Effects of U.S. election on energy ETFs (mean abnormal returns)

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%
	(-1.05)	(-1.05)	(-0.47)	(-0.44)	(-0.54)	(-0.49)	(0.57)	(0.50)	(-1.73)*	(-1.72)*	(-0.12)	(-0.14)	(-0.24)	(-0.25)
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%	—†	—†
	(0.29)	(0.32)	(0.50)	(0.53)	(0.29)	(0.40)	(-4.48)***	(-4.57)***	(-5.17)***	(-5.16)***	(-4.18)***	(-4.22)***		
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%
	(-1.43)	(-1.44)	(0.09)	(0.11)	(-0.16)	(-0.13)	(-0.23)	(-0.26)	(-3.63)***	(-3.63)***	(-1.08)	(-1.09)	(-6.41)***	(-6.44)***
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%
	(-0.52)	(-0.54)	(-1.30)	(-1.27)	(-0.77)	(-0.77)	(-0.98)	(-0.99)	(-0.64)	(-0.63)	(0.99)	(0.99)	(1.08)	(1.08)
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%
	(-0.56)	(-0.57)	(0.58)	(0.60)	(0.49)	(0.51)	(0.68)	(0.66)	(-1.05)	(-1.04)	(0.49)	(0.48)	(-1.89)*	(-1.90)*
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%
	(-2.37)**	(-2.35)**	(1.60)	(1.63)	(1.05)	(1.12)	(-0.28)	(-0.34)	(-0.92)	(-0.91)	(0.10)	(0.07)	(0.90)	(0.89)
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%
	(0.44)	(0.42)	(-0.30)	(-0.27)	(-0.26)	(-0.26)	(1.04)	(1.02)	(-1.44)	(-1.44)	(-0.41)	(-0.41)	(-0.49)	(-0.49)
Number of ETFs	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 U.S. 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: Effects of Paris climate agreement on energy sector using energy indices

	Coal	Oil	Solar	Alternative Energy
$CAAR_{-2,0}$	-2.92%	-0.53%	3.40%	-0.37%
	(-1.19)	(-0.29)	(1.20)	(-0.20)
$CAAR_{-1,0}$	-1.97%	-1.04%	4.11%	1.13%
	(-0.98)	(-0.70)	(1.77)*	(0.76)
$CAAR_{0}$	-1.91%	0.19%	3.91%	1.58%
	(-1.35)	(0.18)	(2.38)**	(1.51)
$CAAR_{0,+1}$	-2.64%	1.89%	5.49%	2.45%
	(-1.32)	(1.27)	(2.37)**	(1.65)*
$CAAR_{0,+2}$	-1.25%	-0.20%	11.67%	6.02%
	(-0.51)	(-0.11)	(4.11)***	(3.31)***
$CAAR_{-1,+1}$	-2.70%	0.66%	5.69%	1.99%
	(-1.10)	(0.36)	(2.00)**	(1.10)
$CAAR_{-2,+2}$	-2.27%	-0.92%	11.16%	4.07%
	(-0.72)	(-0.39)	(3.04)***	(1.73)*
$CAAR_{-10,+2}$	-6.84%	-6.67%	18.71%	6.67%
	(-1.34)	(-1.76)*	(3.16)***	(1.76)*

This table reports the mean cumulative abnormal returns for the widely followed global energy indices. Coal is made up of an equally weighted average of the two main coal indices 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 indices 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: Effects of U.S. election on energy sector using energy indices

	Coal	Oil	Solar	Alternative Energy
$CAAR_{-5,-1}$	-0.50%	-0.90%	-1.67%	-2.52%
	(-0.14)	(-0.37)	(-0.53)	(-1.12)
$CAAR_{0}$	-0.42%	0.32%	-6.29%	-5.94%
	(-0.26)	(0.29)	(-4.44)***	(-5.93)***
$CAAR_{0,+1}$	1.89%	0.31%	-6.30%	-8.07%
	(0.83)	(0.20)	(-3.15)**	(-5.69)***
$CAAR_{0,+2}$	1.95%	-1.15%	-7.50%	-8.93%
	(0.70)	(-0.61)	(-3.06)**	(-5.14)***
$CAAR_{0,+5}$	-3.92%	0.45%	-7.54%	-9.37%
	(-0.99)	(0.17)	(-2.17)*	(-3.81)***

This table reports the mean cumulative abnormal returns for the widely followed global energy indices. Coal is made up of an equally weighted average of the two main coal indices 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 indices 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: Effects of Paris climate agreement on coal stocks†

	Australia	China: Hong Kong	China: Shanghai	China: 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%
	(-1.02)	(0.21)	(0.61)	(0.48)	(1.65)*	(-1.38)	(-0.34)	(-0.93)	(0.59)	(0.03)	(-0.87)	(-1.15)
$CAAR_{-1,0}$	-2.95%	-0.06%	1.44%	2.21%	5.10%	-0.51%	0.03%	-3.71%	0.92%	-0.64%	-0.11%	-6.04%
	(-1.15)	(-0.01)	(0.65)	(0.81)	(1.96)**	(-0.38)	(0.02)	(-1.35)	(0.23)	(-0.23)	(-0.05)	(-2.35)**
$CAAR_{0}$	-2.14%	0.96%	0.76%	1.54%	2.77%	-0.28%	0.72%	-2.33%	1.52%	-0.38%	-1.23%	-3.72%
	(-1.17)	(0.34)	(0.48)	(0.80)	(1.51)	(-0.29)	(0.89)	(-1.19)	(0.53)	(-0.20)	(-0.78)	(-2.05)**
$CAAR_{0,+1}$	-5.40%	1.88%	-0.09%	0.29%	1.20%	0.90%	0.09%	-1.59%	-0.16%	-0.47%	-2.45%	-2.46%
	(-2.09)**	(0.46)	(-0.04)	(0.11)	(0.46)	(0.67)	(0.08)	(-0.58)	(-0.04)	(-0.17)	(-1.10)	(-0.96)
$CAAR_{0,+2}$	-4.90%	-1.57%	-0.22%	0.50%	-1.01%	-0.12%	-0.36%	-5.52%	-0.46%	-0.17%	-2.75%	3.01%
	(-1.55)	(-0.32)	(-0.08)	(0.15)	(-0.32)	(-0.07)	(-0.26)	(-1.63)	(-0.09)	(-0.05)	(-1.00)	(0.96)
$CAAR_{-1,+1}$	-6.16%	0.86%	0.60%	0.96%	3.53%	0.67%	-0.60%	-2.97%	-0.76%	-0.73%	-1.33%	-4.78%
	(-1.95)*	(0.17)	(0.22)	(0.29)	(1.11)	(0.41)	(-0.43)	(-0.88)	(-0.15)	(-0.22)	(-0.49)	(-1.52)
$CAAR_{-2,+2}$	-5.85%	-1.52%	0.68%	0.57%	1.48%	-2.12%	-1.56%	-6.32%	0.94%	0.30%	-3.90%	3.12%
	(-1.44)	(-0.24)	(0.20)	(0.13)	(0.36)	(-1.00)	(-0.87)	(-1.45)	(0.15)	(0.07)	(-1.10)	(0.77)
$CAAR_{-10,+2}$	-8.15%	-4.44%	-1.92%	-0.69%	-0.77%	-7.71%	0.13%	-1.63%	-8.52%	-1.52%	-4.17%	-6.86%
	(-1.24)	(-0.43)	(-0.34)	(-0.10)	(-0.12)	(-2.26)**	(0.04)	(-0.23)	(-0.83)	(-0.22)	(-0.73)	(-1.05)
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: Effects of U.S. election on coal stocks

		China										
	Australia†	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%
	(-0.74)	(-0.22)	(0.14)	(0.02)	(-0.89)	(1.87)*	(-0.60)	(0.13)	(0.15)	(-0.26)	(0.49)	(-0.35)
$CAAR_{0}$	-4.03%	-0.55%	1.28%	1.54%	1.68%	0.69%	-0.57%	-0.79%	-1.38%	-0.55%	3.68%	1.63%
	(-2.66)***	(-0.34)	(0.96)	(0.79)	(1.09)	(0.35)	(-0.54)	(-0.36)	(-0.47)	(-0.31)	(2.40)**	(1.03)
$CAAR_{0,+1}$	-1.45%	0.93%	0.03%	0.73%	1.56%	5.25%	0.11%	1.96%	2.63%	1.36%	3.59%	4.92%
	(-0.68)	(0.40)	(0.02)	(0.27)	(0.72)	(1.90)*	(0.08)	(0.63)	(0.64)	(0.53)	(1.66)*	(2.20)**
$CAAR_{0,+2}$	-0.82%	1.87%	1.30%	4.09%	2.44%	6.83%	-1.15%	2.53%	4.46%	2.08%	4.33%	6.49%
	(-0.31)	(0.65)	(0.57)	(1.21)	(0.92)	(2.01)**	(-0.63)	(0.67)	(0.88)	(0.66)	(1.63)	(2.37)**
$CAAR_{0,+5}$	-3.24%	2.43%	0.90%	5.04%	-3.51%	1.85%	0.38%	3.32%	4.80%	3.10%	0.71%	1.65%
	(-0.87)	(0.60)	(0.28)	(1.05)	(-0.93)	(0.37)	(0.15)	(0.62)	(0.67)	(0.70)	(0.19)	(0.43)
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 -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.

†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: Effects of Paris climate agreement on U.S. listed coal stocks

	United States Full Sample	NYSE	NASDAQ
$CAAR_{-2,0}$	-4.34%	-4.87%	-3.29%
	(-0.85)	(-0.95)	(-0.43)
$CAAR_{-1,0}$	-4.73%	-6.05%	-2.10%
	(-1.14)	(-1.45)	(-0.34)
$CAAR_{0}$	-3.76%	-5.08%	-1.13%
	(-1.28)	(-1.72)*	(-0.26)
$CAAR_{0,+1}$	-3.92%	-4.04%	-3.69%
	(-0.95)	(-0.97)	(-0.59)
$CAAR_{0,+2}$	-3.92%	-2.24%	-7.27%
	(-0.77)	(-0.44)	(-0.95)
$CAAR_{-1,+1}$	-4.89%	-5.01%	-4.66%
	(-0.96)	(-0.98)	(-0.61)
$CAAR_{-2,+2}$	-4.50%	-2.03%	-9.44%
	(-0.69)	(-0.31)	(-0.95)
$CAAR_{-10,+2}$	-13.66%	-11.52%	-17.94%
	(-1.29)	(-1.08)	(-1.12)
Number of stocks	15	10	5

This table reports mean cumulative abnormal returns for the major U.S. 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: Effects of U.S. election on U.S. listed coal stocks

	United States				
	Full Sample		NYSE		NASDAQ
	I	II†	III	IV†	V
$CAAR_{-5,-1}$	-2.16%	-2.91%	-2.51%	-3.68%	-1.38%
	(-0.39)	(-0.57)	(-0.39)	(-0.65)	(-0.27)
$CAAR_{0}$	10.99%	7.78%	10.42%	5.54%	12.26%
	(4.40)***	(3.41)***	(3.60)***	(2.18)**	(5.41)***
$CAAR_{0,+1}$	12.29%	7.87%	11.81%	5.12%	13.37%
	(3.48)***	(2.44)**	(2.88)***	(1.42)	(4.17)***
$CAAR_{0,+2}$	12.63%	9.50%	11.10%	6.21%	16.06%
	(2.92)***	(2.41)**	(2.21)**	(1.41)	(4.10)***
$CAAR_{0,+5}$	10.86%	6.43%	11.04%	4.42%	10.45%
	(1.78)*	(1.15)	(1.56)	(0.71)	(1.88)*
Number of stocks	13	12	9	8	4

This table reports mean cumulative abnormal returns for the major U.S. 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 Corp.

Table 11: Effects of U.S. election on U.S. listed coal stocks (mean abnormal returns)

Day relative to event date (Day 0 = November 9, 2016)	United States				
	Full Sample		NYSE		NASDAQ
	I	II†	III	IV†	V
-5	-0.89%	-0.94%	-0.90%	-0.98%	-0.86%
	(-0.36)	(-0.41)	(-0.31)	(-0.38)	(-0.38)
-4	2.00%	1.95%	2.31%	2.27%	1.31%
	(0.80)	(0.86)	(0.80)	(0.89)	(0.58)
-3	0.88%	0.85%	-0.03%	-0.18%	2.93%
	(0.35)	(0.38)	(-0.01)	(-0.07)	(1.30)
-2	-3.23%	-3.86%	-2.61%	-3.49%	-4.61%
	(-1.29)	(-1.70)*	(-0.90)	(-1.37)	(-2.04)**
-1	-0.92%	-0.92%	-1.26%	-1.30%	-0.15%
	(-0.37)	(-0.40)	(-0.44)	(-0.51)	(-0.07)
0	10.99%	7.78%	10.42%	5.54%	12.26%
	(4.40)***	(3.41)***	(3.60)***	(2.18)**	(5.41)***
+1	1.30%	0.09%	1.39%	-0.42%	1.11%
	(0.52)	(0.04)	(0.48)	(-0.16)	(0.49)
+2	0.34%	1.63%	-0.71%	1.09%	2.69%
	(0.14)	(0.71)	(-0.25)	(0.43)	(1.19)
+3	2.38%	1.53%	3.16%	1.99%	0.62%
	(0.95)	(0.67)	(1.09)	(0.78)	(0.27)
+4	-3.57%	-3.93%	-2.60%	-3.01%	-5.77%
	(-1.43)	(-1.73)*	(-0.90)	(-1.17)	(-2.55)**
+5	-0.57%	-0.67%	-0.62%	-0.77%	-0.46%
	(-0.23)	(-0.29)	(-0.22)	(-0.30)	(-0.20)
Number of stocks	13	12	9	8	4

This table reports mean abnormal returns for the major U.S. 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 Corp.