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Climate Policy and Financial Markets

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Contents

List of Figures

Chapter 1

Chapter 2

Chapter 3

List of Tables

Chapter 1

Chapter 2

Chapter 3

Introduction

Climate change represents a serious, as-yet-unresolved global commons problem. An international policy response has been sought at least since the establishment of the UN Framework Convention on Climate Change (UNFCCC) in 1992, but a global climate agreement has seemed elusive, partly because of disagreements regarding how the burden of emissions reductions would be shared among countries. Despite the disagreements, there has been limited success in the past in the form of the Kyoto Protocol in 1997 and the Doha Amendment to the protocol in 2012. However, many considered the Kyoto structure fatally flawed because it did not adequately take into account the interests of the most powerful nations, it did not ask anything of the non–Annex I countries, and there were insufficient incentives to make parties want to stay in the agreement.[1] In 2009, the 15th Conference of the Parties (COP 15) to the UNFCCC in Copenhagen, which aimed to negotiate a successor to the Kyoto Protocol, ended without results. The collapse of negotiations in Copenhagen highlights the difficulty of reaching a global agreement on emissions reductions.

The approach eventually chosen to deal with the impasse in international climate negotiations was a "pledge and review" process in which each country proposed its own target. In December 2015, following decades of negotiations, 195 nations adopted the Paris Agreement, which aims to keep warming *well below* 2°C above preindustrial levels "and to pursue efforts to limit the temperature increase even further to 1.5°C" (UNFCCC 2015). Some hailed this as a great success, as Paris amounted to a global agreement with fairly ambitious goals, but critics pointed out that there is no mechanism to ensure the countries' contributions add up to the stated goals, nor are there any enforcement mechanisms. In addition, the Paris Agreement does not stipulate the use of efficient policy instruments such as taxes or permit trading, widely advocated by leading economists such as Nordhaus (2007), Weitzman (2014, 2015), and Gollier and Tirole (2015b, 2015a). Its main instrument is the required submission of nationally determined contributions (NDCs), which outline national goals for greenhouse gas emissions reductions. As

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[1] Non–Annex I Parties are mostly developing countries, while Annex I Parties include industrialized countries that were part of the Organisation for Economic Co-operation and Development (OECD) in 1992, as well as economies in transition.

anticipated, the NDCs currently are not ambitious enough to reach the 2°C target set in the Paris Agreement (see Boyd et al. 2015; Climate Action Tracker 2019; Robiou du Pont and Meinshausen 2018; UNEP 2018).

Because of the urgency of the climate change problem and the limited success in addressing the problem so far, more policy measures will likely be needed. The scale of decarbonization required demands that large fossil fuel deposits be left in the ground unexploited (Carbon Tracker Initiative 2013; Leaton 2012). This will inevitably put considerable strain on the balance sheets of many of the world's largest fossil fuel companies and poses a great risk that such assets will fail to maintain their value or could turn into liabilities well ahead of the end of their expected economic life. Climate change–induced risks are also raising concern among central banks that exposure to assets that might be affected by the introduction of carbon prices to address the climate change problem may trigger financial instability (Batten et al. 2016; Carney 2015; Olovsson 2018; Rudebusch 2019).

The United States had been largely expected to lead international climate negotiations and decarbonization efforts. However, the unexpected election of Donald Trump as president in November 2016 changed the expectations about US climate policy. In his campaign, Trump promised to roll back environmental regulations and withdraw from the Paris Agreement. There was global concern that a climate agreement without US participation would hold back the full commitment of other countries, thereby causing a substantial weakening of the Paris Agreement (Pickering et al. 2018; Urpelainen and Van de Graaf 2018). Trump's election presents a case where there is a clear element of surprise and an unambiguous bias in favor of fossil fuels. This provides an ideal setting to examine the reaction of renewable and fossil fuel stock and commodity prices using event studies to get insights regarding the types of policies that the Trump administration was anticipated to implement and the ambitiousness of current climate policies.

This thesis consists of three related but independent chapters. Chapter 1 sheds some light on the role of financial markets in solving the climate change problem through, for instance, imposing a higher cost of capital on carbon-intensive companies. If financial markets work properly, then long-term investors in carbon-intensive companies should demand higher rates of return to compensate for the high risk of investing in assets that will become stranded once carbon emissions are priced meaningfully through a universal efficient climate policy. Chapter 2 seeks to deepen our understanding on whether Trump was expected primarily to help *mine* more coal or *burn* more coal. Specifically, I seek to measure the price effects of the election on fossil fuel commodity markets, which serve as an indication of the types of policies Trump was anticipated to implement. Chapter 3 shifts focus to recent proposals to strengthen the Paris Agreement, either through tightening the NDCs to be compatible with the 2°C goal or by introducing a carbon price. The chapters are summarized as follows.

In Chapter 1 (coauthored with Thomas Sterner), we evaluate the impacts of two high-profile events, the election of President Trump and the Paris climate agreement, on the stock market value of energy sector firms. To identify the stock price changes due to the two events, we exploit the differential impacts of the events on fossil fuel and renewable energy firms. Using the event study and impulse-indicator saturation methods, we find that both events had large and significant effects on the value of renewable energy firms, positive for Paris and negative for the Trump election. The effects on fossil fuel firms have, as expected, the opposite signs.

In Chapter 2, I analyze commodity price movements around the 2016 US election. This analysis allows us to gain more insight on the types of climate policies that were anticipated following Trump's election. The unexpected election of Donald Trump shifted expectations on several dimensions, including lower corporate taxes, (re-)reform of the healthcare system, and changes to immigration and trade policies. Within the fossil fuel industry, environmental regulations were expected to be substantially weakened. Earlier work has shown that the election led to increased profit expectations among fossil fuel firms. While both supply- and demand-side policies boost profits, they would have different effects on the futures market for coal. I use the differential impact of the touted changes in climate policy and other environmental regulations to identify the price changes due to expectations regarding the path of climate policy under Trump. Using event study analysis, I find large price effects in coal and natural gas futures markets. Over the 21-day post-election period, which includes the nomination of the Environmental Protection Agency (EPA) administrator, I observe cumulative average abnormal returns of up to –27% for coal and 19% for natural gas. Changes in fossil fuel commodity prices could induce carbon leakage through international fossil fuel markets. This can potentially undermine the effectiveness of policy within countries that choose to stick to their Paris pledges or seek to increase the ambitiousness of their pledges. Further analysis shows a marked increase in uncertainty and intracommodity return spreads post-election. In addition, the response to the election by futures contracts of different maturities suggests market participants anticipated that the proposed policies would be implemented shortly after Trump took office.

Chapter 3 (coauthored with Thomas Sterner) studies the distributional implications of strengthening the Paris Agreement by incorporating carbon pricing or tightening the NDCs. We quantify a number of different burden-sharing principles that have been proposed by representatives from various countries. These include grandfathering, equal per capita allocation, proportionality to income, tightened NDCs, and carbon prices. Our results suggest that both carbon pricing and tightened NDCs are viable mechanisms that are less extreme and therefore more acceptable than grandfathering, which favors the most fossil-intensive economies, or equal per capita allocation, which favors low-income countries that use less fossil fuel.

In summary, the results in this thesis provide useful insights on the role of financial markets in solving the climate challenge and enhance our understanding of how climate-related political events can affect expectations regarding the path of climate policy. The thesis also demonstrates that as climate negotiations continue, the Paris Agreement can be strengthened to meet stringent climate goals in ways that could be regarded in some sense as fair by most rich and low-income countries.

Chapter 1

Do Markets Trump Politics? Fossil Fuel Market Reactions to the Paris Agreement and the 2016 US Election

Abstract

Are world climate policies ambitious? Environmentalists claim too little is being done. Industry argues policy is too interventionist and warns that stranding significant assets could lead to financial instability. We evaluate the impacts of global climate policymaking in an event study for two high-profile events, the election of President Trump and the Paris climate agreement, on the stock market value of energy sector firms. To identify the stock price changes due to the two events, we exploit the differential impacts of the events on fossil fuel and renewable energy firms. Using the impulse-indicator saturation method, we find that both events had large and significant effects on the value of renewable energy firms, positive for Paris and negative for the Trump election. The effects on fossil fuel firms have, as expected, the opposite signs.

This chapter is joint work with Thomas Sterner.

1. Introduction

Event studies originated in accounting and finance, but their application has spread to other fields. Examples include Dube et al. (2011), analyzing the effects of the CIA's covert operations in toppling foreign governments on the value of US companies in the countries concerned, and Guidolin and La Ferrara (2007), examining the impact of the abrupt end of the Angolan civil war on the value of diamond mining firms. The key assumptions for event studies are that markets are efficient, the event's timing is exogenous, and the event is unanticipated. In this study on stranded assets (for instance, in coal companies), we will be examining two major events that arguably differ in that one was truly unanticipated while the other was only partially unanticipated.

When it comes to climate, the 2015 Paris Agreement has been described as a big step forward, whereas the election of Donald Trump in 2016 has been characterized as a setback (see, e.g., Tricks 2016). No doubt these were exceptional events, but how important are they compared with gradual but fundamental shifts in technology trends and societal preferences? Media generally focuses public attention on high-profile events such as elections and international negotiations. In this paper, we use analytical techniques to evaluate the importance of these events to energy sector firms and climate policy.

An international policy response to climate change has been sought at least since the establishment of the UN Framework Convention on Climate Change (UNFCCC) in 1992. In 2009, the 15th Conference of the Parties (COP) in Copenhagen ended without results. A global climate agreement has seemed very elusive, partly because of disagreements regarding how the burden of emissions reductions would be shared among countries. The run-up to the Paris COP was filled with conflicts, and observers voiced concerns that the COP would once more fail. Nevertheless, on December 12, 2015, 195 nations did adopt the Paris climate agreement. Acclaimed as a significant milestone, it united all but two of the world's countries behind a single text, and that text contained a goal that was deemed surprisingly radical: to keep warming *well below* 2°C above preindustrial levels "and to pursue efforts to limit the temperature increase even further to 1.5°C" (UNFCCC 2015). These facts speak in favor of Paris being classified a success. On the other hand, the treaty did not allocate reductions among countries or stipulate the use of efficient policy instruments such as taxes or permit trading widely advocated by leading economists such as William Nordhaus, Martin Weitzman, or Jean Tirole. Its main instrument is the required submission of (intended) nationally determined contributions ((I)NDCs). There is no mechanism to ensure these contributions add up to the stated goals, nor are there any enforcement mechanisms.

The election of Donald Trump as the 45th US president on November 8, 2016, shifted expectations in the fossil fuel and renewable energy markets. Trump ran a successful presidential campaign that promised, among other things, to withdraw the United States from the Paris Agreement and to significantly roll back domestic climate policies, particularly in the coal industry. Trump's election is interesting for several reasons. First, it came as a surprise not anticipated by opinion polls and prediction markets. Second, among the many differences between the two candidates, a major one lay in their commitments to climate change mitigation. A Clinton presidency would likely have meant a continuation of the status quo in climate policy. A Trump presidency promised, however, to reverse all Obama-era regulations on fossil fuel industries. Last, the United States is one of the largest sources of anthropogenic emissions of carbon dioxide (CO_2). Many observers worried that a global climate agreement without US participation would hinder the full participation of other reluctant countries. The Paris Agreement was a compromise deal among countries that insisted on binding commitments, such as the EU member states; developing countries that demanded adaptation finance as a precondition for participation; and others that were against binding commitments, such as the United States. The unexpected election of Donald Trump a year after the announcement of the Paris Agreement threw into doubt continued US participation in global climate efforts in the medium term.

However, the US election also affected a number of other things, including tax, trade, and immigration policies (see Hachenberg et al. 2017; Pham et al. 2018; Wagner et al. 2018a, 2018b; Wolfers and Zitzewitz 2018). This makes it hard to isolate movements in stock prices that are due to changes in climate policy induced by Trump. In order to identify the stock price changes due to the election outcome, we exploit (a) the candidate's unexpected victory, (b) the major differences in the two candidates' proposed domestic climate policies, and (c) the differential effect of the proposed climate policies on fossil fuel and renewable energy. The Paris Agreement and the US election should have a systematic impact on fossil fuel and renewable energy firms.

We have presented a few arguments as to why these events are important, but evaluating their impacts is difficult because their results in terms of mitigating or exacerbating future climate change depend on many other factors and will not be observed until many decades from now. The purpose of this paper is to seek firmer evidence by studying market effects (stock market values) due to the Paris climate agreement and the 2016 US election on energy sector firms.

The Paris Agreement and the US election came at a time of increasing concern about stranded assets (Carbon Tracker Initiative 2013; Leaton 2012; McGlade and Ekins 2015), and central banks have warned that tough climate policies have the potential to significantly affect financial stability (Batten et al. 2016; Campiglio et al. 2018; Carney 2015; Dafermos et al. 2018; Olovsson 2018; Rudebusch 2019). Stock markets may price climate risks inefficiently without full disclosure of corporate exposures (Hong et al. 2019).[1] Andersson et al. (2016) show that at present, financial

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[1] Climate risk can be defined as a class of risks induced by climate change. These risks can be broadly divided into (a) potential loss in the value of assets due to the introduction of climate policy and (b) loss due to climate damages from severe storms, heat waves, and other natural disasters. Increasingly, fossil fuel firms now face the potential of liability risks from parties that suffer damages due to the effects of climate change. In this paper, we focus on climate risks emanating from decarbonization associated with the introduction of climate policy.

markets are not imposing a higher cost of capital on carbon-intensive firms. Delis et al. (2019) find that banks price climate risks in the cost of borrowing to fossil fuel firms only after 2015. Financial markets could be useful in solving the climate change problem if they could address the need for carbon pricing in the world by imposing a higher cost of capital on carbon-intensive companies. If financial markets work properly, then long-term investors in carbon-intensive companies should demand higher rates of return to compensate for the high risk of investing in assets that will become stranded once CO_2 emissions are priced meaningfully through a universal efficient climate policy. One channel through which the incipient concept of green finance transforms into actual policy is through long-term investors divesting from coal, oil, and natural gas assets, since they will perform badly compared with the entire market once a universal efficient climate policy is implemented. Our paper sheds some light on the role of financial markets in addressing the climate change problem.

We investigate two main hypotheses. The first is that the Paris Agreement (Trump election) has a negative (positive) effect on firms in the fossil fuel industry and a positive (negative) effect on firms in renewable, clean, and alternative energy industries. There are, however, important differences among the fossil fuel industries. Coulomb and Henriet (2018) and Michielsen (2014) show that under reasonable assumptions, the introduction of environmental policy such as a carbon tax should raise profits for oil and gas owners while depressing profits for owners of coal. We therefore expect that within the fossil fuel industry, the Paris Agreement (Trump election) should negatively (positively) affect the value of coal stocks more than that of oil and natural gas.[2] This is because the combustion of coal results in significantly higher emissions per unit of energy produced than with oil, and much higher than with natural gas. The second hypothesis is that the Paris Agreement and Trump election have a differential effect on firms operating in different countries. In this regard, we expect the Paris Agreement to have impacts that are more significant on firms operating in countries with an active climate policy that will feel bound to follow the Paris Agreement. The Paris Agreement might also have more effect in Annex 1 (i.e., rich) countries that have (I)NDCs committing to rapidly reducing reliance on fossil fuels. Following from this, differential impacts across countries may then arise depending on whether a given country is importing or exporting coal to countries that "believe in" climate change or are classified as Annex 1. In addition, coal-producing countries with a high share of domestic use of coal relative to exports should respond differently than countries that have a low share of domestic use relative to exports.

We evaluate the impacts of the Paris Agreement and US election on the stock market value of firms in each specific energy sector. We test the above hypotheses

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[2] While we assume here that climate policy will strand fossil fuels, especially coal, Harstad (2012) shows that a supply-side policy that entails a climate coalition buying foreign fossil-fuel reserves and preserving them can be the best climate policy. However, we are assuming that most of the response to climate policies, such as those in response to the Paris Agreement, will focus on demand-side actions.

by applying the standard event study approach (see, e.g., Campbell et al. 1997; Kothari and Warner 2007) to measure the abnormal returns for a number of fossil fuel stocks in Asia, Australia, Europe, South Africa, and North America. Using event study analysis, we show that both the Paris Agreement and the US election had significant effects on the value of renewable energy firms. We also find a strong statistically significant response to the US election by coal firms operating in Australia, Indonesia, South Africa, Thailand, and the United States. However, the overall global response by the fossil fuel industry to the US election as measured by the exchange-traded funds in our sample is largely statistically insignificant but substantial in magnitude for most of the part. Using the impulse-indicator saturation method, we are able to precisely measure and identify the impacts of these two events while controlling for other common shocks during the sample period. It is important to recognize that economic theory would require two factors as decisive for a significant stock market effect: first, that the event is beneficial or detrimental to the industry concerned, and second, that there is an element of surprise. If the event was expected, then its positive or negative effect will already have been discounted by the markets, and we may therefore detect only a much weaker response by the markets.

One may have legitimate arguments about both the efficacy of the Paris climate agreement and whether it was surprising. Hence, a determination of the presence or absence of effects must take both of these factors into account. The effects may have been moderate because the agreement was partially anticipated. To investigate this, we complement our study by conducting a media content analysis of articles published in one of the leading financial newspapers, the *Financial Times*, during the two months leading up to the climate negotiations and the period afterward until the end of 2015. We also report an expert survey of environmental and resource economists attending the 6th World Congress of Environmental and Resource Economists (WCERE).

In financial markets, information regarding environmental management is reflected by how markets 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. Event studies have been applied in accounting and financial economics to evaluate the impacts of a range of events such as mergers and acquisitions and earnings announcements. Several studies have used event study analysis to assess the relationship between firm financial performance and the release of environment-related news (Dasgupta et al. 2001; Fisher-Vanden and Thorburn 2011; Griffin et al. 2015; Hamilton 1995; Khanna et al. 1998; Sen and von Schickfus 2017). A few closely related event studies were written either contemporaneously with or subsequent to an earlier working paper version of this study (see Aklin 2018; Barnett 2019; Batten et al. 2016; Ramelli et al. 2019).

Ramelli et al. (2019) use a sample of US firms to carry out an event study around the 2016 election. Their results show that carbon-intensive US firms benefited from the election. Surprisingly, they also show that companies displaying a high level of climate responsibility benefited, likely because investors expected stiffer climate policies in the post-Trump period. There are a number of differences in our analysis, but we highlight only two of the most important. In the current paper, we group the firms into different categories of fossil fuel and renewable energy and thus confine our analysis to firms that are classified as energy firms. Our identification strategy therefore relies on the fact that Trump's election should have a systematic impact on fossil fuel and renewable energy stocks. Fossil fuel stocks should be positively affected, while renewable stocks should be negatively affected. There are, however, important differences among the fossil fuels: the US election should affect the value of coal stocks more than those of oil and natural gas. This is because the combustion of coal results in significantly higher emissions per unit of energy produced than with oil, and much higher than with natural gas. However, Ramelli and colleagues first estimate capital asset pricing model (CAPM) adjusted returns and then regress these on industry dummies and firm characteristics to get the abnormal returns for each industry. In the second stage of their analysis, they regress the CAPM-adjusted returns on a *climate responsibility* variable and a number of controls for firm characteristics. From this analysis, they conclude that having a high level of climate responsibility is associated with positive abnormal returns around the US election and the nomination of Scott Pruitt. By construction, we classify climate-friendly firms as those engaged in the renewable energy industry, while Ramelli and colleagues define climate-friendly firms as those graded higher on *climate responsibility*. Because of the smaller sample sizes in each of the energy industries we analyze, this precludes meaningful heterogeneity analysis to uncover mechanisms such as those in Ramelli et al. (2019).

In the current paper, we use a more global sample of firms operating across different countries, while Ramelli and colleagues restrict their analysis to the United States. In addition, we extend our analysis to the Paris Agreement and use the indicator saturation technique to broaden the set of environmental shocks we analyze over the period January 2015 to December 2016. Barnett (2019) considers a much broader range of events over an extended period of time. However, most of the events considered were highly anticipated and therefore did not generate significant abnormal returns. In addition, Barnett considers only oil stocks and finds positive abnormal returns for the US election and negative abnormal returns for the Paris Agreement. Batten et al. (2016) analyzes stock price response to the Paris Agreement, but using a subset of the firms we consider in terms of geographic coverage. Their results are similar to ours in terms of response of renewable energy and fossil fuel firms. Last, the study by Aklin (2018) comes close to ours in terms of geographic coverage, but the analysis is confined to the US election. We contribute to the above literature by providing the most extensive examination to date of the two recent and most important climate events across 13 international stock markets. We use the indicator saturation technique to control and capture the effects of common shocks during the sample period while precisely measuring their impacts on energy stocks. Our use of the indicator saturation method allows us to provide a richer narrative through analyzing additional environmental shocks not previously analyzed in the recent literature. Can we learn something even for partially anticipated events? By analyzing a partially anticipated event (Paris Agreement) alongside a truly unanticipated event (2016 US election), we provide a broader context within which to understand the reaction of energy stock prices to environmental shocks and, by extension, the role of financial markets in solving the climate problem.

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

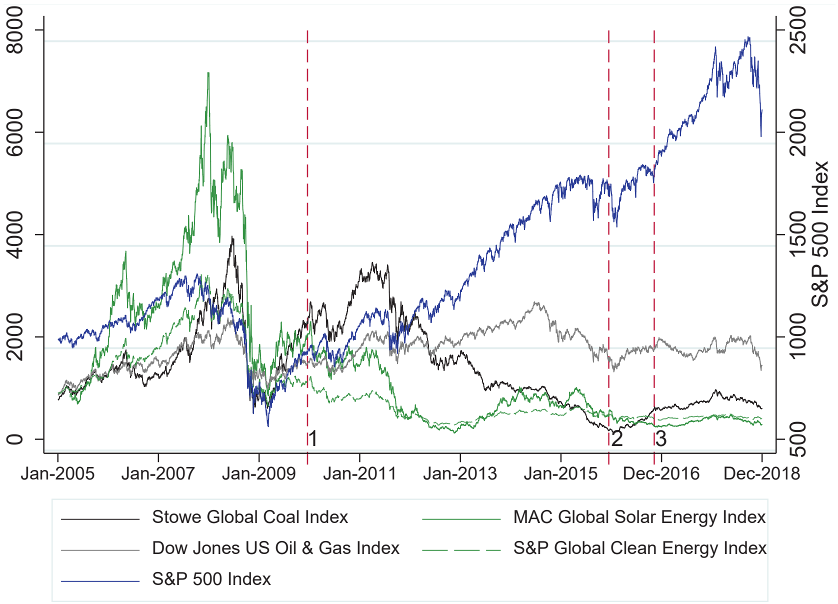
2. Data and Empirical Strategy

Figure 1 shows trends in the energy sector from 2005 to end of 2018. A visual analysis of Figure 1 shows big movements but fails to identify any significant changes in the energy sector around the particular dates that the Paris climate agreement and the US presidential results were announced. A systematic approach using statistical techniques is therefore necessary. In this section, we present the data and the two main methods of analysis used in the paper: event study analysis and impulse-indicator saturation.

2.1 Timeline of Events

Table 1 sets out the timeline of events leading up to the Paris climate agreement and afterward. Before the climate negotiations in Paris, countries had to submit INDCs. Negotiations started on November 30, 2015, culminating with an agreement on December 12. We are treating December 12, 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 175 UNFCCC members on 22 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 NDCs; otherwise, the INDCs submitted ahead of Paris became their first NDCs and the first emissions targets under the Paris Agreement. The agreement was designed to go into effect one month after a “double threshold” was satisfied: (a) the agreement had to be ratified by at least 55 countries, and (b) those 55 countries should be responsible for at least 55% of global emissions of greenhouse gases. The first threshold was met on September 21, 2016, and the second on October 5, setting the agreement to take effect on November 4, 2016. Donald Trump won the US presidential election on November 8, 2016. On June 1, 2017, President Trump announced his intention to withdraw the United States from the Paris climate agreement, citing that the accord would undermine the US economy.

Figure 1. Energy Stock Indexes vs. Global Benchmarks



Note: Figure 1 shows the performance of several energy stock indexes against the S&P 500. The red dashed lines mark dates with significant climate-related political events: (1) December 18, 2009, the Copenhagen Climate Change Conference comes to an end; (2) December 12, 2015, the Paris climate accord is announced; (3) November 8, 2016, Donald Trump wins the US presidential election.

2.2 Sample Selection and Data Description

The energy industry is composed of many firms, some of which 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 that trade continuously during the sample period and have nonmissing 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 five of the largest coal-mining firms in the United States, for example, filed for Chapter 11 bankruptcy protection during the period under analysis.[3]

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[3] Including firms that went bankrupt is not feasible in most cases because they have no market values. During the period of analysis, Patriot Coal Corporation (May 12, 2015), Walter Energy Inc. (July 15, 2015), Alpha Natural Resources Inc. (August 3, 2015), Arch Coal Inc. (January 11, 2016) and Peabody Energy Corporation (April 13, 2016) filed for Chapter 11 bankruptcy protection. Peabody Energy and Alpha Natural Resources were both valued at more than $10 billion at the time of filing for bankruptcy protection. Firms that later became bankrupt are included in the sample up to the point when they filed for bankruptcy protection. We note that because of this exclusion, our methodology may understate how badly a given sector is faring. In some of our estimations, as part of robustness tests, we include Peabody Energy Corporation, which filed for Chapter 11 bankruptcy protection in April 2016 but continued trading on the over-the-counter markets.

Table 1. Timeline of Paris Agreement and Recent Climate Policy Events

Date	Event
December 12, 2014	COP 20 in Lima ends
March 31, 2015	Countries start submitting INDCs
June 1, 2015	Europe's six largest oil and gas companies write an open letter in support of carbon pricing
October 1, 2015	Deadline for submitting INDCs
November 30, 2015	Climate negotiations start in Paris (COP 21)
December 12, 2015	Agreement reached by 195 countries
April 22, 2016	Paris Agreement signed by 175 UNFCCC members; 15 countries submit their instruments of ratification
September 3, 2016	United States and China ratify the agreement
September 21, 2016	55 other countries ratify the agreement (first threshold passed)
October 2, 2016	India ratifies
October 5, 2016	EU ratifies (second threshold passed)
November 4, 2016	Agreement enters into force
November 7, 2016	COP 22 begins in Marrakech
November 8, 2016	Donald Trump elected US president
December 8, 2016	Scott Pruitt officially nominated to lead the Environmental Protection Agency
June 1, 2017	President Trump announces intention to withdraw from Paris Agreement

We use two samples in our analysis. The first sample is made up of exchange-traded funds (ETFs) (see Table 2). ETFs are portfolios or baskets of securities traded on a stock exchange analogous to individual company stocks.[4] They are usually designed to replicate well-known market indexes such as the S&P 500, but others also track customized indexes (see Appendix 1.A for a detailed discussion on ETFs). The ETFs in our samples are composed of firms operating in countries responsible for significant global carbon emissions. For example, in the case of coal, the VanEck Vectors Coal ETF gives us coverage of 12 different countries and includes the largest global coal firms in terms of market capitalization. For renewable energy, the ETFs allow us to capture up to 17 countries in the case of wind energy (Table 2, column 4). These countries are leading in renewable energy and host operations for the largest firms by market capitalization (Table 2, column 3). In terms of the number of firms in each energy industry, the ETFs allow us to capture a large number of the largest publicly listed firms in each of the industries

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[4] Our choice to use ETFs is motivated by the fact that ETFs trade like individual stocks 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 firms listed in different countries and also allow us to detect effects that are likely to have caused stock prices of all companies to move in the same direction. Also, there are no obvious commodity markets for renewable energy to study. Therefore, we prefer to analyze stock prices.

(Table 2, column 2). The analysis using ETFs therefore allows us to analyze the aggregate global reaction to the Paris Agreement and the 2016 US election.

Table 2. Descriptive Statistics for Exchange-Traded Funds

	Number of ETFs	Average # of stocks	Mean ETF size (millions US$)	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

Note: These are the equity-based exchange-traded funds (ETFs) that form our global sample. Our clean and alternative energy subsample 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; or renewable electricity generation (e.g., solar, wind, geothermal). The remaining subsamples comprise companies involved in direct operations (production, mining, and drilling), transportation, production of mining or drilling equipment, or 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. Column 1 lists the average number of stocks in each of the ETF subsamples. Column 4 shows the average number of countries covered by the different ETFs in each energy sector.

The ETFs in our sample are based on equities and follow a particular index composed of a number of stocks. We exclude ETFs based on commodities or futures contracts, as they may respond differently to events similar to the ones under consideration.[5] In addition, movements in commodity prices might be heavily influenced 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.

The second sample includes individual firms in the coal industry across a number of countries (see Table 3). These countries account for significant global coal production or consumption and carbon emissions.[6] We analyze the reactions of

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[5] While the value of commodity firms is heavily influenced by the commodity price, Gorton and Rouwenhorst (2006) show the correlation between commodity futures returns and commodity equity returns was only 0.40 between 1961 and 2003. This implies that investing in commodity futures is not a close substitute to investing in commodity company stocks. In that case, an analysis using a portfolio combining ETFs based on both equities and commodity futures may not be appropriate.

[6] Heede and Oreskes (2016) show that a very large share of the fossil fuel reserves are owned by state-owned entities and nation-states and are therefore not publicly traded and priced by the markets. However, most nation-states have limited capacity to extract these resources. While publicly traded firms possess a small share of the current reserves, they have large financial resources to engage in exploration and development of new reserves over time.

individual firms across different countries here, since the coal market is largely geographic, with most coal used close to source. In this case, firms may react differently depending on details of the political or market landscape in their country of operation. A country-level analysis therefore allows us to directly test for this.

Table 3. Descriptive Statistics for Coal Stocks by Country

Number	Country	Number of stocks	Mean firm size (millions US$)
1	China	52	
	Shanghai	24	4,717
	Hong Kong	21	172
	Shenzhen	7	1,972
2	Australia	24	4,945
3	Indonesia	17	1,184
4	United States	15	1,170
5	South Africa	9	3,646
6	India	5	5,912
7	Thailand	5	707
8	Japan	4	142
9	Russia	4	394
10	Philippines	3	1,150
11	Poland	2	1,443

The analysis is conducted using daily financial data from January 2015 to January 2017 collected from the Thomson Reuters Eikon and Bloomberg databases. The daily prices of securities and ETFs used here are closing prices, the prices at which the last transaction in each of the securities occurred during the trading day.

2.3 Event Window Determination

The Paris Agreement was announced on December 12, 2015, a nontrading day. We therefore choose the next trading day, December 14, 2015, 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 event window [−10, +2], which coincides with the onset of the COP 21 climate negotiations in Paris. Such a window length is necessary because it is unclear when markets started to react to the possibility of a global climate agreement being announced during the negotiation period. Extending the event window beyond this, however, makes it difficult to attribute any observed abnormal returns to the event because of the increased possibility of contamination.[7] We use the 225-trading-day period prior to the event window as the estimation window for the Paris announcement. 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 in Lima, Peru. This is necessary to avoid contamination of the estimation period, which may bias the estimation of the return-generating process parameters (see Aktas et al. 2007). The Lima Call for Climate Action paved the way for a new global climate agreement in Paris. For the US election, we consider the day after the election as the announcement day (November 9, 2016) and analyze abnormal returns during the event window [0,+5]. The estimation window is taken as the 215-trading-day period prior to the event window.

2.4 Was Paris a Surprise?

The Paris Agreement is often described as the most important international agreement in its area. After several earlier failed attempts at a global climate agreement (such as in Copenhagen in 2009), the Paris Agreement was hailed as a major achievement. The press at the time described it as a major surprise that so many disparate nations could agree on something so controversial. On the other hand, one could argue that an agreement signed by almost all countries on one particular day in December 2015 must have been foreseen at least many months before, in the planning stage, and cannot be characterized as a complete surprise. To get some sense of the degree of surprise at the announcement of the Paris Agreement, we carry out a media content analysis of 200 *Financial Times* articles published between October 1 and December 31, 2015 (see Appendix 1.B for details). The *Financial Times* is an important source of financial news internationally, in contrast to other sources of financial news that service mainly a national audience, such as the *Wall Street Journal*.[8] We complement this data with an expert survey of environmental and resource economists attending the 6th WCERE in June 2018. The population from which we sampled is a list of about 1,500 environmental and resource economists attending the congress. The survey was administered online to all participants during and after the congress (see Appendix 1.C for details). The overall response rate was 38%, similar to the response rates for previous surveys of economists (see May et al. 2014).

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[7] The US Solar Investment Tax Credit, for example, was extended on December 18, 2015—day +4 post event day and therefore our event window ends two days before the extension to avoid contaminating our results.

[8] See https://aboutus.ft.com/en-gb/announcements/financial-times-named-the-most-important-business-read-by-the-worlds-largest-financial-institutions/.

2.5 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 profitability in a particular industry should change the stock prices of firms affected. 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 effect on asset prices. The event might take place on the same date or at different points in time for different firms (Kothari and Warner 2007).

We use the standard event study methodology (see Campbell et al. 1997; Kothari and Warner 2007; 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

$$\begin{gathered} r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it} \\ E[\epsilon_{it}] = 0 \text{ and } \mathrm{Var}[\epsilon_{it}] = \sigma^2_{\epsilon_i} \end{gathered} \tag{1}$$

Equation (1) is based on the assumption that in the absence of unexpected news (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 $\widehat{\epsilon}_{it}$ is zero. The firm-specific parameters of the market model are estimated using ordinary least squares and are denoted by $\widehat{\alpha}_i$, $\widehat{\beta}_i$, and $\widehat{\sigma}^2_{\epsilon_i}$.[9] Equation (1) is usually referred to as the single-factor model because it controls only for the market return. The abnormal return $(\widehat{\epsilon}_{it})$ for firm i is generated on a given event-related day t when unexpected news affects the return for the firm (r_{it}) without affecting the market return (r_{mt}).[10] The abnormal return $\widehat{\epsilon}_{it}$ for the ith firm at time t is then given as $\widehat{\epsilon}_{it} = r_{it} - (\widehat{\alpha}_i + \widehat{\beta}_i r_{mt})$. 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.

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[9] 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 Pynnönen (2005) as a partial remedy for 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.

[10] In the next section, we consider instead $r_{st} - r_{ct}$ as the dependent variable, with r_{st} as the return on solar stocks and r_{ct} as the return on coal stocks.

From the estimated residuals in equation (1), the cumulative abnormal return (CAR_{it}) is generated as $CAR_{i,(t_0,t_1)} = \sum_{t=t_0}^{t_1} \widehat{\epsilon}_{it}$, where t_0 is the first day of the event window. The cumulative average abnormal return ($CAAR_{(t_0,t_1)}$) 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, are available, but in the context of event studies, experience has seldom shown these models to be superior, especially for short event windows (Brown and Warner 1980, 1985; Campbell et al. 1997; MacKinlay 1997). We therefore prefer the standard one-factor market model for our analysis.

We assess whether (a) the Paris climate agreement and (b) the 2016 US election had any impact on fossil fuel markets by formally testing the null hypothesis that the events had no impact on stock 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. We therefore conduct the analysis 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.

Event studies analyzing stock reaction to events affecting a number of firms simultaneously, such as regulatory events, are characterized by cross-sectional correlation among the abnormal returns.[11] The presence of event clustering means the abnormal returns and the cumulative abnormal returns are no longer independent across securities, thus affecting inference. Kolari and Pynnönen (2010) show that event clustering can lead to over-rejection of the null hypothesis of zero average abnormal returns when it is true even in cases in which the cross-sectional correlation of abnormal returns is relatively mild. We address this problem through making use of the test statistic presented by Brown and Warner (1980, 1985), which corrects for event clustering by using the portfolio time-series standard deviation. This procedure, termed "Crude Dependence Adjustment" by Brown and Warner, estimates the standard deviation from the time series of sample (portfolio) average abnormal returns during the pre-event period (see Appendix 1.D for details).

2.6 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 traditional event study approach by introducing a more powerful and flexible outlier and structural break detection method that can help detect any relevant significant events. In our case, events of interest include the announcement of the Paris climate agreement, ratification of the agreement by key countries, and the November 2016 US election, as well as other environmental shocks not identified a priori. The evidence of an effect can

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

be seen as stronger if the dates of interest are identified without being imposed a priori. The returns to holding fossil fuel 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 (see Aktas et al. 2007). In this regard, traditional event studies as currently used are potentially misspecified, and indicator saturation addresses this shortcoming in event studies by identifying and controlling for outliers and shifts (structural breaks) during the sample period. In this way, the indicator saturation technique allows us to extend the set of environmental shocks we consider beyond the Paris Agreement and the US election. Indicator saturation has the added advantage of allowing one to test directly for model misspecification, given that no shifts or outliers should be detected outside the event window if an event study is well specified.

Instead of including the event from the onset in a model, we propose to search for outliers or breaks in our dependent variable, and then check whether any detected outliers or 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 outliers and structural breaks, including the step- and impulse-indicator saturation (SIS and IIS) methods and the Chow test (see Castle et al. 2015; Chow 1960; Hendry and Johansen 2015; Santos et al. 2008). The indicator saturation technique is related to the sample quintile test, which is often employed when examining the significance of abnormal returns in single-firm, single-event studies (see Baker 2016; Gelbach et al. 2013; Lemoine 2017).

IIS treats every data point in the time series as a potential impulse (environmental) shock. The technique saturates the entire 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 outliers 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. Indicator saturation (IIS and SIS), 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 or outliers and does not impose a limit on the number of breaks or outliers that can be identified or the length of such breaks. This technique also allows breaks or outliers to occur at the beginning or end of the sample, an advantage over techniques that do not. To overcome the identification problem that is often attributable to insufficient observations (because of dates too near the start or end of the sample), these other 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 outliers:

$$r_{sct} = \beta_0 + \beta_1' x_t + u_t \tag{2}$$

where u_t is a random error term with zero mean and variance δ_u^2 and x_t is a vector of conditioning variables that include the market return (r_{mt}).[12] 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)—in other words, the difference in returns $(r_{st} - r_{ct})$ for these two sectors, where r_{st} is the index return for solar at time t and r_{ct} is the index return for coal at time t. r_{sct} can be interpreted as an index of energy sector sensitivity to climate policy. 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 us obtain greater precision in the model estimation. As in Castle et al. (2015), we add a full set of impulse indicators to equation (2) to get

$$r_{sct} = \beta_0 + \beta_1' x_t + \sum_{j=1}^{T} \delta_j 1_{\{t=j\}} + u_t \tag{3}$$

Equation (3) is analyzed using IIS to identify outliers. We use the *gets* package in R (Pretis et al. 2018a; Sucarrat et al. 2018). 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. With IIS, theory-based conditioning variables (x_t) can be retained without selection, and the distribution of their estimates will be unaltered by selection over the orthogonalized set of candidates (Hendry and Johansen 2015). However, using IIS with additional conditioning variables means that we have more candidate 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 Castle et al. (2015), suggests that overfitting is not a major issue with IIS.

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[12] 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 i.i.d. normal.

3. Market Effects of the Paris Agreement and the US Election

In this section, we first present results from the event study analysis. We then present and discuss the results for the Paris Agreement and the 2016 US election using the impulse-indicator saturation method, which controls for additional environmental shocks not identified a priori. Last, we present some robustness tests.

3.1 Stock Market Reaction to the Paris Agreement Announcement

Table 4 shows the results for all the energy sectors studied over different event windows (see Figure 2 for a plot of the cumulative average abnormal returns). We find no statistically significant mean abnormal returns for fossil fuels on the Paris Agreement announcement day. For renewable energy, we find sizable and significant positive abnormal returns on the event day for solar energy, and the significance of the cumulative average abnormal returns persists as the event window is lengthened to include the entire period of negotiations. For coal, where we expect the strongest effect, we find no significant effect for the event day as well as the postannouncement period. To capture ex ante reactions as a result of market expectations, we include days prior to the announcement date in the calculation of the abnormal returns. We do find large and significant cumulative average abnormal returns for fossil fuel stocks when we extend the event window to consider the entire preannouncement negotiation period. Contrary to our prior expectations, the effects are significantly larger for natural gas and oil compared with coal and more statistically significant for natural gas. This might suggest that market participants do not believe countries will implement cost-efficient policies in reducing carbon emissions. A cost-efficient policy would penalize coal much more than oil and particularly compared with natural gas. In reality, countries want to protect their coal industries, mainly for the sake of employment, which suggests that real climate policy might not be fully efficient in this sense. An analysis of the cumulative average abnormal returns in Table 4 over the announcement and postannouncement period shows that they are largely statistically insignificant except for solar and alternative energy. 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 United States (Batten et al. 2016). The results for solar and alternative energy during the event window [–10,+2] suggest most of the reaction is taking place around the announcement date and the postannouncement period. On the contrary, most of the reaction by fossil fuel stocks is recorded during the preannouncement period. Important details such as the inclusion of the 1.5°C became known ahead of the agreement's announcement. The inclusion of an even lower temperature target indicates that it gradually became clear as negotiations proceeded that an agreement would be reached and that this information was immediately incorporated into fossil fuel stock prices.

Table 4. Effects of Paris Climate Agreement on Energy Sector Using ETFs

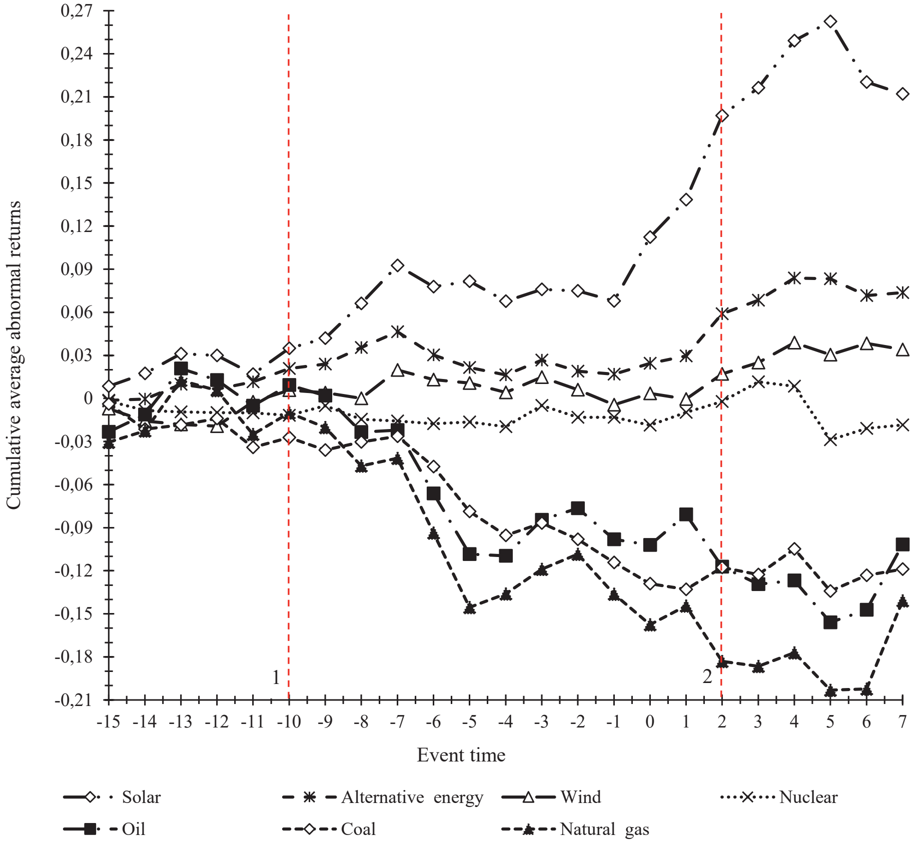
	Coal	Oil	Natural gas	Solar	Wind	Alternative energy	Nuclear
$CAAR_{0,0}$	–1.48%	–0.39%	–2.13%	4.45%	0.79%	0.76%	–0.55%
	(–1.22)	(–0.24)	(–1.18)	(2.55)**	(0.90)	(1.04)	(–0.70)
$CAAR_{0,+2}$	–0.35%	–1.90%	–4.68%	12.91%	2.15%	4.20%	1.10%
	(–0.17)	(–0.67)	(–1.49)	(4.26)***	(1.41)	(3.31)***	(0.81)
$CAAR_{-10,+2}$	–8.36%	–11.20%	–15.80%	18.01%	1.94%	4.74%	0.79%
	(–1.91)*	(–1.89)*	(–2.42)**	(2.86)***	(0.61)	(1.79)*	(0.28)
Number of ETFs	1	4	3	2	1	7	1

Note: This table reports cumulative average abnormal returns (*CAARs*) for renewable and nonrenewable energy ETF subsamples for the Paris climate agreement announcement. The market model is estimated using ordinary least squares (OLS), and the market index is the S&P 500. The estimation period includes trading days –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some of our ETFs are short ETFs, which means that they move in the opposite direction from the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. Before 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 short and long ETFs. 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.

To corroborate our results and deepen the analysis, we also look at various energy stock indexes (Table 5). We find that coal and oil and gas stocks as measured by the various indexes fell by –7.45% and –6.74%, respectively, over the event window [–10,+2]. While substantial in size, the abnormal returns for coal are not statistically significant, whereas those for oil and gas are significant at the 10% level. As noted before, the effects for the renewable energy industry mostly come from the announcement and postannouncement days, whereas the reaction by the fossil fuel industry is driven by preannouncement period events. While the effects for the nonrenewable energy industry are largely statistically insignificant, the Paris climate agreement, if deemed credible and sufficiently ambitious, should significantly depress coal stocks, given coal's large contribution to carbon emissions (even compared with other fossil fuels).

We therefore repeat the analysis of the coal sector (and solar for the United States) using country-level subsamples of coal stocks listed in all the major coal-producing countries. For this analysis, our sample includes firms that satisfy the following criteria: (a) listed in one of the major markets and (b) continuously traded over the sample period, has not filed for bankruptcy protection during this period, and has nonmissing estimation period returns data for at least 100 trading days. Criterion *b* restricts the analysis to a sample in which bankruptcy or listing

Figure 2. Paris Climate Agreement Announcement Cumulative Average Abnormal Returns for Renewable and Nonrenewable Energy



Note: This figure plots the cumulative average abnormal returns from day 15 to day +7. The abnormal returns are calculated using the market model. The relevant event period is the window [-10,+2]. The red dashed lines mark the beginning and end of our event window: (1) November 30, 2015, climate negotiations start in Paris, and (2) December 16, 2015, the event window ends.

events have no influence on the results. These criteria leave us with a sample of 140 companies in 14 different stock markets (Table 3). Most of these companies are constituents of major global coal stock indexes and exchange-traded funds.

For most nations, the Paris accord had a large negative but statistically insignificant effect on domestic coal companies (Tables 6a and 6b) over the event window [–10,+2]. There was, however, a negative statistically significant effect in Australia and South Africa around announcement time, as well as in Indonesia for the event window [–10,+2] coinciding with the onset of the COP 21 climate negotiations in Paris. These three countries are among the biggest coal exporters in the world, and their reliance on coal exports likely exposes them to other

Table 5. Effects of Paris Climate Agreement on Energy Sector Using Stock Indexes

	Coal	Oil and gas	Solar	Alternative energy
$CAAR_{0,0}$	–1.97%	0.16%	3.92%	1.53%
	(–1.39)	(0.15)	(2.39)**	(1.46)
$CAAR_{0,+2}$	–1.44%	–0.35%	11.70%	5.84%
	(–0.59)	(–0.19)	(4.12)***	(3.21)***
$CAAR_{-10,+2}$	–7.47%	–6.74%	18.76%	6.09%
	(–1.46)	(–1.78)*	(3.17)***	(1.61)

Note: In this table, we corroborate our results in Table 4 by reporting the cumulative average abnormal returns (*CAARs*) for the widely followed global energy stock indexes. Coal is made up of an equally weighted average of the two main coal stock indexes, 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). Solar is made up of two stock indexes, 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 –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

countries' climate policies that may affect future exports. We also see substantial abnormal returns in Hong Kong, the Philippines, Poland, Thailand, and the United States over the event period. India, on the other hand, is likely to respond differently. This country is, in per capita terms, a very small emitter of CO_2 and mainly uses its own domestic coal. It probably does not feel that Paris implies that India has to stop or reduce its emissions. Globally, the coal industry has been struggling because of 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 North America and Europe also face increasing pressure from falling natural gas prices. The Paris climate agreement came at a time when the coal industry was in decline and had been for several years (see Figure 1).[13] Tightening environmental regulations (for example, the Mercury and Air Toxics Standards in the United States) 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 renewable energy in recent years, largely driven by technological change (see

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[13] See Kolstad (2017) for a brief on the reasons behind the decline of the US coal industry.

Table 6a. Effects of Paris Climate Agreement on Coal Stocks in Other Countries

		China										
	Australia	Hong Kong	Shanghai	Shenzhen	India	Indonesia	Japan	Philippines	Poland	Russia	Thailand	South Africa
$CAAR_{0,0}$	–2.55% (–1.40)	1.19% (0.43)	0.63% (0.40)	1.37% (0.72)	2.81% (1.53)	–0.04% (–0.04)	0.82% (1.02)	–2.29% (–1.18)	1.79% (0.63)	–0.28% (–0.15)	–1.25% (–0.79)	–3.68% (–2.03)**
$CAAR_{0,+2}$	–5.19% (–1.65)*	–2.45% (–0.51)	–0.39% (–0.14)	0.17% (0.05)	–0.89% (–0.28)	–0.08% (–0.05)	–0.27% (–0.20)	–5.35% (–1.59)	–1.53% (–0.31)	–0.33% (–0.10)	–2.81% (–1.03)	2.86% (0.91)
$CAAR_{-10,+2}$	–9.63% (–1.47)	–5.24% (–0.52)	–2.27% (–0.40)	–1.08% (–0.16)	–0.33% (–0.05)	–7.37% (–2.17)**	0.54% (0.19)	–1.67% (–0.24)	–6.64% (–0.65)	–1.18% (–0.17)	–4.38% (–0.77)	–6.02% (–0.92)
Number of stocks	23	21	22	7	5	16	4	3	2	4	5	9

Note: This table reports country-level cumulative average abnormal returns (*CAARs*) for the major coal-producing and coal-exporting countries. We make use of the Thomson Reuters Business Classification (TRBC) to construct our country-level subsamples, 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. The market model is estimated using OLS, and the market is proxied by the local market index. The estimation period includes trading days –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Kåberger 2018; Wagner et al. 2015). It is against this background that we should interpret the lack of further statistically significant negative effects of the accord.

Table 6b. Effects of Paris Climate Agreement on US Listed Coal and Solar Stocks

	Coal			Solar
	Full sample	NYSE	NASDAQ	
$CAAR_{0,0}$	–3.76% (–1.28)	–5.06% (–1.72)*	–1.30% (–0.29)	2.02% (0.99)
$CAAR_{0,+2}$	–3.72% (–0.73)	–2.05% (–0.40)	–6.90% (–0.90)	12.13% (3.42)***
$CAAR_{-10,+2}$	–14.39% (–1.36)	–11.79% (–1.11)	–20.26% (–1.27)	15.50% (2.10)**
Number of stocks	15	10	5	8

Note: This table reports cumulative average abnormal returns (*CAARs*) for US coal and solar firms. 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 of coal firms and the Dow Jones Industrial Average for the solar firms. The estimation period includes trading days –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series *t*-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The observed results for the coal industry, however, remain a puzzle. There are several reasons why we would expect both a large and statistically significant reaction from coal. First, coal emits more carbon per unit of energy, and we would therefore expect significant stranding of coal assets because of credible and sufficiently ambitious climate policy. Second, the rents from coal are small in comparison with oil, which has large rents because of very low extraction costs and market power. Policies to subsidize renewable energy or introduce a carbon tax can therefore easily eliminate coal rents and lead to the substitution of cleaner energy for coal. Indeed, 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 that climate policy will be more detrimental to coal while they may even benefit (see Coulomb and Henriet 2018; Michielsen 2014). Oil producers may also want the predictability that comes with a climate agreement. Third, the coal market, unlike solar, wind, and alternative energy markets, is largely geographic, with most coal used close to source. Therefore, firms may fail to react significantly to a global climate agreement like the Paris accord, reacting more instead to changes in country-level operating conditions.

The significance of carbon emissions from coal has meant that global efforts to address climate change have largely focused on reducing reliance on coal.[14] In addition, the remaining coal reserves are sizable compared with oil reserves. Proven coal reserves can last up to 150 years at current extraction rates (BP 2017). 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 reserves remaining unused.[15] The fact that we do not find even stronger 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). Whether investors think that (I)NDCs are credible depends on various factors, including whether they are backed by actual policies (see Nemet et al. 2017) and how investors evaluate their own ability to lobby against policies that might follow from the (I)NDCs. It might also be that there are differences in how different investors perceive their ability to lobby down particular policies. Another possible explanation for the lack of stronger reaction concerning fossil fuel stock prices could be that the policy implications of the Paris Agreement were weak enough and removed enough that it would not have a big effect. In other words, the profit-relevant news content was small.

In interpreting our results, there are two key concepts: *surprising* and *strong*. It is only when both of these apply simultaneously that we expect to see a strong statistically significant reaction in the fossil fuel markets on any particular day.[16] Our detailed media content analysis of 200 *Financial Times* articles turned up only 4 articles that framed the announcement of the Paris Agreement as surprising (see Appendix 1.B for details). The results from the expert survey of environmental and resource economists at the 6th WCERE shows that the Paris Agreement was a surprise to about 28% of the surveyed experts. One might therefore conclude the agreement was anticipated to a large extent (see Appendix 1.C for details). Given that we do not find strong support for the surprise here, we attribute the surprise in other media to the fact that the agreement perhaps exceeded expectations, at least regarding its ambitions and given that previous climate change negotiations failed to achieve any common ground. Nevertheless, surprise alone is not sufficient; the agreement needs

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[14] Most institutional investors have announced divestments away from coal and other fossil fuels in recent years, while green financing has broadly sought to direct funding toward sustainable investments (OECD 2017).

[15] 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 Carbon Tracker Initiative 2013; Griffin et al. 2015; Leaton 2012).

[16] 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.

to be strong—that is, it should provide solutions for anthropogenic climate change. The observed effect of the Paris Agreement on fossil fuel stock prices is possibly because the INDCs on which the agreement is anchored were strictly voluntary and therefore not very ambitious. Current commitments in the (I)NDCs are not consistent with temperature increases below the 2°C and 1.5°C stipulated in the agreement (see Table 7).[17]

Table 7. Ambition of NDCs

Country	Rating	Global 2100 warming of NDCs [in °C]		
		Average ambition	High ambition	Low ambition
Australia	Insufficient (<3°C world)	4.4	4.3	4.5
China	Highly insufficient (<4°C world)	5.1	5.1	5.1
European Union (28)	Insufficient	3.2	3.2	3.2
India	2°C compatible (<2°C world)	2.6	2	3.4
Indonesia	Highly insufficient	2.5	1.9	3.4
Japan	Highly insufficient	4.3	4.3	4.3
Philippines	2°C compatible	1.2	1.2	1.2
Poland	—	3.7	3.7	3.7
Russian Federation	Critically insufficient (4°C+ world)	5.1	5.1	5.1
South Africa	Highly insufficient	5.1	4.2	5.1
Thailand	—	5.1	4.5	5.1
United States	Highly insufficient	4	3.9	4
Source	Climate Action Tracker (2019)	Robiou du Pont and Meinshausen (2018)		

Note: This table shows the ambition of each country's NDC following the 2030 emissions they imply. Column 1 shows results for a subset of the 31 countries (including the EU) assessed by Climate Action Tracker (2019). The rating is in terms of the resultant global warming when a country's NDC is taken as a benchmark by other countries. Only the NDCs of India and the Philippines are ambitious enough to keep global temperature below 2°C. In the case of Australia, for example, global warming would be above 2°C and up to 3°C if all countries were ambitious to the same level. The results in column 1 are also in line with those presented by Robiou du Pont and Meinshausen (2018) (columns 2–4) from the pledges made by nearly all the parties to the Paris Agreement. "Low ambition" is based on the unconditional pledges and thus is less ambitious. "High ambition" reflects the conditional pledges (where available) and therefore is more ambitious. The mean of low and high is given as "average ambition." From column 2, when the NDC for Australia is taken as a benchmark by other countries, this gives a global warming of 4.4°C. These warming assessments can be visualized at http://paris-equity-check.org/warming-check.html. Most of the NDCs appear to be very unambitious except for the Philippines.

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[17] The shortcomings of voluntary contributions toward optimal provision of a public good have been studied elsewhere in the literature (see Marwell and 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 the political dynamics created will eventually lead to new rounds of ratcheting up the commitments.

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 captures only 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. The best way to cast light on the role of surprise is to look at an event that really was unexpected, and therefore, in the next section, we present results from an analysis of the US election—an outcome largely unexpected and crucial for global climate policy.

3.2 Stock Market Reaction to the 2016 US Election

The US climate change debate has been characterized by a lack of political consensus (see Brenan and Saad 2018). The disagreements in the US climate debate have been intense. Politicians such as President Trump and many other Republicans are significantly more aligned with coal (and other fossil fuel) 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 3) and therefore presents us with a perfect case where there is a clear element of surprise as well as an unambiguous event in favor of fossil fuels.[18] We note that despite the huge surprise, globally fossil fuels do not appear to have substantially benefited from the election of Trump (Table 8 columns 1–3 and Table 9 columns 1–2), despite his express desire to promote fossil fuel industries such as coal. We could interpret this as indicating the United States' limited power to influence global climate policies. It is more reasonable to interpret Trump's policy as favoring mainly the production and consumption of coal in the United States rather than the production and use of coal internationally. This would lead to a positive reaction mainly among US coal companies. Our results do suggest that a change in US climate policy in favor of its domestic fossil fuel industry in response to the Paris Agreement might indirectly hurt coal companies in *other* countries.

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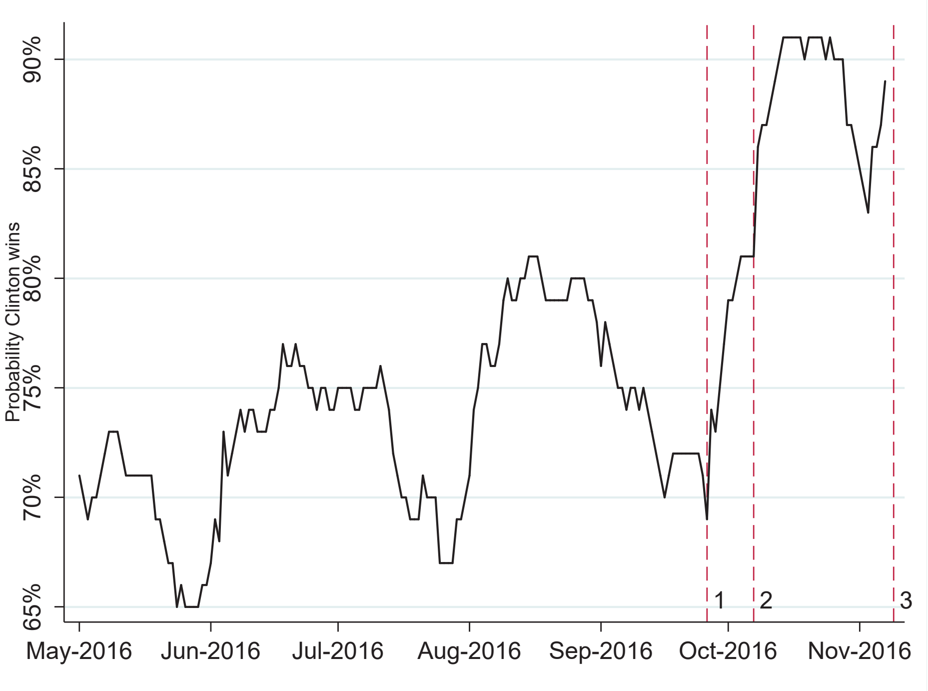
[18] As late as Election Day, a *New York Times* feature reviewed polling data and gave Mr. Trump a 15% chance of winning (Katz 2016). On the other hand, Nate Silver of FiveThirtyEight, widely considered a careful, scientific, prognosticator of election results, predicted on the eve of the presidential election that Hillary Clinton had a 70% chance of winning. Clearly, there was a big chance that Trump would not win. That, in combination with a reasonable expectation that the policies chosen by the two candidates would be very different, suggests one should get a strong market reaction.

Figure 3. US Election Clinton Victory Probability



Source: https://predictwise.com.
Note: The red dashed lines mark days with significant election-related events: (1) September 26, 2016, first presidential debate is won by Hillary Clinton; (2) October 7, 2016, the *Washington Post* releases a video of an outtake from *Access Hollywood*; (3) November 8, 2016, Donald Trump wins the US presidential election.

We do, however, find that renewables and alternative energy experienced substantial and statistically significant negative abnormal returns on the announcement day (Table 8 columns 4–6 and Table 9 columns 3–4). These results persist even as the event window is extended to include five days postannouncement. The observed negative (positive) reaction by renewable energy stocks to the US election (Paris Agreement) demonstrates two key points: (a) the renewable energy sector is more global than the fossil fuel industry (especially coal and natural gas) and therefore responds more to global events,[19] and (b) the reliance of the renewable energy sector on state support makes it more responsive to political events associated with changes in governments or global climate policy. Alternatively, it could be that markets may believe in subsidies and not taxes. The small size of the renewable energy sector also means that any given change in capacity will be a much bigger percentage change than what is observed in the coal sector. From the ongoing analysis, our results seem to provide support for the hypothesis that

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[19] As noted earlier on, the oil sector firms possess significant market power, which may affect how it responds to the events under consideration.

Table 8. Effects of US Election on Energy Sector Using 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%	–1.43%
	(–0.83)	(–0.48)	(–0.44)	(–0.41)	(–1.52)	(–0.50)	–(0.92)
CAAR$_{0,0}$	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$_{0,+2}$	–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

Note: This table reports cumulative average abnormal returns (*CAARs*) for the ETF subsamples for the US presidential election. The market model is estimated using OLS, and the market index is the S&P 500. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some of our ETFs are short ETFs, which means that they move in the opposite direction from the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. Before 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 short and long ETFs. 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.

globally the Paris Agreement (Trump election) has a positive (negative) and statistically significant effect on renewables. However, we find little support at the global level for the hypothesis that the Paris Agreement (Trump election) has a negative (positive) and statistically significant effect on coal.

At the country level, the election of Donald Trump as the 45th US president benefited (negatively affected) US coal (solar) companies (Tables 10b and 10c). We also report statistically significant positive abnormal returns for South Africa, Thailand, and Indonesia (at the 10% level of significance) around the announcement of the US election results (Table 10a). All three countries are coal exporters and might benefit from a more positive policy at least on the *use* of coal (policies that encourage US *production* of coal would actually have the opposite effect for competitors). We report substantial but statistically insignificant abnormal returns over the event window [0,+5] for China, India, Philippines, Poland, and Russia. A notable exception is Australia, which had significant negative abnormal returns on Election Day.[20] It is interesting that Australia (largest exporter of steam coal) is strongly and significantly affected negatively by Trump. There could be an expec-

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[20] The Queensland Parliament passed the Environmental Protection (Underground Water Management) and Other Legislation Amendment Act, which seeks to tighten groundwater license requirements for mines, on November 9, 2016. This could therefore potentially confound the results.

Table 9. Effects of US Election on Energy Sector Using Stock Indexes

	Coal	Oil and gas	Solar	Alternative energy
$CAAR_{-5,-1}$	–0.39% (–0.11)	–1.08% (–0.44)	–1.26% (–0.40)	–2.35% (–1.05)
$CAAR_{0,0}$	–0.42% (–0.26)	0.25% (0.23)	–6.12% (–4.33)***	–5.88% (–5.87)***
$CAAR_{0,+2}$	2.01% (0.72)	–1.27% (–0.67)	–7.22% (–2.95)***	–8.81% (–5.08)***
$CAAR_{0,+5}$	–3.78% (–0.96)	0.23% (0.09)	–7.04% (–2.03)**	–9.16% (–3.73)***

Note: In this table, we corroborate the results in Table 8 by reporting the cumulative average abnormal returns (*CAARs*) for the widely followed global energy stock indexes. Coal is made up of an equally weighted average of the two main coal stock indexes, 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). For solar, we use two stock indexes, 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 –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

tation that the United States will now increasingly export coal, which significantly threatens Australia, since it has very little own use but high export share. (Australia exported 85% of its coal in 2015, and coal exports averaged 80% of domestic production for the 10-year period from 2006 to 2015 (BP 2017).) While Indonesia and South Africa are also significant coal exporters, South Africa has high domestic use, while Indonesia uses an export cap for "energy security reasons." Results in Table 10a (and Table 6a) show that not all firms operating in significant coal-exporting countries (e.g., Poland and Russia) reacted significantly to the US election (and the Paris Agreement). These results are broadly similar to those of Aklin (2018), who also finds weak reaction of fossil fuel stock prices to the US election.

The country-level results presented in Tables 6a, 6b, 10a, and 10b provide some inconclusive support to the hypothesis that the Paris Agreement (Trump election) had a heterogeneous effect across countries. Firms operating in some but not all coal-exporting countries significantly reacted to the Paris Agreement and the Trump election, but we find no significant reaction if the operating country is a coal importer.

3.3 Identifying Crucial Dates

The method employed so far has involved looking for an effect on stock prices at a given date. There is a methodological risk in this approach, since we prespecify

Table 10a. Effects of US Election on Coal Stocks in Other Countries

		China										
	Australia[a]	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)
$CAAR_{0,0}$	–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)
$CAAR_{0,+2}$	–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

Note: This table reports country-level cumulative average abnormal returns (*CAARs*) for the major coal-producing and coal-exporting countries. The market model is estimated using OLS, and the market is proxied by the local market index. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table 10b. Effects of US Election on US Listed Coal and Solar Stocks

	Coal					Solar
	Full sample		NYSE		NASDAQ	
	I	II[a]	III	IV[a]	V	VI
$\mathrm{CAAR}_{-5,-1}$	–2.84% (–0.51)	–2.91% (–0.57)	–3.50% (–0.54)	–3.69% (–0.65)	–1.36% (–0.27)	–0.73% (–0.17)
$\mathrm{CAAR}_{0,0}$	10.74% (4.30)***	7.72% (3.39)***	10.07% (3.48)***	5.46% (2.15)**	12.24% (5.41)***	–7.53% (–3.94)***
$\mathrm{CAAR}_{0,+2}$	12.17% (2.82)***	9.47% (2.40)**	10.44% (2.08)**	6.17% (1.40)	16.07% (4.10)***	–9.23% (–2.79)***
$\mathrm{CAAR}_{0,+5}$	10.03% (1.64)	6.42% (1.15)	9.83% (1.39)	4.39% (0.71)	10.48% (1.89)*	–10.32% (–2.20)**
Number of stocks	13	12	9	8	4	9

Note: This table reports cumulative average abnormal returns (*CAARs*) for US coal and solar firms. 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 of coal firms and the Dow Jones Industrial Average for the solar firms. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] Columns II and IV represent results excluding Peabody Energy, which filed for Chapter 11 bankruptcy protection 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 2016 US presidential election results. We feel it is more of an outlier than the norm for US listed coal stocks, and our results show a much higher abnormal return when it is included in the sample.

the date and do not know if there are many other environmental shocks associated with significant positive or negative price movements. A stronger empirical approach involves conducting the analysis within a unified framework that seeks to combine the analysis of both the Paris meeting and the election without imposing the events a priori. In Table 11, we present results for several specifications using the IIS method. IIS helps us identify and control for significant environmental shocks not identified a priori from theory. Specification I is an augmented market model that includes a dummy variable *Paris* equal to 1 on the day the Paris climate agreement was announced and 0 otherwise. The variable *US Election* is equal to 1 on the day the 2016 US presidential election results were announced and 0 otherwise. From specification I, we note that both the dummy variables' coefficients are statistically significant and show a strong positive reaction by US coal stocks. Using IIS, five additional dates are picked up in specification I, 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, using our index of energy sector sensitivity to climate policy,

Table 10c. Effects of US Election on US Listed Coal and Solar Stocks (Mean Abnormal Returns)

Day relative to event date	Coal					Solar
(Day 0 = November 9, 2016)	Full sample		NYSE		NASDAQ	
	I	II[a]	III	IV[a]	V	VI
–5	–0.91% (–0.36)	–0.88% (–0.39)	–0.94% (–0.33)	–0.90% (–0.35)	–0.83% (–0.37)	0.83% (0.44)
–4	1.96% (0.78)	2.00% (0.88)	2.23% (0.77)	2.33% (0.92)	1.33% (0.59)	–3.00% (–1.57)
–3	0.80% (0.32)	0.88% (0.39)	–0.16% (–0.05)	–0.15% (–0.06)	2.95% (1.30)	0.12% (0.06)
–2	–3.62% (–1.45)	–3.99% (–1.75)*	–3.15% (–1.09)	–3.66% (–1.44)	–4.66% (–2.06)**	–1.04% (–0.54)
–1	–1.07% (–0.43)	–0.92% (–0.41)	–1.48% (–0.51)	–1.31% (–0.52)	–0.15% (–0.07)	2.36% (1.23)
0	10.74% (4.30)***	7.72% (3.39)***	10.07% (3.48)***	5.46% (2.15)*	12.24% (5.41)***	–7.53% (–3.94)***
+1	1.18% (0.47)	0.10% (0.04)	1.21% (0.42)	–0.41% (–0.16)	1.12% (0.49)	–4.19% (–2.19)**
+2	0.25% (0.10)	1.65% (0.73)	–0.84% (–0.29)	1.12% (0.44)	2.71% (1.20)	2.49% (1.30)
+3	2.28% (0.91)	1.55% (0.68)	3.01% (1.04)	2.01% (0.79)	0.63% (0.28)	1.11% (0.58)
+4	–3.77% (–1.51)	–3.96% (–1.74)*	–2.88% (–0.99)	–3.06% (–1.20)	–5.78% (–2.55)**	–3.75% (–1.96)**
+5	–0.65% (–0.26)	–0.64% (–0.28)	–0.75% (–0.26)	–0.74% (–0.29)	–0.44% (–0.20)	1.55% (0.81)
Number of stocks	13	12	9	8	4	9

Note: This table reports mean abnormal returns for US coal and solar firms. 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 for the full sample of coal firms and the Dow Jones Industrial Average for the solar firms. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the mean abnormal returns are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

[a] Columns II and IV represent results excluding Peabody Energy.

the two most important climate-related political events during the two-year period are identified—namely, the Paris climate agreement and the US election. Specification V is similar to IV, but selection is carried out at an even tighter level of significance ($\alpha = 0.0005$). All the previously retained dates are picked up in this

Table 11. Output from IIS to Detect Relevant Climate-Related Political and Market Events between January 2015 and 2017

	I	II	III	IV	V
Market returns	0.3123*** (0.0837)	0.3194*** (0.0840)	0.3332*** (0.0844)	0.3194*** (0.0840)	0.3116*** (0.0850)
Paris	0.0668*** (0.0169)	0.0664*** (0.0169)	0.0666*** (0.0171)	0.0664*** (0.0169)	0.0663*** (0.0171)
US election	–0.0611*** (0.0169)	–0.0635*** (0.0169)	–0.0615*** (0.0171)	–0.0635*** (0.0169)	–0.0637*** (0.0171)
$r_{sc(t-1)}$		0.1419*** (0.0412)		0.1419*** (0.0412)	0.1528*** (0.0416)
March 4, 2015	0.0648*** (0.0169)	0.0604*** (0.0170)	0.0648*** (0.0171)	0.0604*** (0.0170)	
March 5, 2015	0.0736*** (0.0169)	0.0644*** (0.0171)	0.0734*** (0.0171)	0.0644*** (0.0171)	0.0636*** (0.0173)
May 20, 2015	–0.0628*** (0.0169)	–0.0634*** (0.0169)	–0.0629*** (0.0171)	–0.0634*** (0.0169)	–0.0636*** (0.0171)
June 19, 2015	–0.0597*** (0.0169)	–0.0619*** (0.0169)	–0.0597*** (0.0171)	–0.0619*** (0.0169)	–0.0622*** (0.0171)
December 16, 2015	0.0596*** (0.0169)				
Constant	–0.0013* (0.0008)	–0.0010 (0.0008)	–0.0012 (0.0008)	–0.0010 (0.0008)	–0.0009 (0.0008)
Ljung-Box AR(2)	11.5635 [0.0007]	0.2920 [0.8642]	13.2523 [0.0003]	0.2920 [0.8642]	0.3335 [0.8464]
Ljung-Box ARCH(1)	0.5828 [0.4452]	0.0365 [0.8484]	0.7776 [0.3779]	0.0365 [0.8484]	0.0114 [0.9148]
Jarque-Bera	7.5473 [0.0230]	7.9635 [0.0187]	7.9783 [0.0185]	7.9635 [0.0187]	9.4766 [0.0088]
Log-likelihood	1,344.38	1,340.95	1,338.15	1,340.95	1,334.58

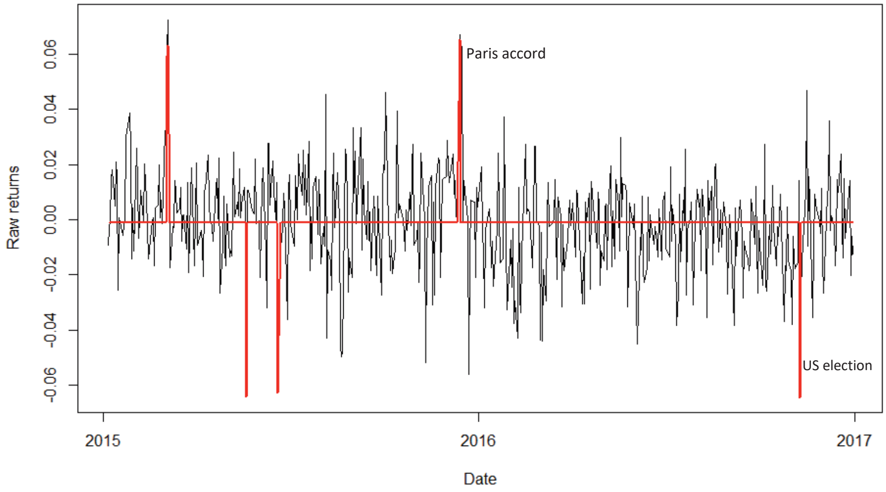
Note: This table presents results from several specifications using Impulse-Indicator Saturation (IIS). Specifications I and II include two additional regressors, *Paris* and *US Election*, retained without selection in addition to the market returns. The dummy variable *Paris* equals 1 on the day the Paris Agreement was announced and 0 otherwise. The variable *US Election* equals 1 on the day the 2016 US presidential election results were announced and 0 otherwise. 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 specifications I–IV are retained in specification V except the date March 4, 2015. The dependent variable used is the stock return differential between solar and coal. The AR and ARCH tests are Ljung and Box (1978) tests of the standardized residuals. The diagnostics suggests the residuals are uncorrelated and homoskedastic for all our specifications that include some dynamics. The numbers in parentheses indicate the lags at which the tests were conducted. Standard errors are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. p-values in square brackets.

last specification except March 4, 2015. 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.

From Table 11, the most striking result is the robustness of our estimates. All specifications tested show a similar pattern, with a positive shock from Paris and a negative shock from the US election for the difference between renewables and coal stock indexes. Using IIS, we find the Paris Agreement and the US election to be equally important among a set of other things. This is despite US election being truly unanticipated while the Paris Agreement was only partially unanticipated.

IIS identifies a number of dates, all in 2015, when our simple index of energy sector sensitivity to climate policy picks up significant environmental shocks. We find positive impacts on March 4 and 5, 2015, as well as December 16, 2015 (Figure 4 and Table 11). On May 20 and June 19, 2015, there was an impact of the opposite sign—good for coal or bad for renewables (Figure 4 and Table 11). We have searched systematically for explanations by reading the relevant news telegrams from a news service, Retriever,[21] using the search words "climate," "renewables," "coal," and "solar." These searches returned a fairly large number of news articles, but we are looking for large and unexpected events of international significance.

Figure 4. IIS-Detected Climate-Related Political and Market Events between January 2015 and December 2017



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

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 November 4, 2016. These are not detected by IIS. Given that the Paris climate agreement was unanimous, one might argue that ratification was anticipated. Evidence from the history of international climate agreements such as the 1997 Kyoto Protocol suggests that ratification almost always follows the adoption of the agreements.

We turn now to the dates identified by IIS. For March 4 and 5, 2015, we find several interesting and quite plausible news items that could be contributing elements. The most striking of these is that the Chinese 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" (Yap 2015). This is 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 and wind investments, reducing coal consumption, and controlling the number of energy-intensive projects in polluted regions (Aizhu et al. 2015; Green 2015). On March 5, 2015, Bloomberg also reported that energy storage in the United States would more than triple in 2015 as regulators allowed use of the technology by utilities and homeowners (Doom 2015). Analysts were quoted as saying that this would strengthen Tesla, with its Gigafactory for batteries that can store solar energy from day to night.

For December 16, 2015, the other date with an impact that was positive for solar and negative for coal, we found 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.

We find quite strong evidence of concern for the climate on May 20. President of France François Hollande gave an important speech at UNESCO voicing concern over how difficult the Paris negotiations would be and how urgent the process was (AFP News 2015). On the same day, big losses were reported for two large solar panel producers in Hong Kong (*Telegraph* 2015). On June 19, negative returns for renewables using our indicator of energy sector sensitivity to climate policy could be explained by several pieces of bad news for wind power in the UK, including large protests against investments and news of important reductions in UK subsidies (*Scotsman* 2015).

3.4 Additional Robustness Tests

In this section, we present additional robustness tests. So far we have shown that our results are robust when the event dates are not imposed a priori. To demonstrate that our findings are not influenced by model choice, we also analyze raw returns in which expected returns are set to zero. We find broadly similar results to those estimated using the market model, thus demonstrating that our findings do not depend on the choice of the underlying model for expected returns. In addition, we also estimate abnormal returns using a market model with a GARCH(1,1) error process to estimate the normal return. (The results are presented in Appendix 1.E.) We show that our results are essentially unchanged in all cases, suggesting that the variance of the stock returns did not change much around the two events.

4. Conclusions

This paper has presented a detailed analysis of the reaction of financial markets to news. Specifically, we have studied the reaction of stock prices for firms in fossil fuels and renewable energy around the announcement of the Paris climate agreement, the 2016 US presidential election, and other significant events. If the Paris Agreement is deemed credible and sufficiently ambitious, then we would expect significant negative (positive) abnormal returns for the fossil fuel industry (renewable energy) stocks around the announcement dates. We do find significant positive reactions to the Paris Agreement (and negative ones to the US election) by both renewable and fossil energy stocks. The strongest and clearest reactions are for renewables, which benefited from the Paris Agreement and were hurt by the election of President Trump. When it comes to fossil fuels, we find reactions in the opposite direction. Coal companies were negatively affected by the Paris Agreement, though this effect is statistically significant only when one considers the entire negotiation period (perhaps some anticipation arose as the negotiations proceeded). In the case of the US election, we find a positive effect on Election Day for US coal companies (the results for coal companies operating in other countries are mixed).

The Paris Agreement came at a time when fossil fuel divestment by institutional investors had already become a well-trodden path. Divestment, at least if generalized, should mean a reduced price for fossil fuel stocks. By the time of the Paris climate meeting, coal shares had already lost 80%–90% of their value in the preceding years. A number of major coal companies were in, or on the brink of, bankruptcy. One could speculate that the investors had already seen the writing on the wall after more than a decade of climate negotiations. Either way, this might have somewhat limited the reactions of the industry to further events. For the whole Paris negotiations period (a 13-day window), we find strong and significant reactions by fossil fuel firms, though the results are not statistically significant on the announcement day. This could most likely be interpreted as saying that the agreement was already anticipated by the last day of negotiations. In the case of the US election, there was a greater element of surprise, and in that case we do see statistically significant effects on the announcement day. The results for US coal stocks are not only significant in the statistical sense but also substantial. The results, however, are not so huge and statistically significant for other countries as to suggest that this type of event (or policy shift) risks causing stranded assets that will seriously threaten the stability of the financial system.

It seems that the sensitivity of fossil fuel stock values to climate policy is real but still somewhat moderate. The absence of an even stronger reaction by global fossil fuel stocks may be a sign that these types of "events" have somewhat less importance for fossil fuels and the transition to a fossil-free world than generally believed in the media. One possible interpretation is that underlying fundamentals are most important, such as technological developments that 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, then, is for both media and policymakers to turn more of their attention to long-run changes in technology and maybe other parameters such as tastes or resource availability. As for climate policy, it should be possible to pursue reasonable goals without fear of stranding assets.

As mentioned, the reaction by renewable industries is stronger. Perhaps financial constraints and uncertainty are more important here. Since both categories of stocks are affected by the same events, we find we can construct a more sensitive indicator of climate policy by looking at the relative performance of renewable to fossil stocks. With this indicator, and with carefully designed methods such as the impulse-indicator saturation technique, we are able to find clear and strong statistical evidence that both of our major events and the Chinese decision to reduce coal all had significant effects on global energy markets. We conclude that the Paris Agreement, the US election, and some other major policy announcements did have both a substantial and statistically significant effect on the relevant financial markets. This suggests that there is enough sensitivity to say clearly that climate policy matters, but so far the policies have not come close to causing disruptive changes as feared in the debate about stranded assets.

Appendix 1

This section provides additional material to complement the analysis in the main paper.

1.A Exchange-Traded Funds (ETFs)

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, which are bought and sold only at the end of the day through mutual fund companies, ETFs trade all day, and investors transact through brokerage firms as done with individual stocks. ETFs are usually designed to replicate well-known market indexes such as the S&P 500, but others also track customized indexes. Customized indexes are not market indexes, as their intention is not to measure the value or performance of financial markets or sectors. To this extent, customized indexes can be considered investment strategies designed for a specific task.

While the supply and demand for ETF shares are driven by the values of the underlying securities in the indexes 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 are chosen at the discretion of the fund manager. The idea is that better performance can be attained through active management than by following a particular index. Since an actively managed ETF invests in a portfolio with securities directly selected by the fund manager, the composition of the portfolio changes more frequently than that of an ETF tracking an index (Ferri 2011). For this reason, actively managed funds are required to disclose their holdings daily.

Leveraged and Short ETFs

Short ETFs move in the opposite direction from 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 US Oil and Gas Index."[22] Short ETFs can also be leveraged, in which case they are designed to

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[22] http://www.proshares.com.

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 US Oil and Gas Index's daily performance.

The Direxion Daily Natural Gas Related Bull 3X Shares (GASL) is a leveraged ETF that seeks returns that are three times (3X) the ISE-Revere 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 reflect to some extent the active management by the fund managers behind them. We feel, however, that 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 adjustments for short ETFs. We do not make any distinction as to whether an ETF follows a customized index or a traditional market index.

1.B Media Framing of Climate Negotiations

An important requirement in event studies is that news announcements should come as a surprise to market participants for one to detect a significant stock price reaction in affected markets. However, it is often hard to measure the impacts of news announcements due to anticipation in markets. In this section, we investigate this issue by conducting a media content analysis of articles published in one of the leading financial newspapers, *Financial Times*, during the two months leading up to the Paris climate negotiations through the year end (with December 31, 2015, as the last day). The Paris climate negotiations started on November 30, 2015, and ended with the announcement of a climate agreement on December 12, 2015.

The intuition behind media content analysis is that newspaper publishers aim to attract and maintain readership in order to maximize profits. Thus they have an incentive to report on timely issues of interest to their target audience. Since readers are interested in events that may affect their economic well-being, newspapers will optimally choose to report on these events. Therefore, there will be a greater number of articles reporting on such things as changes in government taxes, unanticipated political events, significant climate change–related news, and financial crises (Alexopoulos and Cohen 2015). A number of papers in the economics literature have used indicators based on newspaper coverage (see Alexopoulos and Cohen 2015; Baker et al. 2016; Gentzkow and Shapiro 2010).

Here we seek to understand how the Paris climate negotiation process was framed by the news media, particularly the *Financial Times*, an international daily newspaper that places special emphasis on business and economic news coverage and has been in circulation since 1888. We focus particularly on three aspects: (a) framing of the *preconditions* for reaching an agreement, (b) framing of the actual *negotiations* taking place during the summit, and (c) framing of the actual agreement or *final treaty*. The overall purpose is to analyze the extent to which the agreement was framed as surprising or unexpected.

Data Summary

The analysis is based on 200 *Financial Times* articles collected from Factiva using the search strings "Paris" and "climate" and consisting of 2,940 paragraphs. The average number of paragraphs per article is 14.7, with a standard deviation of 7.6. The shortest article consists of just a single paragraph, and the longest has 57 paragraphs. We first analyze the framing of the preconditions for reaching an effective agreement. When we consider the preconditions as framed positively, 48% of the articles analyzed have a positive frame. When we consider the preconditions as framed negatively, 56% of the articles have a negative framing. Roughly half of the articles frame the negotiations as proceeding positively. In terms of the *surprise* of the agreement, 28 articles explicitly address this aspect. Of these, only 4 (9 paragraphs) framed the agreement as a surprise. The rest of the articles (172 articles comprising 2,674 paragraphs) do not address this issue explicitly.

The inclusion of the objective "to pursue efforts to limit the temperature increase even further to 1.5°C" in the final agreement was taken as a surprise by many observers, since previous climate negotiations had centered around the goal of 2°C. However, only 27 *Financial Times* articles published after the announcement of the Paris Agreement explicitly mention the inclusion of 1.5°C in the final agreement. Of these, only 3 paragraphs within 2 articles frame the inclusion of this lower temperature limit as a surprise. In terms of the agreement's credibility, our search strings identified 27 articles explicitly referring to the agreement's credibility. Of these, 13 articles explicitly question the credibility of the agreement. These 27 articles consist of 265 paragraphs, with only 33 of them explicitly questioning the agreement's credibility.

1.C Expert Survey of Environmental and Resource Economists

To ascertain the surprise in the announcement of the Paris Agreement, we complement the media content analysis with an expert survey of environmental and resource economists attending the 6th WCERE in June 2018. The WCERE takes place every four years and brings together three environmental and resource economist associations from Europe, America, and East Asia, as well as representation from Africa and Australia. The survey population is a list of about 1,500 environmental and resource economists attending the WCERE. We administered the online survey to all participants during and after the congress. The overall response rate was 38%, similar to the response rates for previous surveys of economists (see May et al. 2014).

The survey included questions about the experts' own reaction to the announcement of the Paris Agreement, as well as their perception of the public's reaction at the announcement time. We also sought to understand expert reaction to the inclusion of the 1.5°C temperature target, unanimity of the agreement, its feasibility, and its credibility. The survey also included questions seeking to understand perceived weaknesses of the agreement in terms of the most disappointing aspects concerning the lack of specific policies to attain the agreement's specified targets. In terms of surprise, 45% of respondents who answered this question thought the announcement of the agreement came as a surprise to the public, 28% reported that the agreement's announcement came as a surprise to themselves, 33% was neither surprised nor unsurprised, and the remainder was unsurprised. The inclusion of the 1.5°C goal came as a surprise for 49% of the respondents, with 21% neither surprised nor unsurprised and 30% unsurprised. About 56% of the respondents were surprised the agreement was reached unanimously. A majority of the respondents (53%) felt the goals of the agreement were feasible, while 28% felt the agreement was credible. The majority of the respondents (85%) were disappointed the agreement lacked specifics on how to reach the targets. The lack of individual targets (binding agreement) and detailed commitments were the most disappointing aspects for 57% of the respondents, while only 11% reported being disappointed by the absence of a price on carbon. From the survey results, we cannot rule out the presence of anticipation of the Paris Agreement's announcement but note that the survey results suggests some degree of surprise, which varied across the different aspects of the agreement. The presence of anticipation means that we likely underestimate firms' reaction to the announcement of the Paris Agreement.

1.D Hypothesis Testing in Event Studies

In this section, we present the test statistic used to assess the likelihood that the abnormal returns we observe do not arise purely by chance. Given total clustering, the test statistic presented in Brown and Warner (1985, 1980) accommodates event clustering by estimating the standard deviation from the time series of sample (portfolio) average abnormal returns from the pre-event period $t = -235$ to -11. The test statistic is constructed as the ratio of the event-day average abnormal returns to the estimated standard deviation of those average abnormal returns. For any given day t, the test statistic is given as

$$\overline{\epsilon}_t / \widehat{S}(\overline{\epsilon}_t), \tag{1.D.1}$$

where, for notational convenience, $\overline{\epsilon}_t = \overline{\widehat{\epsilon}}_t$ and

$$\overline{\epsilon}_t = \frac{1}{N}\sum_{i=1}^{N}\widehat{\epsilon}_{it}$$

$$\widehat{S}(\overline{\epsilon}_t) = \sqrt{\left(\sum_{t=-235}^{t=-11}(\overline{\epsilon}_t - \overline{\overline{\epsilon}})^2\right)\Big/224}$$

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

where N is the number of stocks. The test statistic presented in equation (1.D.1) follows a Student-t distribution under the null hypothesis if the $\widehat{\epsilon}_t$ are assumed to be independent and identically distributed (i.i.d.) as normal (see Brown and Warner 1985, 1980). According to Brown and Warner (1985, 1980), 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 $CAAR_{(t_0,t_1)}\Big/\left(\sqrt{(t_1 - t_0)}\times\widehat{S}(\widehat{\epsilon}_t)\right)$. While a range of nonparametric tests have been employed in the literature, parametric tests work well with daily data, whereas nonparametric tests often perform poorly (Berry et al. 1990; Brown and Warner 1985; Dyckman et al. 1984).

Thin Trading

Thin trading arises when stocks do not trade every day and presents problems of its own. While this is not a major problem with the US-listed ETFs we analyze, it is a potential problem with some of our country-level analysis (e.g., for Canada and the UK). It is standard for most data sets to treat nontrading 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 nontrading days. In addition, when trading takes place, the absolute value of realized returns tends to be relatively large.

When requesting data from Thomson Reuters Eikon, one can choose how missing prices have to be treated when downloading the data. When one chooses the price on nontrading 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 nonmissing 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 multiperiod interval between two subsequent trades. This, however, leads to some smoothing of returns and ultimately to the same issues with lumped returns. A third alternative, the trade-to-trade procedure, involves first calculating the returns over periods with nonmissing prices. 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 et al. 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 nonmissing return. This is because it is a multiperiod return whose inclusion can lead to unexpected consequences in estimating parameters of the benchmark model. We therefore treat the first nonmissing return following a sequence of missing estimation period returns as a missing value. In cases where the nonmissing return occurs in the event window, we adjust the abnormal returns to account for the multiperiod character of the first postmissing return.

1.E Additional Robustness Tests

In this section, we provide, as part of robustness tests, results from the market model estimated using the GARCH(1,1) error process.

Table 1.E.1. Effects of Paris Climate Agreement on Energy Sector Using ETFs

	Coal	Oil	Natural gas	Solar	Wind	Alternative energy	Nuclear
$CAAR_{0,0}$	–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)
$CAAR_{0,+2}$	–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)
$CAAR_{-10,+2}$	–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

Note: This table reports cumulative average abnormal returns (*CAARs*) for renewable and nonrenewable energy ETF subsamples 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 –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some of our ETFs are short ETFs, which means that they move in the opposite direction from the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. Before 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 short and long ETFs. 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 1.E.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

Note: This table reports mean abnormal returns for renewable and nonrenewable energy ETF subsamples for a 13-day period surrounding the 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 –235 to –11 relative to the event. The null hypothesis is that the mean abnormal returns are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some of our ETFs are short ETFs, which means that they move in the opposite direction from the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. Before 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 short and long ETFs. 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 1.E.3. Effects of US Election on Energy Sector Using ETFs

	Coal	Oil	Natural gas	Solar	Wind	Alternative energy	Nuclear
$CAAR_{-5,-1}$	–2.85% (–0.84)	–1.56% (–0.42)	–2.80% (–0.36)	–1.58% (–0.49)	–2.84% (–1.50)	–0.82% (–0.54)	0.24% (0.15)
$CAAR_{0,0}$	0.48% (0.32)	0.89% (0.53)	1.40% (0.40)	–6.58% (–4.57)***	–4.37% (–5.16)***	–2.86% (–4.22)***	–4.51% (–6.44)***
$CAAR_{0,+2}$	–2.50% (–0.96)	–1.04% (–0.36)	–1.75% (–0.29)	–8.37% (–3.36)***	–7.97% (–5.44)***	–2.92% (–2.49)**	–5.08% (–4.19)***
$CAAR_{0,+5}$	–6.30% (–1.70)*	2.22% (0.54)	3.09% (0.36)	–6.45% (–1.83)*	–10.83% (–5.22)***	–2.83% (–1.71)*	–4.47% (–2.61)***
Number of ETFs	1	4	4	2	1	7	1

Note: This table reports cumulative average abnormal returns (*CAARs*) for energy ETF subsamples for the US presidential election. The market model is estimated using a GARCH(1,1) specification, and the market index is the S&P 500. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series *t*-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some of our ETFs are short ETFs, which means that they move in the opposite direction from the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. Before 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 short and long ETFs. 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 1.E.4. Effects of US Election on Energy Sector Using 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%	—[a]	—[a]
	(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

Note: This table reports mean abnormal returns for a seven-day period around the US election using renewable and nonrenewable energy ETF subsamples. 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 –220 to –6 relative to the event. The null hypothesis is that the mean abnormal returns are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Some of our ETFs are short ETFs, which means that they move in the opposite direction from the index they track and seek to deliver results that correspond to the inverse of the index they track on a daily basis. Before 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 short and long ETFs. 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.

[a] Denotes a day in the event window with missing returns.

Table 1.E.5. Effects of Paris Climate Agreement on Energy Sector Using Energy Stock Indexes

	Coal	Oil	Solar	Alternative energy
CAAR$_{0,0}$	–1.91%	0.19%	3.91%	1.58%
	(–1.35)	(0.18)	(2.38)**	(1.51)
CAAR$_{0,+2}$	–1.25%	–0.20%	11.67%	6.02%
	(–0.51)	(–0.11)	(4.11)***	(3.31)***
CAAR$_{-10,+2}$	–6.84%	–6.67%	18.71%	6.67%
	(–1.34)	(–1.76)*	(3.16)***	(1.76)*

Note: This table reports the cumulative average abnormal returns (*CAARs*) for the widely followed global energy stock indexes. Coal is made up of an equally weighted average of the two main coal stock indexes, 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). Solar is made up of two stock indexes, 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 (SP-GTCED). 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 –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series *t*-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.E.6. Effects of US Election on Energy Sector Using Energy Stock Indexes

	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$_{0,0}$	–0.42%	0.32%	–6.29%	–5.94%
	(–0.26)	(0.29)	(–4.44)***	(–5.93)***
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)***

Note: This table reports the cumulative average abnormal returns (*CAARs*) for the widely followed global energy stock indexes. Coal is made up of an equally weighted average of the two main coal stock indexes, 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). For solar, we use two stock indexes, 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 (SP-GTCED). 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 –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series *t*-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.E.7. Effects of Paris Climate Agreement on Coal Stocks in Other Countries

		China										
	Australia	Hong Kong	Shanghai	Shenzhen	India	Indonesia	Japan	Philippines	Poland	Russia	Thailand	South Africa
$CAAR_{0,0}$	–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)**
$CAAR_{0,+2}$	–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)
$CAAR_{-10,+2}$	–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

Note: This table reports country-level cumulative average abnormal returns (*CAARs*) for the major coal-producing and coal-exporting countries. We make use of the Thomson Reuters Business Classification (TRBC) to construct our country-level subsamples 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. 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 –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.E.8. Effects of US Election on Coal Stocks in Other Countries

		China										
	Australia[a]	Hong Kong	Shanghai	Shenzhen	India	Indonesia	Japan	Philippines	Poland	Russia	Thailand	South Africa
$CAAR_{-5,-1}$	–2.52% (–0.74)	–0.81% (–0.22)	0.41% (0.14)	0.09% (0.02)	–3.06% (–0.89)	8.18% (1.87)*	–1.42% (–0.60)	0.61% (0.13)	0.99% (0.15)	–1.06% (–0.26)	1.66% (0.49)	–1.23% (–0.35)
$CAAR_{0,0}$	–4.03% (–2.66)***	–0.55% (–0.34)	1.28% (0.96)	1.54% (0.79)	1.68% (1.09)	0.69% (0.35)	–0.57% (–0.54)	–0.79% (–0.36)	–1.38% (–0.47)	–0.55% (–0.31)	3.68% (2.40)**	1.63% (1.03)
$CAAR_{0,+2}$	–0.82% (–0.31)	1.87% (0.65)	1.30% (0.57)	4.09% (1.21)	2.44% (0.92)	6.83% (2.01)**	–1.15% (–0.63)	2.53% (0.67)	4.46% (0.88)	2.08% (0.66)	4.33% (1.63)	6.49% (2.37)**
$CAAR_{0,+5}$	–3.24% (–0.87)	2.43% (0.60)	0.90% (0.28)	5.04% (1.05)	–3.51% (–0.93)	1.85% (0.37)	0.38% (0.15)	3.32% (0.62)	4.80% (0.67)	3.10% (0.70)	0.71% (0.19)	1.65% (0.43)
Number of stocks	24	20	23	5	4	15	4	3	2	4	5	8

Note: This table reports country-level cumulative average abnormal returns (*CAARs*) for the major coal-producing and coal-exporting countries. 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 –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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

Table 1.E.9. Effects of Paris Climate Agreement on US Listed Coal and Solar Stocks

	Coal			Solar
	Full sample	NYSE	NASDAQ	
$\text{CAAR}_{0,0}$	–3.76%	–5.08%	–1.13%	2.14%
	(–1.28)	(–1.72)*	(–0.26)	(1.05)
$\text{CAAR}_{0,+2}$	–3.92%	–2.24%	–7.27%	12.43%
	(–0.77)	(–0.44)	(–0.95)	(3.50)***
$\text{CAAR}_{-10,+2}$	–13.66%	–11.52%	–17.94%	17.52%
	(–1.29)	(–1.08)	(–1.12)	(2.37)**
Number of stocks	15	10	5	8

Note: This table reports cumulative average abnormal returns (*CAARs*) for US coal and solar firms. 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 of coal firms and the Dow Jones Industrial Average for the solar firms. The estimation period includes trading days –235 to –11 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as December 14, 2015, the first day markets opened following the announcement of the Paris climate agreement on Saturday, December 12, 2015. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 1.E.10. Effects of US Election on US Listed Coal and Solar Stocks

	Coal					Solar
	Full sample		NYSE		NASDAQ	
	I	II[a]	III	IV[a]	V	VI
$\text{CAAR}_{-5,-1}$	–2.16%	–2.91%	–2.51%	–3.68%	–1.38%	–0.63%
	(–0.39)	(–0.57)	(–0.39)	(–0.65)	(–0.27)	(–0.15)
$\text{CAAR}_{0,0}$	10.99%	7.78%	10.42%	5.54%	12.26%	–7.42%
	(4.40)***	(3.41)***	(3.60)***	(2.18)**	(5.41)***	(–3.88)***
$\text{CAAR}_{0,+2}$	12.63%	9.50%	11.10%	6.21%	16.06%	–9.02%
	(2.92)***	(2.41)**	(2.21)**	(1.41)	(4.10)***	(–2.73)***
$\text{CAAR}_{0,+5}$	10.86%	6.43%	11.04%	4.42%	10.45%	–10.13%
	(1.78)*	(1.15)	(1.56)	(0.71)	(1.88)*	(–2.16)**
Number of stocks	13	12	9	8	4	9

Note: This table reports cumulative average abnormal returns (*CAARs*) for US coal and solar firms. 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 for the full sample of coal firms and the Dow Jones Industrial Average for the solar firms. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the *CAARs* are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[a] Columns II and IV represent results excluding Peabody Energy.

Table 1.E.11. Effects of US Election on US Listed Coal and Solar Stocks (Mean Abnormal Returns)

Day relative to event date	Coal					Solar
(Day 0 = November 9, 2016)	Full sample		NYSE		NASDAQ	
	I	II^{a}	III	IV^{a}	V	
–5	–0.89% (–0.36)	–0.94% (–0.41)	–0.90% (–0.31)	–0.98% (–0.38)	–0.86% (–0.38)	0.79% (0.41)
–4	2.00% (0.80)	1.95% (0.86)	2.31% (0.80)	2.27% (0.89)	1.31% (0.58)	–3.02% (–1.58)
–3	0.88% (0.35)	0.85% (0.38)	–0.03% (–0.01)	–0.18% (–0.07)	2.93% (1.30)	0.09% (0.05)
–2	–3.23% (–1.29)	–3.86% (–1.70)*	–2.61% (–0.90)	–3.49% (–1.37)	–4.61% (–2.04)**	–0.87% (–0.46)
–1	–0.92% (–0.37)	–0.92% (–0.40)	–1.26% (–0.44)	–1.30% (–0.51)	–0.15% (–0.07)	2.38% (1.25)
0	10.99% (4.40)***	7.78% (3.41)***	10.42% (3.60)***	5.54% (2.18)**	12.26% (5.41)***	–7.42% (–3.88)***
+1	1.30% (0.52)	0.09% (0.04)	1.39% (0.48)	–0.42% (–0.16)	1.11% (0.49)	–4.10% (–2.15)**
+2	0.34% (0.14)	1.63% (0.71)	–0.71% (–0.25)	1.09% (0.43)	2.69% (1.19)	2.50% (1.31)
+3	2.38% (0.95)	1.53% (0.67)	3.16% (1.09)	1.99% (0.78)	0.62% (0.27)	1.11% (0.58)
+4	–3.57% (–1.43)	–3.93% (–1.73)*	–2.60% (–0.90)	–3.01% (–1.17)	–5.77% (–2.55)**	–3.73% (–1.95)*
+5	–0.57% (–0.23)	–0.67% (–0.29)	–0.62% (–0.22)	–0.77% (–0.30)	–0.46% (–0.20)	1.52% (0.80)
Number of stocks	13	12	9	8	4	9

Note: This table reports mean abnormal returns for US coal and solar firms. 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 for the full sample of coal firms and the Dow Jones Industrial Average for the solar firms. The estimation period includes trading days –220 to –6 relative to the event. The null hypothesis is that the mean abnormal returns are zero. The announcement date ($t = 0$) is taken as November 9, 2016. Portfolio time-series t-statistics are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
[a] Columns II and IV represent results excluding Peabody Energy.

Chapter 2

Climate Policy: Effects of the Trump Election on Fossil Fuel Commodity Markets

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Abstract

The unexpected election of Donald Trump shifted expectations on several dimensions, including lower corporate taxes, (re-)reform of the healthcare system, and changes to immigration and trade policies. Within the fossil fuel industry, environmental regulations were expected to be substantially weakened. Earlier work has shown that the election led to increased profit expectations among fossil fuel firms. This paper seeks to nuance the picture and understand whether Trump was expected primarily to help *mine* more coal or *burn* more coal. While both supply- and demand-side policies boost profits, they would have different effects on the futures market for coal. We use the differential impact of the touted changes in climate policy and other environmental regulations to identify the price changes due to expectations regarding the path of climate policy under Trump. Using event study analysis, we find large price effects in coal and natural gas futures markets. Over the 21-day post-election period, which includes the nomination of the Environmental Protection Agency (EPA) administrator, we observe cumulative average abnormal returns of up to –27% for coal and 19% for natural gas. Further analysis shows a marked increase in uncertainty and intracommodity return spreads post-election. In addition, the reaction by futures contracts of different maturities suggests market participants anticipated that the proposed policies would be implemented shortly after Trump took office.

1. Introduction

The unexpected election of Donald Trump as US president a year after the signing of the Paris climate agreement in December 2015 and barely a week after the agreement's entry into force on November 4, 2016, led to changed expectations about US climate policy. Trump's campaign promises to roll back environmental regulations and withdraw from the agreement, together with his skeptical views on anthropogenic climate change, led to significant decreases in renewable energy stock prices. US coal stocks, whose future had looked uncertain, experienced large price increases in response to Trump's unanticipated election (Doyle and Davis 2016; Mufson 2016). On the other hand, fossil fuel commodity futures markets experienced increased volatility (Kantchev and Mcfarlane 2016).

The reaction of renewable energy and fossil fuel stocks to the US election has been studied by Mukanjari and Sterner (2018) and Ramelli et al. (2019) using event studies. The two papers show that on Election Day, there was a large positive reaction by US coal stocks. This result supports the narrative that markets anticipated Trump would implement policies that were beneficial for the coal industry. The purpose of this paper is to delve deeper into the question of how the Trump administration would help the coal industry: by helping the miners *mine* more coal or by helping the utilities and industries *burn* more coal. While both supply- and demand-side policies would be expected to increase the profitability of fossil fuel firms, the implications for commodity prices would be quite different. Supply-side policies such as opening up federal lands to exploitation would, other things equal, lead to a fall in the future price of coal. Demand-side policies such as removing environmental constraints on power plants would increase the demand for coal and thus tend to raise the future price of coal. Therefore, both supply- and demand-side policies would raise profits and quantities burned but have different mechanisms and thus would have different effects on expected prices. Naturally, the Trump administration was likely to do some of both, but the question remains which policies were expected to dominate. As mentioned, earlier work has already analyzed profits, and by now adding an analysis of futures prices, we are able to understand better whether the election affected coal and natural gas prices and in which way. This is useful as an indication of whether the expected Trump administration policies would be primarily supply- or demand-side policies.

Commodity futures markets provide an ideal setting for analyzing the effects of the election outcome because of their first-order importance for firm decision-making (Brogaard et al. 2018). According to Black (1976, 176), "The big benefit from futures markets is the side effect: the fact that participants in the futures markets can make production, storage, and processing decisions by looking at the pattern of futures prices, even if they don't take positions in that market."[1] Examining the reaction

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[1] Pindyck (2001) notes the important role played by the futures market for producers and suppliers who want to hedge against price risks.

within commodity futures markets is helpful in that it allows us to understand the implications of the election for energy use and emissions.

The effects of Trump's proposed measures also have important international implications. If the proposed measures increase US coal supply, this could induce carbon leakage through international fossil fuel markets, which could undermine the effectiveness of climate policies within countries that choose to stick to their Paris pledges or seek to increase the ambitiousness of their pledges. If they increase coal prices, this might make it easier for countries to meet their individual commitments but may reduce the effectiveness of climate policy at a global level.

To examine the net effect of the anticipated measures on coal and natural gas prices, this paper uses the event study approach. Event studies have become a standard technique to measure the reaction of asset prices to new information and are widely used in accounting and financial economics to evaluate the impact of a range of events, such as mergers and acquisitions and earnings announcements. Several studies have used event study analysis to assess the relationship between firm financial performance and the release of environment-related news (see, for example, Barnett 2019; Dasgupta et al. 2001; Fisher-Vanden and Thorburn 2011; Flammer 2018, forthcoming; Griffin et al. 2015; Hamilton 1995; Khanna et al. 1998; Mukanjari and Sterner 2018; Ramelli et al. 2019; Sen and von Schickfus 2017). A few event studies in this area analyze events using futures markets data. A recent example is Lemoine (2017), who conducted a traditional event study to examine the reaction of coal and natural gas futures to the collapse of the Kerry-Graham-Lieberman climate bill in 2010. In our study, we follow a similar approach. However, as in Mukanjari and Sterner (2018) and Ramelli et al. (2019), we use the conventional two-step approach, in which we first estimate the market model parameters over a pre-event period that does not include the event dates that we seek to test, and then estimate the event abnormal returns in a second stage.

The key assumptions for event studies are that markets are efficient, the event is unanticipated, and the timing is exogenous. While there have been many large and important climate policy events, such as divestment announcements and the annual United Nations Framework Convention on Climate Change Conference of the Parties meetings, most have been partially anticipated. Generally, new information will have an effect on asset prices that depends on (a) its importance for asset prices and (b) how unexpected it is. A completely expected event will thus have no effect on asset prices when it happens. The Trump election has a number of advantages from an event study perspective. First, the election result came as a surprise. On Election Day, Trump's chances stood at 28.6% on FiveThirtyEight and 11% on PredictWise. Even though it is possible that market participants responsible for pricing commodity futures had put higher probabilities on Trump's winning, it is not a strong assumption that these were substantially below one. Second, one major difference between the two candidates was in their commitments to climate policy, the focus of this paper. A Clinton presidency would likely have meant a continuation of the Obama administration's climate policy. The anticipation that there was a substantial chance Trump would not win, in combination with a reasonable expectation that the policies chosen by the two would be very different, suggests that the election shifted expectations about climate policies.

In addition to the large surprise element and sharp differences in the two candidates' climate policies, there are other reasons to anticipate a strong reaction in futures markets. For a start, many of the environmental regulations by the Obama administration, including the ratification of the Paris Agreement, came into existence through executive orders. Consequently, no Senate approval would be required for their repeal. This implies that the Obama administration's environmental policies could be rolled back fairly quickly, and this should have made the price reaction even stronger. Furthermore, the 2016 election of Donald Trump as the 45th US president came at a time of increased pressure on fossil fuels from many directions. For example, the US coal industry has been struggling, with early retirement of coal power plants and many large coal companies going bankrupt. At the same time, there is growing concern about stranded assets risk (Carbon Tracker Initiative 2013; Leaton 2012; McGlade and Ekins 2015), with central banks increasingly worried about climate change–induced financial instability (Batten et al. 2016; Campiglio et al. 2018; Carney 2015; Dafermos et al. 2018; Olovsson 2018; Rudebusch 2019). The divestment movement has brought further challenges for the fossil fuel industry. Given all this, it is sensible to expect that the reverse climate policy shock in the form of the Trump election would be accompanied by large price effects in fossil fuel futures markets.[2]

The realization of some of Trump's energy-related campaign promises is, however, conditional on the willingness and effectiveness of the Environmental Protection Agency (EPA) administrator. The importance of the EPA nomination is highlighted by Ramelli et al. (2019), who find positive abnormal returns by US stocks upon the nomination of Scott Pruitt. We therefore examine fossil fuel commodity price behavior on Election Day and during the ensuing EPA nomination period. For our analysis, the EPA nomination has an advantage over Election Day in that it had implications only for environmental policy. However, the event was of moderate surprise, given that almost all the candidates interviewed for the position were climate skeptics, although Pruitt could be characterized as the most extreme.

This paper exploits Trump's unexpected victory and the major differences in the two candidates' commitments to climate change mitigation to identify the election's price effects due to anticipated changes in climate policy. Using the event study methodology and the indicator saturation technique to control and capture the effects of common shocks during the sample period, we find that on Election

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[2] The Trump election is interesting for other reasons beyond those elaborated here. Before the election, the United States was widely expected to lead international climate negotiations and decarbonization efforts. Furthermore, the United States is one of the largest sources of anthropogenic carbon dioxide (CO_2) emissions. A climate agreement without US participation would hold back the full commitment of other countries, leading to a substantial weakening of the Paris Agreement (Pickering et al. 2018; Urpelainen and Van de Graaf 2018), despite broad consensus that current efforts as contained in the Paris pledges are insufficient to avoid global warming in excess of the 2°C target (UNEP 2018).

Day, there were no significant changes in coal and natural gas prices. The only explanation likely consistent with this observation, knowing the US coal stock market reaction, is that market participants expected both supply and demand policies to be implemented. That no policies were expected is not consistent with the positive effect on US coal stock prices. During the time until Scott Pruitt's nomination to lead the EPA, we see a tendency for a decline in coal prices, which indicates that market participants over time became more confident that mostly supply-side policies would be implemented. Around Pruitt's nomination, this trend changed, and we see a tendency for an increase in coal prices. This suggests that market participants started to believe in more demand-oriented policies.

Surprisingly, we find the opposite pattern for natural gas prices. Starting from Election Day until around Pruitt's nomination, we see a tendency for an increase in natural gas prices. This suggests that in spite of all the rhetoric, market participants over time became more confident that the Trump administration's policies would actually end up benefiting the continued use and expansion of natural gas. Following Pruitt's nomination, this trend was partially reversed.

Our results further suggest that the election induced significant changes in the futures return variance and intracommodity return spreads. In addition, the reaction across futures contracts of different maturities is in line with the narrative that market participants anticipated that the proposed policies would be implemented soon after Trump took office. For reasons unrelated to the climate, Trump also pledged to support ethanol through the Renewable Fuel Standard (RFS). Our results suggest that the effect of this on ethanol futures markets was limited to Election Day.

The rest of the paper is organized as follows: Section 2 provides a timeline of EPA-related events after the 2016 US election. Section 3 uses a simple framework to illustrate how the anticipated policies interact to determine fossil fuel prices and consumption. Section 4 describes the data and empirical strategy used to identify the election's effect on energy commodity futures markets. Section 5 presents results from the event study, mean and variance comparison tests, and the indicator saturation technique, alongside some robustness checks. Section 6 concludes.

2. Timeline of Events

In this section, we explicitly outline a timeline of events related to the EPA nomination process post-election. Evidence from opinion polls and prediction markets suggests that the election result was a substantial news shock—it was quite far from being completely anticipated. The main identification challenge is establishing that the EPA nomination–related events implied news shocks such that prices responded to the EPA news. Here we discuss the event timeline in detail to shed more light on the crucial events that followed the election result announcement.

We argue that these events constituted additional useful information to market participants regarding the likely path of climate policy under Trump.

Following the announcement of the US election result, attention turned to the process of filling cabinet positions in the Trump administration. A key cabinet-level position is the EPA administrator, who decides the future course of domestic environmental regulation. To determine the sequence of events, we did a systematic search of the international news database Factiva (factiva.com) using the key words EPA or Environmental Protection Agency and the nominee names. This brought up news stories from all the major newspapers and publications in the world, including the *Wall Street Journal* and the *New York Times*. The intuition behind using contemporary news reports is that newspaper publishers aim to attract and maintain readership with timely reporting on issues of interest to their target audience. Since readers are interested in events that may affect their economic well-being, newspapers will optimally choose to report on these events. Table 1 summarizes the timeline of events.

The EPA nomination process started a few months ahead of the elections with the appointment of the EPA transition team tasked with identifying potential candidates for the EPA administrator position. Several news reports first suggested in September 2016 that Myron Ebell, a well-known climate change skeptic, had been nominated to lead Trump's EPA transition team.[3] This constituted an early indication that Donald Trump, if elected, would follow through on his campaign promise to pull out of the Paris Agreement and significantly loosen domestic environmental regulations. Following the election on November 8, 2016, several news sources reported on November 9 and 10 that Myron Ebell would be leading the EPA transition team. The *New York Times* and *Inside EPA* also corroborated these reports on November 11. On November 9, *E&E News* was the first to report that Scott Pruitt was among the candidates for EPA administrator. On November 16, the *Sun* reported that Scott Pruitt had been tapped to lead the EPA.

Reuters started a regularly updated series on November 18 that listed potential candidates for Trump's administration based on *Reuters* sources and media reports. The initial *Reuters* EPA lists did not include Scott Pruitt, while subsequent *Reuters* lists made no mention of one of only two candidates widely reported to have been interviewed for the position (see, for example, Gibson and Cowan 2016). The *Reuters* lists usually featured four or five top EPA contenders. Scott Pruitt appeared for the first time on the fifth *Reuters* list, on November 30, and became a permanent feature up through the eighth and final list, updated on December 6. Four of the contenders were featured on all lists published by *Reuters* since November 18.

On November 28, *E&E News* and *CBS News* reported that Scott Pruitt was one of two candidates due to meet with Donald Trump to discuss the EPA position. On December 4, the *Wall Street Journal* reported for the first time that another EPA

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[3] See https://www.eenews.net/climatewire/2016/09/26/stories/1060043398

Table 1. Timeline of Events of 2016 US Presidential Election and EPA Nomination

Date	Event
November 8	Donald Trump is elected US president.
November 9	Myron Ebell is confirmed as leading the EPA transition team. Scott Pruitt, Patrick Morrisey, Craig Butler, and Kathleen H. White are rumored as candidates for the EPA administrator position.
November 10 and 11	More newspapers repeat the news about Myron Ebell and Scott Pruitt.
November 16	The Sun reports that Scott Pruitt has been tapped to lead the EPA.
November 18	*Reuters* names Jeff Holmstead, Michael Catanzaro, Robert E. Grady, Leslie Rutledge, and Carol Comer as contenders for the EPA administrator position.
November 28	Kathleen H. White and Scott Pruitt meet with Donald Trump to discuss the EPA administrator position.
November 30	*Reuters* includes Scott Pruitt on its list of top EPA contenders.
December 4	The *Wall Street Journal* reports that Carl Icahn is on the EPA transition team. The *Hill* names Kathleen H. White, Scott Pruitt, Jeff Holstead, Donald Van der Vaart, and Myron Ebell as contenders for EPA administrator.
December 5	Donald Trump meets with Al Gore. The *New York Times* names Jeffrey Holmstead, Scott Pruitt, and Kathleen H. White as leading contenders for EPA administrator. Donald Van der Vaart and Myron Ebell are also named in other reports.
December 7	*CBS News* reports that Trump has met again with Scott Pruitt. *CBS News* later reports that Scott Pruitt will be named as EPA nominee. The *New York Times* reports that Trump has picked Scott Pruitt to lead the EPA.
December 8	Scott Pruitt is officially nominated to lead the EPA.

critic was also on the EPA transition team.[4] On the same day, reports in the *Hill* cited Scott Pruitt and four other names as potential contenders—an indication the race was still open and far from over. On December 5, the *New York Times* also named Scott Pruitt as one of three leading contenders. In addition to these three names, *North State Journal* also mentioned two others.

On December 7, Donald Trump met again with Scott Pruitt at 1:40 p.m. ET to discuss the EPA administrator position. At 3:00 p.m. ET, *CBS News* reported that Scott Pruitt would be nominated to lead the EPA. Several other news outlets, including *Inside EPA* and the *New York Times*, also reported this news. On Thursday, December 8, 2016, at 07:30 a.m. ET, Trump's transition team issued a news release formally announcing the nomination of Scott Pruitt as EPA administrator.

From the ongoing discussion, the sequence of events suggests that the EPA nomination process was not anticipated and that each event provided useful information to market participants regarding the future path of climate policy. First, even though the entire composition of the EPA transition team was not publicly known, two of its members were known to be EPA critics. Second, the majority of contenders for the EPA administrator position shared similar critical views on climate change. Only one of the contenders, Robert E. Grady, was described as

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[4] See https://www.wsj.com/articles/carl-icahn-critic-of-the-epa-is-helping-donald-trump-shape-it-1480863601.

"too moderate."[5] During an interview with the *New York Times* on November 26, 2016, however, Trump maintained that he had an open mind regarding the United States' role in leading global efforts to address climate change.[6] Around the same period, he also engaged with environmentalists, most notably Al Gore, regarding the future of US participation in the Paris Agreement.[7] Until the second meeting between the president-elect and Scott Pruitt on December 7, it was not clear who would eventually be nominated to lead the EPA, and several reports narrowed the EPA nomination race to about five contenders. Scott Pruitt was not mentioned in some of the early lists of top contenders. The inclusion of a moderate candidate might be interpreted to mean that Trump was to some extent expected to become more conventional when elected.[8] While the majority of the candidates all held critical views on climate change, Scott Pruitt was the most extreme. His nomination therefore offered the clearest indication of the president-elect's intentions.

3. Environmental Deregulation and Fossil Fuel Prices

We seek to understand how the election result and expectations of significant environmental deregulation affected fossil fuel commodity prices as an indication of the type of policies anticipated. In principle, we can divide policies that directly affect coal and natural gas prices into those affecting demand and those affecting supply. A subset of the anticipated energy policies by Trump includes promoting the coal and natural gas industries through lifting the moratorium on energy production in federal areas, removing restrictions on new drilling technologies, and renewing the permit application for the Keystone XL pipeline (Trump 2016). Each of these policies, if implemented, would make it easier or cheaper to supply coal and natural gas. Therefore, if those were the policies that market participants expected to be implemented, one would see a negative impact on coal and natural gas prices.

Another subset of the anticipated policies includes rescinding the Clean Power Plan, which set national standards on reducing carbon emissions from existing power plants, and withdrawing from the Paris climate agreement (Trump 2016). There was also anticipation that the 2011 Mercury and Air Toxics Standards, which regulate mercury and other toxins such as lead and arsenic, would be significantly relaxed. In addition, existing federal support for renewables was anticipated to be

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[5] See https://insideepa.com/daily-news/grady-considered-likely-too-moderate-serve-trumps-epa-chief.

[6] The full interview transcript is available at https://www.nytimes.com/2016/11/23/us/politics/trump-new-york-times-interview-transcript.html?.

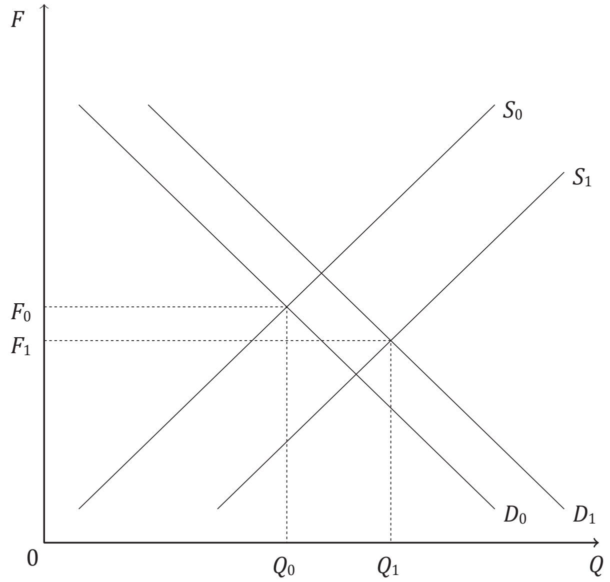
[7] On December 5, Trump met with Al Gore. The meeting, described as "very productive" by Al Gore, generated a sense of renewed hope for environmentalists that Trump would pull back on some of his energy-related campaign promises. See https://www.theatlantic.com/science/archive/2016/12/why-did-al-gore-go-to-trump-tower/509771/.

[8] Many presidents in the past have been polarizing during election campaigns but try to unite when elected.

removed upon expiration or significantly downscaled. This would indirectly promote fossil fuels through slowing the growth of renewable energy. If these were the only policies, we would see an increase in demand, leading to an increase in coal and natural gas prices. We can infer that some of these policies must have been expected to materialize, judging by the large positive reaction by US coal stock prices (see Mukanjari and Sterner 2018; Ramelli et al. 2019). However, the positive stock price reaction provides no information about the compositions of supply- and demand-related policies. Our approach is to look at the net effect on coal and natural gas prices.

To analyze the interplay of these anticipated measures on fossil fuel prices and consumption in general, we present a simple example in Figure 1 to illustrate how the suggested policies interact to determine fossil fuel prices. In the following example, we abstract from differences between coal, oil, and natural gas.

Figure 1. Simultaneous Demand-Side and Supply-Side Policies



Let F be the anticipated global market price of fossil fuels some time after the election, while Q is quantity. The anticipated future market demand and supply before the election are given by D_0 and S_0, respectively. The Trump climate policy shock simultaneously affects both future fossil fuel demand and supply. Consider one of the proposed policy measures that would make it easier to extract fossils: the removal of the moratorium on energy production in federal lands. Such a policy will result in an increase in quantity supplied to the market in the future, and the supply curve shifts rightward to S_1. Considered in isolation, the policy will reduce the price of fossil fuels below F_0 and increase consumption. At the same time, Trump promised measures that would increase the demand for fossil fuels during his administration. Consider one of the proposed policies that would make it easier to burn fossil fuels: rescinding the Clean Power Plan. This will result in an increase in quantity demanded, and the future demand curve shifts rightward to D_1. Considered in isolation, the policy will increase the price of fossil fuels above F_0 but also stimulate consumption. The net effect of the two simultaneous demand- and supply-side policies will be to stimulate consumption. Equilibrium price might rise, fall, or remain unchanged, depending on whether increases in demand are more than, less than, or equal to the increase in supply. In Figure 1, the strength of the supply-side policies outweighs the demand-side policies, and the expected price for fossil fuels falls.

4. Data and Empirical Strategy

In this section, we discuss our sample selection and data, followed by the empirical strategy used to examine the fossil fuel commodity futures price reaction to the 2016 US election. The objective is to assess market expectations regarding climate policy under Trump. The paper employs three complementary empirical strategies. Sections 4.3–4.5 outline the event study methodology and the indicator saturation technique used to measure the abnormal returns related to the US election and the EPA nomination process. In Section 5, we use variance and mean comparison tests to assess different ways in which the election affected coal and natural gas commodity markets. The empirical strategy for that analysis is laid out in Sections 5.1 and 5.2.

4.1 Sample Selection and Data Description

Our sample consists of coal, natural gas, and ethanol commodity futures, all of which would directly benefit from Trump's election.[9] For coal, we use the Rotterdam and Central Appalachian (CAPP) CSX coal futures contracts traded on the Intercontinental Exchange (ICE) Futures Europe. For natural gas futures prices, we use the benchmark Henry Hub futures contract traded on the New York Mer-

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[9] We drop oil for a number of reasons. First, it was not clear Trump would be good for oil companies after dismissing the industry as a "special interest" (see, for example, Schor 2016). Second, the oil and gas industry campaign donations to Donald Trump ($1,069,181) compared with donations to Hillary Clinton ($967,336) suggest Trump was not a favorite of the industry. This is a significant departure from the past. In 2012, the Republican candidate Mitt Romney received $6,662,856 compared with $982,778 received by Barack Obama. When one considers campaign donations from the coal industry, Donald Trump received $280,189 compared with $4,302 for Hillary Clinton (see www.opensecrets.org). Third, Trump's support for ethanol was not considered to be in the interests of the oil industry. In addition, a Trump presidency could increase geopolitical tensions due to Trump's hostility toward Iran. Finally, oil supply largely depends on developments at the Organization of the Petroleum Exporting Countries (OPEC).

cantile Exchange (NYMEX). The ethanol prices used are for the denatured fuel ethanol futures contract traded on the Chicago Board of Trade (CBOT).

The Rotterdam coal futures contract is priced against Argus/McCloskey's API2 index, with delivery to the Amsterdam-Rotterdam-Antwerp (ARA) region.[10] The API2 index is taken as the primary reference coal price for northwest Europe. The CSX coal futures contract is based on the price of coal delivered via the Eastern Rail network from the Central Appalachian mining region in the United States. The Rotterdam coal futures contract is the most liquid global coal contract. In contrast, the CSX coal futures contract is significantly less liquid.[11] The contract's open interest—the total number of active or outstanding contracts held by market participants at the end of each day and a measure of the liquidity of a futures contract—is often several times smaller than that of the Rotterdam coal contract. The CSX and Rotterdam coal futures prices have a correlation coefficient above 0.7. The Rotterdam coal futures should contain useful information related to US events insofar as climate policy is concerned in addition to northwest Europe events. It was largely feared the US withdrawal from the Paris Agreement would trigger the withdrawal of other countries or a weakening of their commitments (Pickering et al. 2018). This links the European coal futures market and the event of interest.

Futures contracts are often subject to exchange-imposed price limits, which restrict prices from rising above or falling below prespecified levels. The coal contracts in our sample are not subject to price limits, but the natural gas and ethanol contracts halt trading after a large movement in the price. Price limits do not appear in the estimation or event windows. In the absence of such restrictions, the daily settlement prices should fully reflect all the relevant available information in the market. The contracts therefore have the added advantage of being informationally efficient during the sample period.

The source of our data is the Commodity Research Bureau, which provides daily commodity settlement prices for individual futures contracts.[12] At any given time, there are usually several individual futures contracts of different matur-

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[10] The price is quoted cost, insurance, and freight (CIF), since ARA is a consumption region. The coal traded in this region originates from Australia, Colombia, Indonesia, Russia, South Africa, and the United States. The coal should meet certain quality specifications. In particular, the energy content must be 6,000 kcal/kg and the sulfur content no greater than 1%.

[11] The absence of sufficient liquidity in the CSX coal futures contract highlights the challenges faced by the coal industry in the United States. In December 2016, the NYMEX Central Appalachian contract, regarded as the reference contract for coal in the North American market, was delisted.

[12] Since all futures trading is done on margin, clearing houses issue a settlement price for each futures contract on a daily basis. The settlement price represents the price by which open positions are marked to market and is not always the last trade price as with stocks.

ities trading side by side.[13] Although futures contracts are traded with maturities stretching several years into the future, only the contracts nearing maturity often have sufficient liquidity. The trading volume is typically concentrated in the near-maturity contracts. The CSX coal futures contract, in particular, exhibits both zero open interest and volumes (i.e., total amount of trading activity) for long periods, with only nonzero open interest recorded about a month from maturity. Conversely, the Henry Hub natural gas futures contract is actively traded and is characterized by both large open interest and volumes, even for contracts with more than a year before maturity. We make use of only those contracts that matured during the first year of Trump's presidency because of worries about thin trading (see Adämmer et al. 2016). The low trading volume and open interest that characterize thinly traded futures contracts may affect the efficient transmission of information to market prices. In that case, the lack of sufficient liquidity may have negative effects on the price discovery process (Tomek 1980). Several of the futures contracts maturing during this period are traded as quarterly strips, and only one contract within each quarterly strip is included in the sample.[14] Finally, we exclude the contract maturing during the event month, November 2016. This avoids the possibility of picking up spurious relationships due to excessive noise and volatility in the futures price series. Daily futures prices of contracts nearing maturity tend to exhibit increased levels of volatility as the futures and spot price converge (Miller 1979; Samuelson 1965).

Figure 2 plots the coal, natural gas, and ethanol futures prices for contracts of different maturities over the period from January to December 2016. Panel (a) of Figure 2 shows prices of the CSX coal futures contract. Note that the intracommodity spread is large before August 2016 and the forward curve is upward sloping (longer-dated contracts are more expensive than shorter-dated contracts).[15] The large intracommodity spread suggests a strong view in this market that the contract prices would be very different on maturity. After August, the intracommodity spread narrows and the forward curve becomes downward sloping (longer-dated contracts are cheaper than shorter-dated contracts), before the intracommodity

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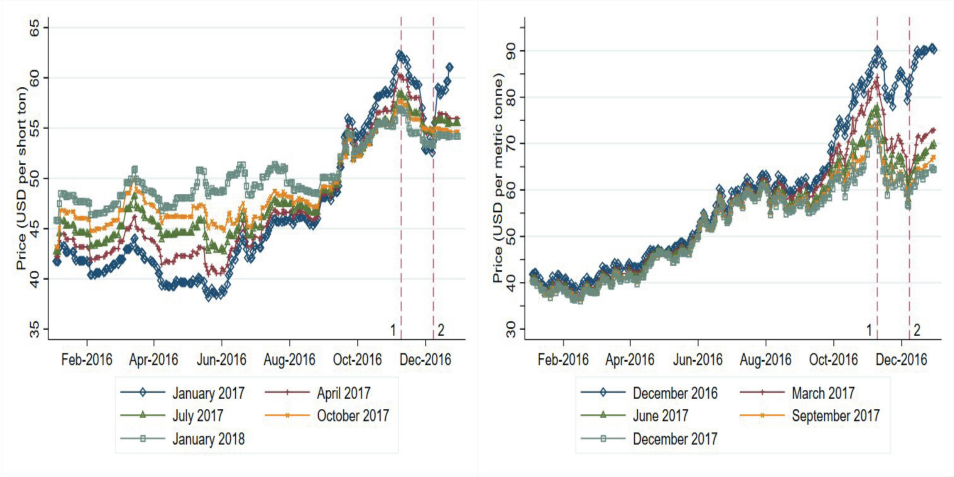
[13] We analyze futures prices because spot prices are often more prone to the influence of daily price fluctuations that arise from temporary shortages or surpluses and seasonality (see Boyer and Filion 2007; Gorton and Rouwenhorst 2006; Oberndorfer 2009; Sadorsky 2001). In addition, seasonality in spot prices is unlikely to affect futures returns, since futures already impound predictable price fluctuations (Gorton and Rouwenhorst 2006). While one can use cash prices, it is important to note that cash prices usually represent average daily prices and often include discounts and premiums that arise because of goodwill between buyers and sellers (Pindyck 2001). However, since we are interested in understanding expectations about future climate policy, futures prices tend to serve us better.

[14] Quarters are defined as strips of three consecutive months, always January–March, April–June, July–September, or October–December.

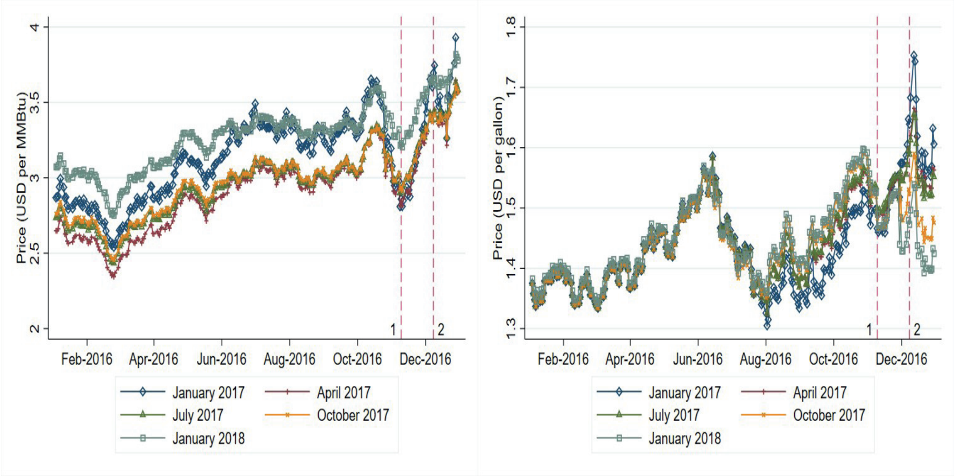
[15] Generally, the forward curve tends to slope upward because longer-dated contracts tend to have higher prices because of financing, storage, and insurance costs. Keynes (1930) uses the term *contango* to refer to the case where the forward curve is upward sloping. He terms the reverse situation *backwardation.*

Figure 2. Prices for the Energy Commodity Futures Contracts during the Sample Period



(a) CSX Coal Futures

(b) Rotterdam Coal Futures



(c) Henry Hub Natural Gas Futures

(d) CBOT Ethanol Futures

Note: The red dashed lines mark days with significant election-related events: (1) November 8, 2016, Donald Trump wins the US presidential election; (2) December 8, 2016, Scott Pruitt is officially nominated to lead the EPA.

spread begins to increase again until the end of the sample period. The CSX coal futures contract also exhibits several periods during which the settlement prices were not changing much, highlighting the lack of liquidity in this contract. In contrast, panel (b) of Figure 2 exhibits a narrower intracommodity spread for the Rotterdam coal futures contract until around August 2016. This suggests that expectations over this period were that the Rotterdam coal futures contract prices, unlike the CSX coal futures, would not be very different upon maturity. After

August, the intracommodity spread starts to widen.[16] The Rotterdam coal futures forward curve is downward sloping throughout the entire sample period. At the end of the sample period, the price of the December 2016 contract is 28% higher than that of the December 2017 contract, reflecting expectations of a significantly lower coal price a year after the election.

For both coal contracts, prices started around \$40 at the beginning of the sample period. The Rotterdam coal contract prices, however, more than doubled over the sample period, with the December 2016 contract reaching \$90/metric tonne on Election Day. The comparable CSX coal futures contract reached only \$62/short ton over the same period. Starting around February 2016, the Rotterdam coal futures contract experienced a sustained period over which prices increased, until they stabilized again from July onward. This period was then followed by an upward movement in prices starting around September and continuing until Election Day. In comparison, the CSX coal futures did not experience any sharp price increases until around September, after which prices rose sharply in tandem with the Rotterdam coal futures. For both coal contracts, we notice a significant decrease in the futures price from Election Day until the EPA nomination before they started to rise again.

In panel (c) of Figure 2, we see that the natural gas futures contracts behaved differently than the other commodity futures in that both of the contracts maturing in January had a higher price than contracts maturing in the other months. The intracommodity spread between the contracts maturing in January and the other contracts is large. However, the intracommodity spread among contracts maturing in months other than January is much smaller, and the spread narrows as we approach the event period. Starting in January 2016, natural gas futures prices fell before starting to rise from the end of February until stabilizing from the beginning of July until the end of September. This was followed by a sharp increase in October, before the prices started to fall again until Election Day. Prices then increased sharply from Election Day before reaching a peak on the EPA nomination day.

The ethanol futures prices are shown in panel (d) of Figure 2. The series exhibits a narrower intracommodity spread until the end of July 2016. Over this period, prices increased, reaching a peak in June before falling until the end of July. After this point, the intracommodity spread widens, while the prices started to increase again before reaching a peak at the end of October. Over this period, the forward curve is upward sloping before becoming downward sloping around election time. Prices fell sharply during November until Election Day before initially rising and then becoming more volatile.

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[16] The increasing intracommodity spread could be due to more information becoming available as the contracts near maturity.

4.2 Identification Strategy

The election of Trump affected several aspects, such as tax, trade, and immigration, as well as climate policy. In this paper, we want to identify changes in the commodity futures prices that are driven by anticipated changes in climate policy as a result of Trump's election. To identify the price effects due to Trump's anticipated changes in climate policy, we exploit the unexpected election of Trump and the major differences in the two candidates' commitments to climate change mitigation. The election of Trump would imply that the Clinton climate policies are not undertaken. Clinton would be expected to implement policies that are particularly negative for coal production and consumption, less so for oil and natural gas, and maybe positive for ethanol. This is because the combustion of coal results in significantly larger emissions per unit of energy produced than natural gas, and global efforts to address climate change have largely focused on reducing reliance on coal. Coal futures prices are thus expected to be more sensitive to the anticipated climate policy reversals, while oil and natural gas may be less responsive (see Coulomb and Henriet 2018; Michielsen 2014). In addition, we should see a much larger reaction in coal prices, given that there were more restrictive measures on coal than on natural gas and ethanol before the election.

Even though ethanol is a renewable energy source that is mostly blended with gasoline, it also was expected to benefit from Trump's election.[17] On the campaign trail, at the 10th Annual Iowa Renewable Fuels Summit on January 19, 2016, Trump pledged to support ethanol and the RFS for reasons unrelated to the climate:

> *The RFS, which is renewable fuel standard, is an important tool in the mission to achieve energy independence to the United States. I will do all that is in my power as president to achieve that goal. . . . As president, I will encourage Congress to be cautious in attempting to charge and change any part of the RFS. . . . As president, I would encourage regulators to end restrictions that keep higher blends of ethanol and biofuel from being sold.*

The RFS came into existence in 2005 and mandates refiners to blend an increasing amount of ethanol and other biofuels into petroleum. Even though Trump's proposed energy policies were largely in favor of fossil fuel, ethanol was an exception. We therefore expect to find a small response for ethanol relative to the other two energy commodities.

There were several possible motivations for the proposed measures. For example, it could have been that Trump cared about workers in some sectors, that he did

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[17] When it comes to renewable energy in general, many factors were involved. The prospects of renewable energy would largely depend on (a) the performance of renewable energy investments in the absence of federal mandates, (b) what would happen to renewable tax credits upon expiration, and (c) the extent to which planned renewable energy projects would be disrupted by the election outcome. Mukanjari and Sterner (2018) show that globally, renewable energy stocks reacted negatively to the 2016 US election.

not care about the climate, or that he was more concerned with attaining energy independence. Whatever his motivation, it is clear that Trump wanted to help coal and natural gas industries and perhaps ethanol. The proposed policies have clear climate effects that are relevant for climate policy regardless of whether climate policy was the reason that Trump promised these measures.

While the US election outcome had the advantage of being largely unexpected, the election altered expectations about many other policies. The estimated impacts may therefore pick up the effects of other proposed policy changes. Nevertheless, we can expect differential effects on coal, natural gas, and ethanol commodity markets. However, this does not completely isolate the price changes due to anticipated changes in climate policy, but we hope that the observed patterns for the different energy commodities are consistent with the expected impact of climate policy under Trump. One challenge with our identification strategy is that we have only three commodities in our sample. In addition, while the election surprise is the same for all fossil fuel commodities, the proposed policies do not represent a uniform policy change across the fossil fuels. Nevertheless, after we control for general movements in commodity markets, the election should have a greater impact on coal than on natural gas and ethanol.[18]

4.3 Event Study Methodology

Asset prices incorporate new information as it arrives. As noted earlier, new information will have an effect that depends on (a) its importance for asset prices and (b) how unexpected it is. A completely expected event will thus have no effect on asset prices when it happens. In this paper, we consider an identical asset (commodity futures contracts are standardized) whose only difference is the maturity date. Commodity futures are different from other assets such as stocks in that changes in the asset price in response to new information allows one to capture market expectations at different time horizons or contract maturities. Assume F_d is the price, before election, of a futures contract deliverable in month d after election. Let $F_{d,T}$ and $F_{d,C}$ denote the expected price of the futures contract conditional on Trump and Clinton winning, respectively. We can denote the probability of each of the two outcomes as p_T and p_C, with $p_C = 1 - p_T$. Assuming risk is not priced, the contract's price before the election is given as

$$F_d = p_T F_{d,T} + (1 - p_T) \cdot F_{d,C}$$

The change in the contract's price if Trump wins is given as

$$\Delta F_d = F_{d,T} - F_d = (F_{d,T} - F_{d,C})(1 - p_T)$$

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[18] Climate policy is expected to have a disproportionate effect on energy sources that produce higher emissions per unit of energy produced. A reverse shock in the form of the US election should thus benefit such commodities more.

The price change due to the election of Trump is therefore the difference between the two outcomes multiplied by the size of the election surprise. The larger the spread between $F_{d,T}$ and $F_{d,C}$, the larger the price reaction for a given election surprise. The anticipation that there was a substantial probability Trump would not win, in combination with a reasonable expectation that the policies chosen by the two would be very different, therefore suggests that one should get a strong price reaction. The return on the asset once the election results are known is then given as

$$\Delta F_d / F_d = (F_{d,T} - F_{d,C})(1 - p_T) / F_d$$

Our main empirical strategy follows the event study approach to compute abnormal returns across coal, natural gas, and ethanol futures contracts of different maturities. Event studies have been applied to examine stock price reactions to various firm-specific and economy-wide events (see Campbell et al. 1997; Kothari and Warner 2007; MacKinlay 1997). With the growth of futures markets, event studies have been adapted and applied to analyze futures returns (see, for example, Demirer and Kutan 2010; Draper 1984; Lemoine 2017; Pruitt et al. 1987). Mckenzie et al. (2004) use simulation methods similar to those of Brown and Warner (1985) to examine the performance of event studies using daily futures returns and conclude that such event studies are well specified.

To examine an asset's abnormal price behavior, a normal return for the asset must be established. Brown and Warner (1980, 1985) have shown that for short-horizon event studies, the standard one-factor market model is often adequate. We estimate the normal return using the benchmark market model:

$$F_{it} = \alpha_i + \beta_i R_{Mt} + \epsilon_{it}, \tag{1}$$

where F_{it} is the log futures return, $i \in \{1, \cdots, k\}$ indexes the futures contract by month of maturity, and t indexes the trading day.[19] R_{Mt} is the daily log return of the market index. We use the Thomson Reuters/Jefferies CRB futures index, which represents broader commodity market movements and covers 19 different commodities, as the market index. While the single-index model is the standard benchmark model in event studies, one potential problem is that it does not control for other potentially relevant factors. As a robustness check, we therefore use the Baltic Dry Index (BDI) as an additional covariate. The BDI reflects the cost of shipping raw materials such as iron ore and coal by sea. Since some of the market indexes we use are traded in different markets than the futures contracts, we fol-

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[19] Futures contracts require no initial investment, and futures positions therefore cannot be said to yield rates of returns in the traditional sense (see Black 1976; Dusak 1973).

low the standard approach in the literature (see Andersen et al. 2003) and exclude all returns where one market is closed.

The estimation period for the parameters of equation (1) is set to 180 trading days ending 28 trading days before the event (January 12–September 30, 2016). The estimated abnormal return for futures contract i on day t during the event period is then given by $AR_{it} = F_{it} - (\widehat{\alpha}_i + \widehat{\beta}_i R_{Mt})$, where $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are the OLS estimates from the market model using returns from days −207 to −28 relative to November 9, 2016. The average abnormal return (AAR_t) for a sample of N futures contracts is then calculated as $AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}$ and cumulated over the event window of days t_0 to t_1 to generate the cumulative average abnormal return $\left(CAAR_{(t_0,t_1)} = \sum_{t=t_0}^{t_1} AAR_t\right)$. We consider different event windows – abnormal returns on the day after the election and up to 21 trading days after the election.

A key requirement for the validity of event studies is that no other nonevent news moved markets during the event window—in other words, there should be no confounding news. The announcement of some other news during the event period would therefore contaminate the results. In this regard, we carry out a systematic search for confounding news using the international news database Factiva. Another important aspect is that when futures returns contain a lot of unexplained variation, it will be difficult to pick up the event's signal. To address this, we include additional covariates in other specifications and also use a more refined error structure to explain more of the nonevent variation in futures returns. While including covariates can help ensure identification through absorbing other news around the event day, Lemoine (2017) argues this can also bias the estimates toward zero, since additional covariates also absorb some of the event's effect into the explained portion of returns. We therefore use the BDI and day-of-the-week binary variables as additional controls in some of our specifications of the market model. The market model is also estimated using a generalized autoregressive conditional heteroskedasticity (GARCH (1,1)) error process.

4.4 Event Clustering and Event-Induced Volatility

From an event study perspective, the Trump election has the advantage that it was unanticipated, but it also affected expectations about many other things—a notable disadvantage, as pointed out by Wagner et al. (2018a). Another complication is event clustering, which arises when the event of interest affects the entire market simultaneously. The most common examples of event clustering arise within the context of market-wide events, such as regulatory changes (e.g., the Sarbanes-Oxley Act). Event clustering gives rise to cross-sectional correlation of the abnormal returns and cumulative abnormal returns across the different contracts, thereby affecting inference. This results in the overrejection of the null hypothesis of zero abnormal returns, even in the presence of mild cross-sectional correlation of the abnormal returns (Kolari and Pynnönen 2010).

Because of the seriousness of event clustering when using daily futures return data, most studies tend to consider shorter estimation windows (see, for example, Demirer and Kutan 2010; Lusk and Schroeder 2002; Moghadam et al. 2013; Paiva 2003) compared with at least 120 days common in event studies using stock returns (see, for example, Mckenzie et al. 2004; Moghadam et al. 2013). This is because event clustering in this literature mostly tends to be within the context of several events occurring one after another over a short period of time. Lemoine (2017), in his analysis of the collapse of the Kerry-Graham-Lieberman bill, addresses event clustering by analyzing the abnormal returns without aggregation. As in Lemoine (2017), we consider a single event that affects futures contracts of differing maturities at the same time. To address the resultant clustering, we use the test statistic presented in Brown and Warner (1980, 1985) to test the significance of the cumulative average abnormal returns (*CAARs*). The crude dependence adjustment (CDA) procedure proposed by Brown and Warner (1980, 1985) uses the portfolio time series standard deviation. We estimate the standard deviation from the time series of sample (portfolio) average abnormal returns during the estimation period (see Appendix 2.A for details).

However, the Brown and Warner test statistic assumes the absence of event-induced volatility. Several events often result in changes in both the asset risk and return, thereby causing a temporary increase in the variance of abnormal returns accompanying the mean shift (see Brown et al. 1988, 1993). An increase in the variance of the returns during the event period has been shown to result in an overrejection of the null hypothesis of zero abnormal return when it is in fact true (Boehmer et al. 1991). To address potential event-induced volatility, we also make use of the adjusted standardized cross-sectional (ADJ-BMP) test statistic developed by Kolari and Pynnönen (2010). The ADJ-BMP test statistic takes into account both event clustering and event-induced volatility by building on an earlier test statistic by Boehmer et al. (1991), which takes into account only event-induced variance inflation.

4.5 Indicator Saturation

The standard event study approach suffers from two related potential problems. First, outliers and structural breaks during the estimation period give rise to contamination of the estimation period, which may pose problems (see Aktas et al. 2007). This problem is generally not addressed within the traditional event study literature. However, outliers and structural breaks unknown to the researcher could pose problems if not controlled for. Second, the presence of contamination during the estimation period implies that traditional event studies as currently applied in the literature are potentially misspecified. We use the indicator saturation (IS) technique as an alternative method since we want to be detailed. The IS technique allows one to complement the event study methodology with econometric methods that help identify and model outliers and structural breaks (see Castle et al. 2012; Castle et al. 2015; Hendry and Johansen 2015; Santos et al. 2008).

The IS method addresses the distorting effect of outliers and structural breaks in econometric models. Indicator saturation is a useful and powerful technique to detect and model outliers and proceeds by taking every data point as an outlier or structural break until proven statistically otherwise. The technique does not require prior knowledge of the location of the outliers and breaks and does not impose a limit on the number of outliers and breaks that can be identified or the length of such breaks. Outliers and breaks can be allowed to occur at the beginning and end of the sample—an advantage over techniques that do not accommodate breaks at the beginning or end of the sample. In addition, both outliers and breaks can be jointly identified and modeled. Combining the event study method with the IS technique helps detect and control for significant events not identified a priori and taking place during the sample period. An additional advantage of IS is that we are not imposing the event dates from the onset as with event study methodology. Starting from a general model, IS allows one to test directly for model misspecification. Therefore, taking the IS approach implies the possibility that the event study method is misspecified. No shifts or outliers outside the prespecified event window should be detected if an event study is well specified. IS therefore allows us to identify and measure the impact of relevant events taking place during the sample period. In some cases, the event date is uncertain, thus enhancing the attractiveness of IS. The IS technique is related to other tests, such as the sample quintile test used by Gelbach et al. (2013), Baker (2016), and Lemoine (2017) to examine the significance of abnormal returns in single-firm, single-event studies. The IS technique is also related to earlier literature testing for structural breaks with a known breakpoint (Chow 1960) or unknown breakpoints (Andrews 1993).

The general model is formulated as

$$F_{p,t} = \beta_0 + \beta_1 D_1 + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 R_{Mt} + \text{indicators} + \epsilon_{p,t} \qquad (2)$$

where $F_{p,t}$ is an equally weighted portfolio of the log futures returns $\left(F_{p,t} \approx \sum_{i=1}^{N} w_i F_{it}\right)$ and p is a portfolio that places a weight w_i on futures contract i. $\epsilon_{p,t}$ is an error term assumed to follow an independent normal distribution with zero mean and variance $\sigma^2_{\epsilon_p} (\epsilon_{p,t} \sim \text{IN}(0, \sigma^2_{\epsilon_p}))$.[20] β_0 is Monday's average return, D_1 is a dummy variable for Tuesday ($D_1 = 1$ if observation t falls on a Tuesday and 0 otherwise), D_2 is a dummy variable for Wednesday, etc. The dummy variable coefficients measure the deviation of the average daily return from Monday's return. Since it is impractical to estimate equation (2), the indicators are partitioned into batches. Indicators significant within each batch at a chosen significance level p_α are then combined

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[20] 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 independent and identically distributed (i.i.d.) and follow a normal distribution.

and selected over to yield the final model.[21] For estimation purposes, we use Autometrics (see Doornik 2009). The statistical power of indicator saturation has been shown theoretically and through simulations to be high. This gives one confidence that the procedure is able to detect significant changes in the properties of the time series data under study. Under the null hypothesis of no structural breaks and outliers, on average $p_\alpha(T-1)$ step indicators and $p_\alpha \times T$ impulse indicators are retained by chance at significance level p_α and sample size T. Therefore, the selection of p_α is critical. One usually chooses a tighter significance level than commonly used in regression analysis. In our case, we choose $p_\alpha = 0.001$. In alternative specifications, we also retain the BDI as an additional conditioning variable without selection. Indicator saturation has recently been applied successfully to a range of climate-related problems (see Pretis et al. 2015; Pretis et al. 2016; Pretis et al. 2018b).

5. Price Effects of the US Election

In this section, we start by discussing results from the event study analysis. Next, we investigate the impact of the event on the mean return, return variance, and intracommodity return spreads using mean and variance comparison tests. Finally, we present the indicator saturation results.

We test whether the election and the subsequent EPA nomination process had any cumulative impact on energy commodity futures in two ways. We first carry out a visual inspection of the *CAAR* plots during the 22-day event period. A downward (upward) sloping *CAAR* plot is consistent with the hypothesis that Trump was anticipated to implement policies that promote coal (natural gas) supply (demand) more than demand (supply). We then formally test the null hypothesis that the event had no impact on *CAARs* using the parametric test statistics proposed by Brown and Warner (1980, 1985) and Kolari and Pynnönen (2010). It is important to point out that failing to reject the null hypothesis would imply that given the stock market reaction, the only explanation consistent with no effect would be that market participants had an unclear view regarding what would happen or expected both of these types of policies to be implemented.

Two sets of policies were presented by candidate Trump at various points during the campaign period. The first set of policies included measures to promote the coal and natural gas industries through lifting the moratorium on energy production in federal areas, removing restrictions on new drilling technologies, and

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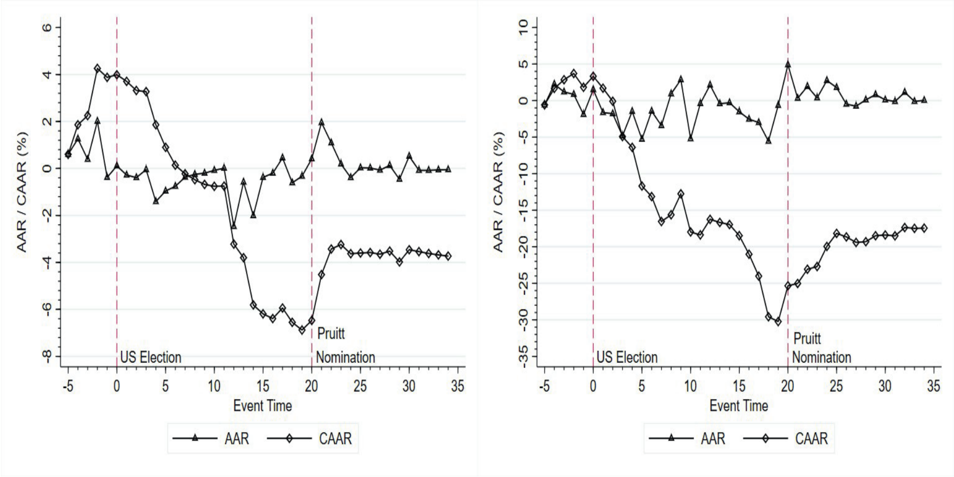
[21] Using IS means that we have a large number of potential independent variables. When additional controls are included without selection together with impulse and step indicators, we have more variables than the number of observations. This is resolved through applying a general-to-specific selection over the impulse and break functions. Although we start with a large number of potential regressors, only a few are retained. According to Doornik et al. (2013), this suggests that overfitting is not a major issue with IS.

renewing the permit application for the Keystone XL pipeline. If each of these policies were implemented in isolation, they would have the effect of making it easier or cheaper to supply coal or natural gas. Therefore, if those were the policies that market participants expected to be implemented, one would see a negative impact on coal and natural gas prices. This would show up as a downward-sloping *CAAR* plot and negative *CAARs*. The second set of policies presented sought to repeal the Clean Power Plan, which set national standards on reducing carbon emissions from existing power plants, and withdraw from the Paris climate agreement. In addition, the 2011 Mercury and Air Toxics Standards, which regulate mercury and other toxins such as lead and arsenic from power plants, would be relaxed. At the same time, it was anticipated that existing federal support for renewables would be significantly downscaled or not renewed upon expiration. If only this second set of policies were implemented, they would have the effect of increasing demand for coal and natural gas. Therefore, if those were the policies that market participants expected to be implemented, one would see a positive impact on coal and natural gas prices. This would show up as an upward-sloping *CAAR* plot and positive *CAARs*. However, judging from the reaction of coal stock prices, we know that market participants must have expected a combination of at least some policies from each set to be implemented, although we do not know the composition. The slope of the *CAAR* plots and the sign of the *CAARs* indicate whether more demand- or supply-side policies were anticipated. In addition, if the restrictions on coal supply before the US election were much stricter than those imposed on natural gas, the supply effect for coal will more likely be much bigger than that for natural gas. In turn, this will give us larger demand effects for natural gas. The Obama administration imposed stricter restrictions on fossil fuels, especially coal.

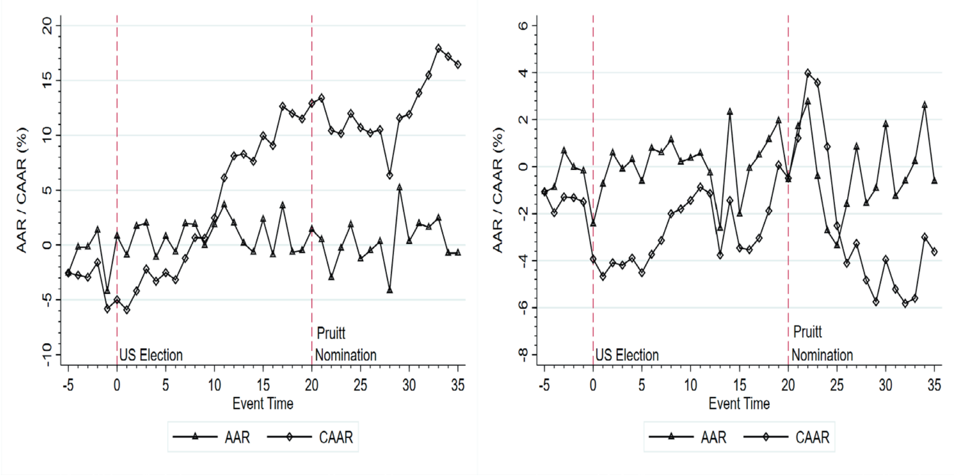
Figure 3 shows the evolution of the average abnormal returns (*AARs*) and the *CAARs* for the different commodity futures during the event period. The graphs are plotted from five days before the US election until December 30, 2016. From panels (a) and (b) of Figure 3, we do not observe any sizable abnormal returns for coal futures before the US election. We do, however, observe a sizable decrease in the *CAARs* from the day after the election until the nomination of Scott Pruitt. The decrease in the *CAAR* plot is more pronounced for the Rotterdam coal contract. The tendency for the *CAAR* plot to decline over this period suggests that over time, market participants became more confident that mostly supply-side policies would dominate. The evolution of the *AARs* shows that there were days within the event window on which significantly negative *AARs* were recorded. As a result, the *CAARs* declined significantly over the same period. However, around November 8, 2016—the day Scott Pruitt was nominated—we notice a change in the slope of the *CAAR* plot. This suggests markets believed that at least some of the effect would come through demand-side policies. Indeed, all but one of the 14 lawsuits initiated by Scott Pruitt against the EPA in his previous role as Oklahoma attorney

Figure 3. Cumulative and Average Abnormal Returns for the Energy Commodity Futures



(a) CSX Coal Futures

(b) Rotterdam Coal Futures



(c) Henry Hub Natural Gas Futures

(d) Ethanol Futures

Note: The abnormal returns are calculated using the market model. The parameters of the market model are estimated using a 180-day estimation period.

general mostly had to do with clean air regulations (i.e., demand-side policies).[22] This possibly explains part of the price change we see upon his nomination. From panels (a) and (b) of Figure 3, it appears that the post-election period was associated with significant movements in coal futures prices. These results provide some preliminary evidence that participants in this market appear to have anticipated that Trump would have a greater effect on coal supply than demand.

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[22] See https://www.edfaction.org/scott-pruitts-web-fundraising-and-lawsuits.

Even though Trump's election campaign statements were largely focused on promoting coal, some of the touted measures would also benefit natural gas directly or indirectly. Removing restrictions on new drilling technologies and renewing the permit application for the Keystone XL pipeline were two such policies that if implemented, would directly increase natural gas supply and thus decrease its price. On the other hand, measures to scale down support to renewables or withdraw from the Paris Agreement if implemented would lead to an increase in natural gas demand and hence price. Natural gas substitutes for coal in electricity generation and produces lower emissions per unit of energy compared with coal. Fewer supply-side restrictions on natural gas before the election should lead to strong demand effects.

Panel (c) of Figure 3 plots the *AARs* and *CAARs* for the natural gas futures. We notice that the plots are characterized by large swings of the *AARs* and *CAARs*, indicative of high volatility, which often typifies natural gas prices. The upward-sloping *CAAR* plot during the event period provides suggestive evidence of the election's positive effect on natural gas futures prices. The tendency for the *CAARs* to increase over this period suggests that over time, market participants became more confident that mostly demand-side policies would dominate. A possible explanation consistent with this observation would be that the supply-side restrictions on coal during the Obama administration were much stricter than on natural gas. As with coal, we notice a change in the slope of the *CAAR* plot around Pruitt's nomination.

In panel (d) of Figure 3, we plot the *AARs* and *CAARs* for ethanol. The graph shows no clear discernible pattern. This suggests that even though Trump promised to promote ethanol, the market's interpretation of this gesture was somewhat ambiguous or neither effect dominates. It is, however, important to note that Trump's position on ethanol was in contrast to his overall position on climate change and largely motivated by other concerns, likely mainly to do with energy independence (or purely electoral tactics).

In Table 2, we formally test the statistical significance of the results shown in Figure 3. We test the null hypothesis that the election had no effect on energy commodity futures prices and present the *CAARs*, since we are interested in whether the event had any cumulative effect. The reported results use a 180-day estimation period for the market model parameters. As a robustness check, a much shorter estimation period of 60 days (−87, −28) is also used (see Table 2.B.1 in Appendix 2.B). The relevant event window beginning with the event day is denoted by $(0, t_1)$. Table 2 reports the raw and market model abnormal returns. We do not find significant abnormal returns on Election Day for any fossil fuel commodity futures. A possible explanation consistent with this result, given the election's effect on coal stock prices, is that market participants likely had an unclear view or expected both types of policies to be implemented. Again, it must have been that they expected some policies of each type, because of the effect on coal stock prices, but it appears that market participants did not have a clear expectation of whether

Table 2. Price Effects of US Election on Commodity Futures

	(0, 0)	(0, 4)	(0, 9)	(0, 14)	(0, 19)	(0, 21)
CSX Coal Futures			Panel A. Raw Returns			
CAAR	0.20%	−1.68%	−3.65%	−8.34%	−8.97%	−6.42%
CDA test	0.203	−0.755	−1.163	−2.168**	−2.019**	−1.377
ADJ-BMP test	0.939	−2.822***	−1.485	−0.579	−0.611	−0.732
			Panel B. Market Model			
CAAR	0.11%	−2.03%	−4.57%	−9.70%	−10.77%	−8.41%
CDA test	0.110	−0.919	−1.460	−2.532**	−2.434**	−1.813*
ADJ-BMP test	0.630	−7.094***	−1.722*	−0.604	−0.640	−0.771
Rotterdam Coal Futures			Panel C. Raw Returns			
CAAR	1.85%	−7.34%	−11.34%	−14.00%	−25.81%	−19.85%
CDA test	1.025	−1.822*	−1.990**	−2.005**	−3.202***	−2.348**
ADJ-BMP test	0.223	−0.281	−0.663	−0.523	−0.489	−0.428
			Panel D. Market Model			
CAAR	1.51%	−8.22%	−14.58%	−18.78%	−32.06%	−26.83%
CDA test	0.900	−2.190**	−2.747***	−2.888***	−4.270***	−3.408***
ADJ-BMP test	0.201	−0.342	−0.933	−0.772	−0.663	−0.635
Henry Hub Natural Gas Futures			Panel E. Raw Returns			
CAAR	0.90%	2.62%	7.23%	14.59%	18.79%	20.89%
CDA test	1.025	1.333	2.600***	4.287***	4.780***	5.067***
ADJ-BMP test	0.660	1.276	3.248***	5.596***	8.299***	5.782***
			Panel F. Market Model			
CAAR	0.82%	2.50%	6.43%	13.44%	17.29%	19.20%
CDA test	0.967	1.323	2.409**	4.106***	4.577***	4.846***
ADJ-BMP test	0.460	1.781*	1.400	1.940*	1.421	1.250
Ethanol Futures			Panel G. Raw Returns			
CAAR	−2.34%	−2.30%	0.54%	1.26%	3.13%	4.48%
CDA test	−2.197**	−0.966	0.160	0.306	0.657	0.897
ADJ-BMP test	−2.011**	−0.501	0.059	0.060	0.090	0.121
			Panel H. Market Model			
CAAR	−2.43%	−2.38%	−0.29%	0.06%	1.58%	2.73%
CDA test	−2.371**	−1.040	−0.089	0.016	0.346	0.569
ADJ-BMP test	−2.497**	−0.530	−0.032	0.002	0.045	0.073

Note: This table reports cumulative average abnormal returns (*CAARs*) for the different energy commodities. The CRB index is used as the market index. The estimation period includes trading days −207 to −28 relative to the event. The announcement date ($t = 0$) is taken as November 9, 2016. The null hypothesis is that the *CAARs* are zero. The t-statistics are computed using the CDA procedure presented in Brown and Warner (1980, 1985) and the ADJ-BMP test proposed by Kolari and Pynnönen (2010). The CDA test statistic accounts for cross-sectional correlation due to event clustering, while the ADJ-BMP test statistic accounts for both cross-sectional correlation and event-induced volatility. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the policies implemented would be more on the demand or supply side. However, we find evidence that coal and natural gas futures prices responded significantly during the subsequent EPA nomination period.

Panels A and B in Table 2 report results from the CSX coal futures. The *CAARs* from the market model become more negative as the event window is lengthened to include more EPA nomination period days. The *CAARs* in some of the event windows are, however, statistically insignificant but still relatively large in size. In panels C and D, we present the *CAARs* for Rotterdam coal futures. The *CAARs* are generally significant at the 5% level using both raw and market model abnormal returns. The abnormal returns are much larger in magnitude than for the CSX coal futures. This suggests that market expectations were that coal prices would fall more in northwest Europe than in the United States. While the Rotterdam coal contract is significantly more liquid than the CSX coal futures contract, this could be because the US demand-side effects, while still lower than the supply-side effects, are much stronger than in northwest Europe. As with the CSX coal futures, the Rotterdam coal futures *CAARs* become more negative as the event window is widened to include days with more news related to the EPA nomination, except for the last event window (0, 21), which contains the EPA nomination day. The behavior of the *CAARs* as the event window is lengthened supports our earlier observation that market participants appear to have become more confident over time that mostly supply-side policies would dominate. We note that following the nomination of Scott Pruitt, the magnitude of the *CAARs* in the last window (0, 21) changed significantly relative to the preceding event window (0, 19). The *AARs* on the EPA nomination announcement day using the benchmark market model are 4.9%, significantly higher than on any other day during the event period. From panels C and D, the *CAARs* become insignificant when we use the ADJ-BMP test statistic, which controls for both event clustering and event-induced volatility. This highlights the important role of volatility during this period.

In panels E and F of Table 2, we present the *CAARs* associated with the natural gas futures. We note that for natural gas, the event generates large and statistically significant *CAARs* from event window (0, 9). Over the event period, we see that market participants became more confident that mostly demand-side policies would be implemented. As with coal, we notice a change in the slope of the *CAAR* plot around Pruitt's nomination. This suggests that for natural gas, market participants believed that at least some of the effect would come through supply-side policies. An explanation consistent with this observation is that the supply-side restrictions on natural gas during the Obama administration were less strict than on coal, giving rise to stronger demand effects for natural gas. However, as with the coal futures, the *CAARs* from the market model are statistically insignificant when we use the ADJ-BMP test statistic. The results from the ethanol futures contract are shown in panels G and H. Except on Election Day, the *CAARs* are statistically insignificant over the entire EPA nomination period.

Overall, the estimated price effects—positive for natural gas and negative for coal—suggest that over time, market participants realized that in spite of all the rhetoric, the real policies that the Trump administration would follow through with would actually end up benefiting the continued use and expansion of natural gas. Inasmuch as there would be real support for the coal industry, it would be largely a show of support for miners, which would increase supply, but there would not be an effective increase in demand for coal, hence the expectation that coal prices would fall over time. Instead, there appears to have been a realization that future energy demand would be oriented toward the burning of more natural gas.

Although not reported in Table 2, we also examine the abnormal returns during the pre-event window (−5, −1). The pre-event *CAARs* are insignificant, suggesting that the event was not anticipated and there was no leakage in the markets. We also test for any price reaction in the markets after the nomination of the EPA administrator (i.e., event window (22, 35)). The *CAARs* in this post-event window are largely indistinguishable from zero. Our results are also stable across different models, suggesting that the findings are not influenced by the choice of the underlying model for expected returns.[23] We also carry out an examination of the *AARs* for each day during the event window (0, 21). From this examination, we note that the fossil fuel commodity futures reacted on all days with significant news related to the EPA nomination (see Table 1).

If the observed changes in fossil fuel commodity futures prices over this period were due to anticipated changes in climate policy, we would expect to see this in the magnitude of the reaction by the different commodity futures. Regardless of the underlying motive, the set of measures proposed by Trump has clear climate effects. As noted earlier, the election of Trump would imply that the Clinton climate policies are not undertaken. Clinton, on the other hand, would be expected to implement policies that are particularly negative for coal production and consumption, less so for oil and natural gas, and maybe positive for ethanol. In addition, the coal industry is expected to be more sensitive to climate policy, while oil and natural gas may be less responsive (see Coulomb and Henriet 2018; Michielsen 2014). Furthermore, there were more restrictive measures on coal production and consumption than on natural gas before the election. We therefore expect the absolute *CAARs* for coal to be much larger than those for natural gas. From Table 2, we note that with the exception of the raw returns in the event windows (0, 14) and (0, 21), the absolute *CAARs* for the Rotterdam coal futures are larger than those for the Henry Hub natural gas futures. In turn, absolute *CAARs* for the ethanol futures are smaller than those of the natural gas and coal futures. This pattern is consistent with the expected impact of the election on the different fossil fuel commodities. The significantly lower absolute *CAARs* for the Rotterdam coal con-

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[23] Though not reported in Table 2, we also estimate the constant-mean model and market-adjusted returns, use the BDI as an additional control in the market model, and employ a GARCH(1,1) error process in estimating the parameters of the benchmark market model in equation (1). The results are broadly similar to those presented in Table 2.

tract during the event window (0, 21) relative to event window (0, 19) can be explained by the strong reaction of coal relative to natural gas on the day Scott Pruitt was nominated as EPA administrator (event day +20). As highlighted earlier, the *AARs* on the EPA nomination announcement day were 4.9% for the Rotterdam coal contract. The absolute *CAARs* for the CSX coal futures are, however, lower than those for natural gas and the Rotterdam coal contract. The lack of sufficient liquidity in this contract makes it difficult to draw firm conclusions. The absence of sufficient liquidity can limit the contract's price response to new information. From the results in Table 2, we conclude that the election had a systematic impact on the different energy commodities. The price effects were larger for coal than for natural gas, while the natural gas price effects are in turn larger than those for ethanol.

A potential threat to the validity of our results is the possibility that the observed abnormal returns might have been driven by other events unrelated to the election. Therefore, we examine the occurrence of other news announcements in the *Financial Times* during the event period that might account for the price reactions we observe.[24] We note that in February 2016, the Chinese State Council imposed operational constraints on coal mines to address overcapacity in the domestic coal industry. In a press conference on November 9, 2016, the National Development and Reform Commission (NDRC) announced that operating restrictions on coal mines would remain in place until the end of the winter heating season in March 2017. The effect of this decision in isolation would have been to raise coal prices. The combined effect of the NDRC decision and the US election, if any, is indeterminate. On November 17, the NDRC issued a directive reversing the operating restrictions.[25] This decision should have resulted in a fall in coal futures prices and hence significantly more negative *AARs* on event days 6 and 7 postelection. There were also other news announcements during this period that might have had an effect on returns. For example, on November 30, 2016, OPEC countries reached an agreement to cut oil production. However, we do not believe this decision could have had a significant impact on coal and natural gas markets.

As an additional robustness check, we also test an implicit assumption within the standard event study methodology that the distribution of the futures returns is identical for all weekdays. Usually the return on Monday is computed over three calendar days instead of one because of the weekend. The mean return and variance on Monday can therefore be different from those observed on any other trading day. Using a dummy variable regression, we test for day-of-the-week effect in the futures contracts (see Tables 2.B.2–2.B.5 in Appendix 2.B). For most of the futures contracts, we are unable to reject the null hypothesis. We repeat

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[24] The *Financial Times* is a crucial source of financial news internationally, in contrast to other sources that mainly serve a national audience, such as the *Wall Street Journal* (see https://aboutus.ft.com/en-gb/announcements/financial-times-named-the-most-important-business-read-by-the-worlds-largest-financial-institutions/).

[25] See http://www.ndrc.gov.cn/xwzx/xwfb/201611/t20161117 826858.html.

the analysis in Table 2 while controlling for the day-of-the-week effect, and our results remain unchanged.

5.1 Variance Comparison Tests

One potential channel through which the US election affected financial markets, and in particular energy commodity markets, is through increased volatility (see, for example, Kantchev and Mcfarlane 2016). The election outcome was expected to significantly increase uncertainty in fossil fuel commodity markets for a number of reasons. First, Trump was expected to pull back on some promises made during the campaign or to change his position on certain policies or the determination with which he would pursue them. Second, many of the proposed policy changes would require an EPA administrator who shared the same beliefs. Finally, the election campaign energy-related speeches were lacking in detail. We therefore expect that in addition to the shift in the mean return, the election also affected the return variance. We examine the behavior of short-term volatility around the announcement of the election result and the period leading up to the nomination of Scott Pruitt. Let s_1^2 and s_2^2 be the sample variances of the daily data grouped by event and nonevent days, respectively. If the abnormal returns are assumed to be independent and identically distributed (i.i.d.) and to follow a normal distribution, then the test statistic $\mathrm{F} = s_1^2 / s_2^2$ has an F-distribution with $n_1 - 1$ and $n_2 - 1$ degrees of freedom (where n_1 is the number of observations during the event period and n_2 is the number of observations during the nonevent period). However, if the data are not normally distributed, the F-test is inappropriate. The Levene (1960) test statistic is robust to non-normality. Brown and Forsythe (1974) modified the Levene (1960) test statistic to be robust when the data are skewed and also in small samples (Conover et al. 1981).

Table 3 presents a formal analysis of the null hypothesis that the variances across the event and nonevent days are equal using the Brown and Forsythe (1974) modified Levene (1960) test statistic. Panels A and B present the test statistics associated with the null hypothesis for each of the five futures contracts across the three commodities. The null hypothesis is overwhelmingly rejected at the 1% level for the Rotterdam coal futures contracts and the Henry Hub natural gas futures contracts. In Panel C, we apply the same test to intracommodity return spreads. From Panel C, we conclude that the variance of the intracommodity return spreads during the event period is significantly different from that during the nonevent period. While the election result affected expectations about a range of aspects, for fossil fuel commodities, environmental factors dominate. Trump could be good for business—for example, through corporate tax reductions—but may also lead to trade wars. Perhaps the biggest aspect he changed is uncertainty with respect to several aspects, including trade, foreign policy, and climate policy. Many of these anticipated changes may have an effect on fossil fuel prices.

Table 3. Tests for Differences in the Variance of Futures Returns between Event Days and Nonevent Days

Contract (*i*)	Jan-17	Apr-17	Jul-17	Oct-17	Jan-18
		Panel A. Raw Returns			
CSX Coal	7.06***	0.001	0.99	0.96	0.63
Rotterdam Coal	2.32	12.43***	14.08***	16.93***	16.76***
Henry Hub Natural Gas	15.77***	20.13***	18.40***	18.94***	16.15***
CBOT Ethanol	0.93	0.039	0.012	1.49	5.05**
		Panel B. Market Model Abnormal Returns			
CSX Coal	6.75**	0.0009	1.14	1.22	0.63
Rotterdam Coal	5.71**	11.65***	12.87***	14.92***	13.83***
Henry Hub Natural Gas	17.64***	21.53***	19.28***	20.47***	17.37***
CBOT Ethanol	0.80	0.14	0.07	1.27	4.87
		Panel C. Return Spreads			
	Apr-17−Jan-17	Jul-17−Jan-17	Oct-17−Jan-17	Jan-18−Jan-17	
CSX Coal	36.81***	25.92***	22.17***	19.62***	
Rotterdam Coal	99.64***	133.60***	156.44***	133.89***	
Henry Hub Natural Gas	26.03***	24.32***	23.24***	23.46***	
CBOT Ethanol	26.66***	30.05***	20.34***	33.14***	

Note: The intracommodity return spread at time t is calculated as $F_{s,t} = \ln(f_{2,t}/f_{2,t-1}) - \ln(f_{1,t}/f_{1,t-1})$, where $f_{2,t}$ is the price of the longer-dated contract at time t and $f_{1,t}$ is the price of the shorter-dated contract at time t. $^{**}p < 0.05$, $^{***}p < 0.01$.

5.2 Mean Comparison Tests

If the US election had an effect on coal and natural gas prices, the size of the price changes during the event days would be significantly different from those on nonevent days. We therefore test the null hypothesis that the raw and market model abnormal returns are the same across the event and nonevent days. From Table 4, we note that the null hypothesis is largely rejected except for ethanol. Looking at the difference of means in column 3, the event period daily average abnormal returns for coal (natural gas) are significantly lower (higher) than those during nonevent days.

To get a sense of the market expectations regarding the timing of the implementation of the energy policies proposed by Trump, we focus on the magnitude of the abnormal returns during the event period and over the different contract maturities (column 1 of Table 4). If the market expectation was that the proposed policies would be implemented fairly quickly, we expect contracts maturing and deliverable at the beginning of Trump's presidency to have a stronger reaction than longer-dated contracts. Contracts deliverable after the election but before Trump came into office should react less than those deliverable during Trump's presidency. There are several reasons to expect that most of the measures would be implemented shortly

Table 4. Tests for Differences in the Mean of Futures Returns between Event Days and Nonevent Days

	Event Period (0, 21)	Estimation Period (−207, −28)	Difference of Means	Mann-Whitney |*z*|-values	Kolmogorov-Smirnov *p*-value
	(1)	(2)	(3)	(4)	(5)
		Panel A. CSX Coal (Raw Returns)			
Jan-17	−0.0051	0.0012	−0.0063**	2.370**	0.028
	(0.0040)	(0.0008)	(0.0027)		
Apr-17	−0.0032	0.0010	−0.0042*	2.208**	0.033
	(0.0021)	(0.0008)	(0.0024)		
Jul-17	−0.0020	0.0008	−0.0028	2.169**	0.032
	(0.0014)	(0.0008)	(0.0023)		
Oct-17	−0.0021	0.0006	−0.0027	2.107**	0.118
	(0.0013)	(0.0007)	(0.0022)		
Jan-18	−0.0022	0.0005	−0.0026	2.210**	0.027
	(0.0013)	(0.0007)	(0.002)		
		Panel B. CSX Coal (Abnormal Returns)			
Jan-17	−0.0064	-2.2610^{-9}	−0.0064**	2.345**	0.025
	(0.0041)	(0.0008)	(0.0027)		
Apr-17	−0.0043	-5.9610^{-9}	−0.0043*	2.171**	0.055
	(0.0021)	(0.0008)	(0.0024)		
Jul-17	−0.0029	1.3010^{-9}	−0.0029	2.094**	0.027
	(0.0014)	(0.0008)	(0.0023)		
Oct-17	−0.0028	2.0010^{-9}	−0.0028	2.044**	0.080
	(0.0014)	(0.0007)	(0.0022)		
Jan-18	−0.0027	-4.5110^{-9}	−0.0027	1.974**	0.132
	(0.0014)	(0.0007)	(0.0020)		
		Panel C. Rotterdam Coal (Raw Returns)			
Dec-16	−0.0041	0.0027	−0.0067*	1.234	0.335
	(0.0048)	(0.0013)	(0.0041)		
Mar-17	−0.0127	0.0026	−0.0154***	2.954***	0.004
	(0.0071)	(0.0013)	(0.0045)		
Jun-17	−0.0100	0.0024	−0.0124***	2.129**	0.002
	(0.0069)	(0.0014)	(0.0046)		
Sep-17	−0.0090	0.0024	−0.0114**	1.982**	0.039
	(0.0069)	(0.0014)	(0.0046)		
Dec-17	−0.0093	0.0023	−0.0116**	2.249**	0.020
	(0.0073)	(0.0014)	(0.0047)		
		Panel D. Rotterdam Coal (Abnormal Returns)			
Dec-16	−0.0075	-1.5610^{-8}	−0.0075*	1.422	0.034
	(0.0048)	(0.0012)	(0.0039)		
Mar-17	−0.0160	4.8210^{-8}	−0.0160***	3.373***	0.000
	(0.0068)	(0.0012)	(0.0043)		
Jun-17	−0.0131	-2.0310^{-8}	−0.0131***	2.562**	0.002
	(0.0064)	(0.0013)	(0.0043)		
Sep-17	−0.0121	-2.5210^{-8}	−0.0121***	2.179**	0.040
	(0.0063)	(0.0013)	(0.0043)		
Dec-17	−0.0123	-3.8810^{-8}	−0.0123***	2.492**	0.013
	(0.0067)	(0.0013)	(0.0044)		

cont.

Table 4, cont.

	Event Period (0, 21)	Estimation Period (−207, −28)	Difference of Means	Mann-Whitney $\lvert z \rvert$-values	Kolmogorov-Smirnov *p*-value
	(1)	(2)	(3)	(4)	(5)
			Panel E. Henry Hub Natural Gas (Raw Returns)		
Jan-17	0.0138	0.0007	0.0131***	2.768***	0.001
	(0.0047)	(0.0009)	(0.0032)		
Apr-17	0.0102	0.0006	0.0095***	2.473**	0.005
	(0.0034)	(0.0007)	(0.0023)		
Jul-17	0.0087	0.0005	0.0082***	2.523**	0.003
	(0.0028)	(0.0006)	(0.002)		
Oct-17	0.0082	0.0004	0.0077***	2.314**	0.007
	(0.0028)	(0.0006)	(0.002)		
Jan-18	0.0067	0.0003	0.0064***	2.152**	0.013
	(0.0025)	(0.0005)	(0.0017)		
			Panel F. Henry Hub Natural Gas (Abnormal Returns)		
Jan-17	0.0127	3.4810^{-9}	0.0127***	2.886***	0.001
	(0.0046)	(0.0009)	(0.0030)		
Apr-17	0.0093	-9.2710^{-9}	0.0093***	2.438**	0.005
	(0.0033)	(0.0007)	(0.0023)		
Jul-17	0.0080	-9.1510^{-9}	0.0080***	2.492**	0.005
	(0.0028)	(0.0006)	(0.0019)		
Oct-17	0.0075	-1.2710^{-8}	0.0075***	2.326**	0.005
	(0.0028)	(0.0006)	(0.0019)		
Jan-18	0.0062	3.5410^{-9}	0.0062***	2.218**	0.017
	(0.0025)	(0.0005)	(0.0017)		
			Panel G. CBOT Ethanol (Raw Returns)		
Jan-17	0.0053	0.0003	0.005*	1.654*	0.190
	(0.0031)	(0.0008)	(0.0026)		
Apr-17	0.0027	0.0005	0.0022	1.070	0.452
	(0.0026)	(0.0008)	(0.0025)		
Jul-17	0.0023	0.0005	0.0018	0.904	0.452
	(0.0026)	(0.0008)	(0.0025)		
Oct-17	0.0009	0.0006	0.0003	0.721	0.490
	(0.0031)	(0.0008)	(0.0025)		
Jan-18	−0.0009	0.0006	−0.0014	0.711	0.490
	(0.0041)	(0.0008)	(0.0026)		
			Panel H. CBOT Ethanol (Abnormal Returns)		
Jan-17	0.0047	-1.1410^{-8}	0.0047*	1.681*	0.230
	(0.0028)	(0.0008)	(0.0025)		
Apr-17	0.0019	-8.7310^{-9}	0.0019	1.051	0.602
	(0.0023)	(0.0008)	(0.0024)		
Jul-17	0.0014	-6.6110^{-9}	0.0014	0.914	0.602
	(0.0023)	(0.0008)	(0.0024)		
Oct-17	−0.00002	-1.6710^{-9}	−0.00002	0.645	0.632
	(0.0030)	(0.0007)	(0.0024)		
Jan-18	−0.0017	-4.9010^{-9}	−0.0017	0.599	0.632
	(0.0039)	(0.0007)	(0.0025)		

Note: The abnormal returns are from the market model. The last three columns report the test statistics for a test of the null hypothesis of equality of means. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

after Trump took office. First, most of the environmental regulations in place came through executive orders and are therefore relatively easy to repeal. Second, even though the Paris Agreement does not allow immediate formal withdrawal, the agreement is entirely voluntary and nonbinding. A country that is a party to the agreement could therefore opt for noncompliance pending formal withdrawal. Finally, operational fuel switching should make it easy for electricity power producers to respond to Trump's measures fairly quickly.

In Table 4 panels A and B (column 1), the raw and market model abnormal returns for the January 2017 CSX coal contract are –0.51% and –0.64%, respectively. The CSX coal contract ceased trade on the 25th day of the month prior to the contract month. This means that part of the delivery period for the January 2017 contract included the time during which Trump was already in office (Trump took office on January 20). The results in panels A and B show that the January 2017 contract deliverable partly after Trump came into office reacted more but that the effect weakened over time. The large reaction at the beginning of Trump's presidency suggests that the proposed policies were expected to be implemented fairly quickly. Because of the expiration date for this contract, we do not analyze data for the contract that would be deliverable in December 2016, before Trump took office. This is because trade in this contract ceased in November 2016, therefore coinciding with the event month. The price of this contract may thus be more volatile as the spot and futures prices converge. In addition, the contract also had fewer trading days, as it ceased trading before the end of our designated event window (November 9–December 8, 2016). However, for the Rotterdam coal contract, we observe the price for the December 2016 contract, which matured and was delivered before Trump took office. Trading in the Rotterdam coal contract ceased on the day of expiration of the delivery month. For this contract, the raw and market model abnormal returns for the December 2016 contract are –0.41% and –0.75%, respectively. On the other hand, the raw and market model abnormal returns for the March 2017 contract, which matured after Trump took office, are much larger, at –1.27% and –1.6%, respectively. While the abnormal returns for the longer-dated Rotterdam coal contracts remain significantly larger than those for the shorter-dated December 2016 contract, the effect tends to weaken over time. The results also suggest that Trump was anticipated to have an impact over a time horizon of at least a year after his election.

In Table 4 panels E and F, we note that the raw and abnormal returns for the January 2017 natural gas contract are larger (1.38% and 1.27%, respectively) than in any maturity month after Trump took office. The effect tends to weaken over time. The January 2017 Henry Hub natural gas contract ceased trading three business days before the first day of the delivery month. This contract therefore ceased trading in December 2016, but delivery took place up to the end of January, when Trump was in office. As with the CSX coal contract, the contract maturing before the January 2017 contract coincides with the event month and also has fewer trading days, as it ceased trading before the end of our designated event window. The price of this contract may also be more volatile, as the spot and futures prices converge and the contract is thus not analyzed.

From Table 4, comparing contracts with matching maturities, we observe that the election has a systematic impact on the commodity futures prices. The absolute *AARs* for the Rotterdam coal futures contract for all matching maturity months except for the December 2016 contract are greater than those of the corresponding Henry Hub natural gas futures contract. The *AARs* for the Henry Hub natural gas futures contract are in turn greater than those of the ethanol futures contract. As before, the CSX coal futures contract has much lower absolute *AARs* during the event period than the Henry Hub natural gas futures contract.

One interesting aspect is the election's impact on intracommodity return spreads. An increase in return spreads around the event dates may suggest the arrival of new information in the market. From panel (b) of Figure 3, we notice that the intracommodity return spread for the Rotterdam coal contract increased significantly. At the end of December 2016, the participants in the coal markets believed that the price for coal would be much lower a year later. In this section, we test whether there are significant differences in the intracommodity return spreads between the event and nonevent days. While studies examining the performance of event studies using futures returns have concluded event studies using daily futures returns are well specified (see Mckenzie et al. 2004), commodities usually do not conform to traditional asset-pricing models (Anson 2008). Working with return spreads has the added advantage that one does not necessarily need to worry about appropriateness of the return-generating model used for futures returns.[26] Table 5 presents similar tests to those in Table 4 but using intracommodity return spreads. From Table 5, we note significant differences between the intracommodity return spreads using both parametric and nonparametric tests. These results suggest that the election significantly increased the intracommodity return spreads between the shorter-dated contract maturing a month after the election and longer-dated contracts maturing later during Trump's first year of presidency. Given the insufficient liquidity that characterizes the CSX coal futures contract, the return spreads for the contract's event and nonevent days are not significantly different when we use nonparametric tests.

5.3 Results for the Indicator Saturation Methodology

The event study approach used so far involves looking for a price reaction at a given date or time interval and assumes no other events took place during the estimation period. However, commodity prices can be influenced by random events such as war or geopolitical tension, unexpected production disruptions, and regulatory announcements. Indicator saturation (IS) helps us control for such events, which may bias the overall analysis if not identified and dealt with. In addition, one often has to demon-

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[26] Since we are working with similar contracts, it is reasonable to assume the difference between the $\widehat{\alpha}_i$s and $\widehat{\beta}_i$s is very small.

Table 5. Tests for Differences in the Mean of Futures Returns between Event Days and Nonevent Days Using Return Spreads

	Event Period (0, 21)	Estimation Period (−207, −28)	Difference of Means	Mann-Whitney |*z*|-values	Kolmogorov-Smirnov *p*-value
	(1)	(2)	(3)	(4)	(5)
Rotterdam Coal					
Mar-17−Dec-16	−0.0086 (0.0043)	−0.0001 (0.0003)	−0.0085*** (0.0016)	3.771***	0.000
Jun-17−Dec-16	−0.0058 (0.0038)	−0.0003 (0.0003)	−0.0055*** (0.0016)	1.943*	0.000
Sep-17−Dec-16	−0.0048 (0.0043)	−0.0004 (0.0004)	−0.0045** (0.0018)	1.495	0.000
Dec-17−Dec-16	−0.0051 (0.0053)	−0.0005 (0.0004)	−0.0047** (0.0022)	1.360	0.000
CSX Coal					
Apr-17−Jan-17	0.0019 (0.0023)	−0.0003 (0.0002)	0.0021** (0.001)	0.568	0.064
Jul-17−Jan-17	0.0030 (0.0031)	−0.0005 (0.0003)	0.0035** (0.0014)	0.870	0.083
Oct-17−Jan-17	0.0030 (0.0036)	−0.0006 (0.0004)	0.0036** (0.0018)	0.646	0.106
Jan-18−Jan-17	0.0029 (0.0033)	−0.0008 (0.0004)	0.0037** (0.0016)	0.619	0.190
Henry Hub Natural Gas					
Apr-17−Jan-17	−0.0036 (0.0019)	−0.00004 (0.0003)	−0.0036*** (0.0012)	2.032**	0.001
Jul-17−Jan-17	−0.0051 (0.0027)	−0.0002 (0.0005)	−0.0049*** (0.0017)	2.013**	0.001
Oct-17−Jan-17	−0.0056 (0.0027)	−0.0002 (0.0005)	−0.0054*** (0.0017)	2.086**	0.001
Jan-18−Jan-17	−0.0070 (0.0031)	−0.0003 (0.0006)	−0.0067*** (0.002)	2.245**	0.006
CBOT Ethanol					
Apr-17−Jan-17	−0.0026 (0.0008)	0.0002 (0.0001)	−0.0028*** (0.0005)	3.248***	0.000
Jul-17−Jan-17	−0.003 (0.0009)	0.0002 (0.0001)	−0.0032*** (0.0005)	3.428***	0.000
Oct-17−Jan-17	−0.0044 (0.0016)	0.0003 (0.0002)	−0.0047*** (0.0008)	3.621***	0.000
Jan-18−Jan-17	−0.0062 (0.0023)	0.0003 (0.0002)	−0.0064*** (0.001)	3.643***	0.000

Note: The tests are carried out using raw returns. The last three columns report the test statistics for a test of the null hypothesis of equality of means. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

strate that the abnormal returns detected using the standard event study approach are not an artifact of the prespecification of the event window or the test statistic used. The IS technique provides a more powerful and robust alternative empirical approach to examine whether the US election had any impact on coal and natural gas prices without imposing the event dates a priori. Any significant changes in the time series properties of the data are then detected as impulse or structural breaks in the data.

We estimate equation (2) using the IS technique and daily data for the period January 2016 to December 2016. We select over both impulse and step indicators at a very tight significance level of $p_\alpha = 0.001$. The other controls in equation (2) are retained without selection. Since there are $T = 248$ observations, we have $M = 495$ indicators in the candidate set (T impulse indicators and $T - 1$ step indicators). Under the null hypothesis that no indicators are needed, $p_\alpha M = 0.001 \times 495 \approx 0.5$ of an indicator will be retained adventitiously. $p_\alpha M$ is the theoretical gauge and tells us that one indicator will be retained by chance approximately half the time these choices are applied to new data sets with the same configuration of T.

Equation (3) shows results from applying IS to the CSX coal futures:

$$
\begin{aligned}
F_{p,t} = {} & \underset{(0.001)}{0.004} - \underset{(0.002)}{0.003}\, D_1 - \underset{(0.001)}{0.003}\, D_2 - \underset{(0.001)}{0.003}\, D_3 - \underset{(0.001)}{0.004}\, D_4 \\
& + \underset{(0.036)}{0.041}\, R_{Mt} - \underset{(0.001)}{0.026}\, \mathrm{I}_{\text{04-Feb}} + \underset{(0.001)}{0.027}\, \mathrm{I}_{\text{07-Mar}} + \underset{(0.001)}{0.021}\, \mathrm{I}_{\text{07-Jul}} \\
& + \underset{(0.001)}{0.042}\, \mathrm{I}_{\text{30-Aug}} + \underset{(0.001)}{0.034}\, \mathrm{I}_{\text{15-Sep}} + \underset{(0.001)}{0.037}\, \mathrm{I}_{\text{19-Sep}} + \underset{(0.001)}{0.033}\, \mathrm{I}_{\text{22-Sep}} \\
& - \underset{(0.001)}{0.041}\, \mathrm{I}_{\text{27-Sep}} - \underset{(0.001)}{0.027}\, \mathrm{I}_{\text{28-Nov}} - \underset{(0.002)}{0.019}\, \mathrm{I}_{\text{30-Nov}} + \underset{(0.001)}{0.021}\, \mathrm{I}_{\text{09-Dec}} \\
& - \underset{(0.003)}{0.031}\, \mathrm{S}_{\text{06-Jan}} + \underset{(0.003)}{0.031}\, \mathrm{S}_{\text{08-Jan}} + \underset{(0.002)}{0.013}\, \mathrm{S}_{\text{15-May}} - \underset{(0.002)}{0.017}\, \mathrm{S}_{\text{19-May}} \\
& + \underset{(0.002)}{0.017}\, \mathrm{S}_{\text{20-Jun}} - \underset{(0.002)}{0.014}\, \mathrm{S}_{\text{24-Jun}}
\end{aligned}
\tag{3}
$$

$\overline{\mathsf{R}}^2 = 0.61 \quad \mathsf{F}_{\mathsf{AR}}(2, 222) = 1.54 \quad \mathsf{F}_{\mathsf{ARCH}}(1, 245) = 0.07 \quad \chi^2_{\mathsf{nd}}(2) = 20.53^{**} \quad \mathsf{F}_{\mathsf{ARCH}}(12, 223) = 1.08 \quad \mathsf{F}_{\mathsf{Reset}}(2, 222) = 4.86^{**}$

$\overline{\mathsf{R}}^2$ is the adjusted R-squared, F_{AR} is a test for residual autocorrelation (see Godfrey 1978), $\mathsf{F}_{\mathsf{ARCH}}$ tests for autoregressive conditional heteroskedasticity (see Engle 1982), $\mathsf{F}_{\mathsf{Het}}$ is the White (1980) test for residual heteroskedasticity, χ^2_{nd} is a test for non-normality, and $\mathsf{F}_{\mathsf{Reset}}$ is the Ramsey (1969) RESET test. Heteroskedasticity and autocorrelation consistent (HAC) standard errors (see Donald 1991; Newey and West 1987) are reported in parentheses for all the model regressions. The selected impulse and step indicators are denoted as I_{xx-xxx} and S_{xx-xxx}, respectively. The subscript xx-xxx denotes the observation selected as an outlier or the end of a step shift. The diagnostic tests for non-normality and model specification are significant. From equation (3), IS detects eleven impulse indicators and six step indicators despite the very tight significance level. Of these, only three impulse indicators fall within the event window. Of these three, two of them are on dates (November 28 and 30) given in our timeline in Table 1 and have the expected negative sign in line with the *CAARs* in Table 2 panels A and B. The positive impulse indicator detected on December 9 is likely a delayed response to the nomination of Scott Pruitt on December 8. The detected significant dates outside the event period imply that the market model within traditional event studies is misspecified when the estimation period is contaminated. The coefficients on the impulse and step indicators in equation (3) are interpreted as abnormal returns and are thus not directly comparable to the *CAARs* presented in Table 2. All the day-of-the-week binary variables are significant in line with the day-of-the-week results in Table 2.B.2. The coefficient on the Thomson Reuters/Jefferies CRB futures index (R_{Mt}) is insignificant.

Next, we consider the Rotterdam coal futures. From equation (4), all the diagnostic tests are insignificant except for $\mathsf{F}_{\mathsf{Het}}$. From the results reported in equation (4), we are able to detect five impulse indicators within the event period, all of which have the expected signs. The first four indicators have negative signs and are large in magnitude (at least −5%), with some of them coinciding with specific dates in our timeline of events. The last impulse indicator coincides with the EPA nomination and has the expected positive sign. The detected abnormal return of 4.7% on the EPA nomination day is slightly smaller than the abnormal return of 4.9% detected using the traditional event study method. No other events are detected post-nomination. None of the binary variables for the days of the week are significant in line with the day-of-the-week results in Table 2.B.3. Overall, the results shows that the Trump election had a statistically significant negative effect on Rotterdam coal futures prices.

$$
\begin{aligned}
F_{p,t} = \;& \underset{(0.004)}{0.006} - \underset{(0.003)}{0.003}\, D_1 - \underset{(0.004)}{0.001}\, D_2 - \underset{(0.004)}{0.002}\, D_3 - \underset{(0.004)}{0.005}\, D_4 \\
& + \underset{(0.09)}{0.46}\, R_{Mt} + \underset{(0.003)}{0.049}\, \mathrm{I}_{\text{20-Jun}} - \underset{(0.002)}{0.051}\, \mathrm{I}_{\text{21-Jun}} - \underset{(0.003)}{0.05}\, \mathrm{I}_{\text{19-Oct}} \\
& - \underset{(0.004)}{0.053}\, \mathrm{I}_{\text{14-Nov}} - \underset{(0.003)}{0.057}\, \mathrm{I}_{\text{16-Nov}} - \underset{(0.003)}{0.055}\, \mathrm{I}_{\text{23-Nov}} - \underset{(0.003)}{0.057}\, \mathrm{I}_{\text{06-Dec}} \\
& + \underset{(0.003)}{0.047}\, \mathrm{I}_{\text{08-Dec}} + \underset{(0.009)}{0.024}\, \mathrm{S}_{\text{29-Jul}} - \underset{(0.009)}{0.072}\, \mathrm{S}_{\text{05-Aug}} + \underset{(0.004)}{0.047}\, \mathrm{S}_{\text{08-Aug}}
\end{aligned}
\tag{4}
$$

$$
\overline{\mathsf{R}}^2 = 0.33 \;\; \mathsf{F}_{\mathsf{AR}}(2,228) = 3.96^{*} \;\; \mathsf{F}_{\mathsf{ARCH}}(1,245) = 2.34 \;\; \chi^2_{\mathsf{nd}}(2) = 0.34 \;\; \mathsf{F}_{\mathsf{Het}}(8,229) = 0.99 \;\; \mathsf{F}_{\mathsf{Reset}}(2,228) = 0.54
$$

Equation (5) report results for the Henry Hub natural gas futures. None of the diagnostic tests are significant except for $\mathsf{F}_{\mathsf{Het}}$. As before, we present HAC standard errors in parentheses. We are able to detect two impulse indicators and a single step indicator falling within the designated event period. The detected impulse indicators have the expected positive signs in line with the *CAARs* in Table 2.

The step indicator found within the event period coincides with Election Day on November 8. Consistent with the large swings in *AARs* and *CAARs* observed in panel (c) of Figure 3, IS detects a number of indicators outside the designated event period. All the binary variables for the days of the week are insignificant in line with the day-of-the-week tests in Table 2.B.4.

$$\begin{aligned} F_{p,t} = \; & \underset{(0.005)}{0.009} - \underset{(0.002)}{0.002}\, D_1 + \underset{(0.002)}{0.0001}\, D_2 + \underset{(0.002)}{0.001}\, D_3 - \underset{(0.002)}{0.001}\, D_4 \\ & + \underset{0.048)}{0.24}\, R_{Mt} - \underset{(0.004)}{0.026}\, \mathrm{I}_{\text{02-Nov}} + \underset{(0.002)}{0.033}\, \mathrm{I}_{\text{25-Nov}} + \underset{(0.002)}{0.03}\, \mathrm{I}_{\text{05-Dec}} \\ & - \underset{(0.002)}{0.035}\, \mathrm{I}_{\text{12-Dec}} + \underset{(0.001)}{0.036}\, \mathrm{S}_{\text{24-Oct}} - \underset{(0.004)}{0.037}\, \mathrm{S}_{\text{26-Oct}} + \underset{(0.005)}{0.041}\, \mathrm{S}_{\text{07-Nov}} \\ & - \underset{(0.002)}{0.045}\, \mathrm{S}_{\text{08-Nov}} + \underset{(0.002)}{0.045}\, \mathrm{S}_{\text{19-Dec}} - \underset{(0.002)}{0.092}\, \mathrm{S}_{\text{20-Dec}} + \underset{(0.004)}{0.044}\, \mathrm{S}_{\text{21-Dec}} \end{aligned} \tag{5}$$

$\overline{\mathsf{R}}^2 = 0.40 \;\; \mathsf{F}_{\mathsf{AR}}(2, 229) = 1.63 \;\; \mathsf{F}_{\mathsf{ARCH}}(1, 246) = 0.077 \;\; \chi^2_{\mathsf{nd}}(2) = 2.41 \;\; \mathsf{F}_{\mathsf{Het}}(10, 230) = 2.26^* \;\; \mathsf{F}_{\mathsf{Reset}}(2, 229) = 0.67$

The results for ethanol futures are presented in equation (6). All the diagnostic tests are insignificant. IS detects two step indicators, neither of which falls within the designated event window, suggesting the event largely had no impact on ethanol futures. This is in line with the results shown in Table 2 panels G and H, in which we find small but significant *AARs* of about –2% on Election Day. In conformity with the large swings after the EPA nomination shown in panel (d) of Figure 2 and panel (d) of Figure 3, IS detects two step indicators over this period. The binary variables for the days of the week are significant in line with the day-of-the-week tests in Table 2.B.5.

$$\begin{aligned} F_{p,t} = \; & \underset{(0.003)}{0.004} - \underset{(0.002)}{0.007}\, D_1 - \underset{(0.002)}{0.005}\, D_2 - \underset{(0.002)}{0.004}\, D_3 - \underset{(0.002)}{0.0003}\, D_4 \\ & + \underset{(0.066)}{0.31}\, R_{Mt} + \underset{(0.002)}{0.026}\, \mathrm{S}_{\text{13-Dec}} - \underset{(0.003)}{0.026}\, \mathrm{S}_{\text{16-Dec}} \end{aligned} \tag{6}$$

$\overline{\mathsf{R}}^2 = 0.19 \;\; \mathsf{F}_{\mathsf{AR}}(2, 238) = 1.42 \;\; \mathsf{F}_{\mathsf{ARCH}}(1, 246) = 3.55 \;\; \chi^2_{\mathsf{nd}}(2) = 1.60 \;\; \mathsf{F}_{\mathsf{Het}}(8, 239) = 0.81 \;\; \mathsf{F}_{\mathsf{Reset}}(2, 238) = 0.18$

Using the IS technique, we have been able to estimate the abnormal returns due to the US election. IS as applied here resembles the regression approach to event studies, but without prespecifying the event dates, while simultaneously controlling for outliers and structural breaks during the estimation period. In all our regression models, IS identifies outliers and structural breaks outside the designated event period. The IS approach therefore suggests the estimation period used to estimate the parameters of the market model is contaminated. This could affect the precision with which the normal return is estimated within traditional event studies. IS allows us to address this shortfall and thus get more precise estimates of the abnormal returns.

6. Conclusions

The unanticipated election of Donald Trump was widely interpreted as a significant setback for an active climate policy seeking to reduce carbon emissions. Trump promised "to put the miners back to work," significantly loosen domestic environmental regulations, and withdraw from the Paris climate agreement. While most of Trump's campaign promises sought to promote coal, he also presented policy measures that would promote natural gas and ethanol. This paper explores how, if at all, coal, natural gas, and ethanol prices reacted from Election Day until the EPA nomination. We study the US election's price effects on coal and natural gas futures markets to better understand the mechanisms through which the election was anticipated to affect energy commodity markets and consequently fossil fuel production and consumption decisions. Analyzing price effects allows us to get more insights on what types of policies were anticipated and how coal and natural gas prices were affected as an indication of whether the proposed measures were expected to have a greater effect on the demand or supply side. The effects of Trump's proposed measures differ depending on whether the effects on fossil fuel futures markets are driven mainly by supply rather than demand. Changes in coal prices could induce carbon leakage in international fossil fuel markets, which can undermine the effectiveness of climate policy.

We do not detect any significant impact on coal and natural gas futures prices on Election Day. In isolation, this could lead to the conclusion that Trump did not have much of an impact on energy commodity markets. However, the finding that coal stock prices increased significantly on Election Day provides evidence against this conclusion. In combination, the two findings are consistent with the interpretation that either market participants had an unclear view regarding whether mostly demand- or supply -side policies would be implemented or that they expected both types of policies to be implemented. During the period until Scott Pruitt's nomination as EPA administrator, we see a tendency for a decline in coal prices. This suggests that market participants over time became more confident that mostly supply-side policies would dominate. This view appears to have changed with the nomination of Pruitt, suggesting that at least some of the anticipated effects on coal would be through demand-side policies. We find opposite effects for natural gas, suggesting that market participants anticipated that demand-side policies would dominate. The results for coal and natural gas taken together suggest that market participants anticipated that despite Trump's promised policies to promote coal, future energy demand will be oriented toward natural gas.

From studying the reactions of futures contracts of different maturities, our results suggest that market participants anticipated both that the proposed policies would be implemented soon and that the election's effect on the coal and natural gas futures markets would last at least a year after Trump's election. This is in line with the observation that most of the environmental regulations by the Obama administration, including the ratification of the Paris Agreement, came into existence through executive orders. While the election outcome resulted in substantial abnormal returns for coal and natural gas and an increase in the intracommodity return spreads, we find that it was also accompanied by a marked increase in uncertainty within fossil fuel commodity markets.

Appendix 2

2.A Hypothesis Testing in Event Studies

In this section, we present two parametric test statistics used to assess that the abnormal returns detected do not arise purely by chance. The crude dependence adjustment (CDA) test statistic proposed by Brown and Warner (1980, 1985) corrects for event clustering. Event clustering arises when the event becomes news at the same time for the entire industry. The presence of event clustering means the abnormal returns are no longer independent across the different contracts and this affects inference. The test statistic is computed as the ratio of the event day abnormal returns to its estimated standard deviation. The test accommodates event clustering by estimating the standard deviation from the time series of sample abnormal returns during the estimation period. For any given day t, the test statistic is given as

$$t_{CDA} = \overline{AR}_t / \widehat{S}(\overline{AR}_t), \tag{2.A.1}$$

where

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it},$$

$$\widehat{S}(\overline{AR}_t) = \sqrt{\left(\sum_{t=-207}^{t=-28}(\overline{AR}_t - \overline{\overline{AR}})^2\right)\cdot\frac{1}{179}}$$

$$\overline{\overline{AR}} = \frac{1}{180}\sum_{t=-207}^{t=-28}\overline{AR}_t,$$

where N is the number of futures contracts in the sample. Trading days −207 to −28 are designated as the estimation period for estimating the parameters of the market model in equation (1). The test statistic presented in equation (2.A.1) follows a Student−t distribution under the null hypothesis if the $\overline{AR}_t$ are independent, identically distributed, and normal. The test statistic is assumed unit normal. For event windows greater than a single day, the test statistic is presented as $CAAR_{(t_0,t_1)} / \left[\sqrt{(t_1 - t_0)} \times \widehat{S}(\overline{AR}_t)\right]$. While a range of nonparametric tests have been employed in the literature, this test statistic has been shown to work well with daily data (Berry et al. 1990; Brown and Warner 1985; Dyckman et al. 1984).

However, the CDA test statistic fails in the presence of event-induced volatility, which leads to an overrejection of the null hypothesis of zero average abnormal returns when it is true (Boehmer et al. 1991). Kolari and Pynnönen (2010) introduce a test statistic that modifies the Boehmer et al. (1991) t-statistic to accommodate both event clustering and event-induced volatility. The Boehmer et al. (1991) (BMP) test statistic compensates for possible event-induced variance increase through estimating the average event-day-volatility cross-sectionally but using the usual sample standard deviation. The adjusted Boehmer et al. (1991) (ADJ-BMP) test statistic proposed by Kolari and Pynnönen (2010) is robust to event clustering. Using the market model and denoting the log futures return for contract i on day t by R_{it} and the daily log return of the market index by R_{mt}, the standardized cross-sectional test statistic for day t is given as

$$Z_t = \frac{N^{-1/2}\sum_{i=1}^{N}\left(AR_{it}/s_{it}\right)}{\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(AR_{it}-\overline{AR}_t\right)^2}}$$

where

$$s_{it} = \sqrt{\left(\frac{1}{M_i-2}\sum_{k=-207}^{-28}AR_{ik}^2\right)\left[1+\frac{1}{M_i}+\frac{\left(R_{mt}-\overline{R}_m\right)^2}{\sum_{k=-207}^{-28}\left(R_{mk}-\overline{R}_m\right)^2}\right]}$$

M_i is the number of nonmissing estimation period returns for futures contract i used to estimate the market model. $\overline{R}_m$ is the mean daily market return in the estimation period. For multiday windows, we use a test statistic that corrects for serial dependence created by construction through cumulating individual prediction errors that are based on the same parameter estimates of α and β (see Mikkelson and Partch 1988). The multiday test statistic starts with the standardized cumulative abnormal return:

$$SCAR_{i(t_0,t_1)} = CAR_{i(t_0,t_1)}/S_{CAR_{i(t_0,t_1)}}$$

where t_0 is the first day of the event period and t_1 is the last day. The estimated standard deviation of $CAR_{i(t_0,t_1)}$ with the serial dependence adjustment is given as

$$S_{CAR_{i(t_0,t_1)}} = \left(\frac{1}{M_i-2}\sum_{k=-207}^{-28}AR_{ik}^2\right)^{1/2}\left\{T_i\left[1+\frac{T_i}{M_i}+\frac{\left(\sum_{t=t_0}^{t_1}R_{mt}-T_i\overline{R}_m\right)^2}{\sum_{t=-207}^{-28}\left(R_{mt}-\overline{R}_m\right)^2}\right]\right\}^{1/2}$$

where T_i is the number of nonmissing daily returns for futures contract i in the event period and equals $t_1 - t_0 + 1$. The standardized cross-sectional statistic for the event period is

$$Z_{t_0,t_1} = \frac{\sum_{i=1}^{N}SCAR_{i(t_0,t_1)}}{\sqrt{N}\,S_{SCAR}}\sqrt{\frac{1-\overline{r}}{1+(n-1)\overline{r}}}$$

where $\overline{r}$ is the mean of the sample cross-correlations of the estimation-period residuals and

$$S_{SCAR}=\left[\frac{1}{N-1}\sum_{i=1}^{N}\left(SCAR_{i(t_0,t_1)}-\frac{1}{N}\sum_{i=1}^{N}SCAR_{i(t_0,t_1)}\right)^2\right]^{1/2}$$

The factor $\sqrt{\frac{1-\overline{r}}{1+(n-1)\overline{r}}}$ is the adjustment recommended by Kolari and Pynnönen (2010) to correct for cross-sectional correlation of abnormal returns due to event clustering.

2.B Additional Robustness Checks

Table 2.B.1 tests the robustness of the results presented in Table 2 using a 60-day estimation window.

So far, we have assumed in our analysis that the distribution of futures returns is identical for all days of the week. However, the distribution of futures returns may vary according to the day of the week. For example, the return on Monday is calculated over three calendar days instead of one because of the weekend. The mean return and variance can therefore be expected to be different on Monday than on other days. We thus test for day-of-the-week effect in the different futures contracts using the following dummy variable regression model:

$$F_t=\beta_0+\beta_1 D_1+\beta_2 D_2+\beta_3 D_3+\beta_4 D_4+e_t \tag{2.B.2}$$

where β_0 is Monday's average return, D_1 is a dummy variable for Tuesday ($D_1=1$ if observation t falls on a Tuesday and 0 otherwise), D_2 is a dummy variable for Wednesday, and so on. The regression coefficients measure the deviation of the average daily return from Monday's return. We assume the error term (e_t) is i.i.d. with mean zero. The null hypothesis is that the distribution of the futures returns is identical for all days of the week. Tables 2.B.2–2.B.5 present the regression analysis for the day-of-the-week effect for the different futures contracts over the entire sample period. From Tables 2.B.2–2.B.4, we cannot reject the null hypothesis of no day-of-the-week effect as shown by the F-statistic. However, the significant coefficients in Table 2.B.2 indicate that average return on Monday are significantly higher than on other days, while the average return on Wednesday is significantly different from Monday's average return. In Table 2.B.5, based on the F-statistic, we reject the null hypothesis that the distribution of futures returns is identical for all days of the week. The average returns on Tuesday and Wednesday are significantly different from Monday's average return. Although not reported, we carry out the event study analysis again, controlling for the day-of-the-week effect, and the results remain unchanged.

Table 2.B.1. Price Effects of US Election on Commodity Futures

	(0, 0)	(0, 4)	(0, 9)	(0, 14)	(0, 19)	(0, 21)
CSX Coal Futures			Panel A. Raw Returns			
CAAR	0.20%	−1.68%	−3.65%	−8.34%	−8.97%	−6.42%
CDA test	0.162	−0.601	−0.926	−1.726*	−1.608	−1.097
ADJ-BMP test	0.760	−2.345**	−1.190	−0.465	−0.490	−0.586
			Panel B. Market Model			
CAAR	−0.06%	−2.94%	−6.29%	−12.29%	−14.22%	−12.21%
CDA test	−0.050	−1.054	−1.595	−2.545**	−2.551**	−2.088**
ADJ-BMP test	−0.245	−1.814*	−1.079	−0.497	−0.524	−0.601
Rotterdam Coal Futures			Panel C. Raw Returns			
CAAR	1.85%	−7.34%	−11.34%	−14.00%	−25.81%	−19.85%
CDA test	0.980	−1.742*	−1.903*	−1.918*	−3.062***	−2.246**
ADJ-BMP test	0.178	−0.220	−0.519	−0.409	−0.384	−0.337
			Panel D. Market Model			
CAAR	1.67%	−8.06%	−13.12%	−16.64%	−29.31%	−23.72%
CDA test	0.887	−1.917*	−2.206**	−2.285**	−3.485***	−2.690***
ADJ-BMP test	0.171	−0.261	−0.599	−0.517	−0.448	−0.413
Henry Hub Natural Gas Futures			Panel E. Raw Returns			
CAAR	0.90%	2.62%	7.23%	14.59%	18.79%	20.89%
CDA test	1.082	1.408	2.746***	4.527***	5.048***	5.352***
ADJ-BMP test	0.760	0.947	2.287**	1.957*	2.971***	3.986***
			Panel F. Market Model			
CAAR	0.89%	2.92%	7.13%	14.49%	18.72%	20.76%
CDA test	1.121	1.654*	2.853***	4.733***	5.293***	5.597***
ADJ-BMP test	0.555	1.418	2.092**	3.459***	2.550**	2.142**
Ethanol Futures			Panel G. Raw Returns			
CAAR	−2.34%	−2.30%	0.54%	1.26%	3.13%	4.48%
CDA test	−2.083**	−0.916	0.152	0.290	0.623	0.851
ADJ-BMP test	−1.815*	−0.593	0.076	0.075	0.116	0.160
			Panel H. Market Model			
CAAR	−2.52%	−2.61%	−1.16%	−1.22%	−0.09%	0.86%
CDA test	−2.402**	−1.111	−0.349	−0.300	−0.019	0.176
ADJ-BMP test	−2.076**	−0.590	−0.144	−0.076	−0.009	0.023

Note: This table reports cumulative average abnormal returns (*CAARs*) for the different energy commodities. The CRB index is used as the market index. The estimation period includes trading days –87 to –28 relative to the event. The announcement date ($t = 0$) is taken as November 9, 2016. The null hypothesis is that the *CAARs* are zero. The t-statistics are computed using the CDA procedure presented in Brown and Warner (1980, 1985) and the ADJ-BMP test proposed by Kolari and Pynnönen (2010). The CDA test statistic accounts for cross-sectional correlation due to event clustering, while the ADJ-BMP test statistic accounts for both cross-sectional correlation and event-induced volatility. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.B.2. Tests for the Day-of-the-Week Effect for CSX Coal Futures

	Contract (i)				
	Jan-17	Apr-17	Jul-17	Oct-17	Jan-18
Tuesday	–0.0055*	–0.0035	–0.0039	–0.0035	–0.0032*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Wednesday	–0.0071**	–0.0040*	–0.0041**	–0.0040**	–0.0034**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Thursday	–0.0028	–0.0015	–0.0024	–0.0029	–0.0019
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Friday	–0.0048*	–0.0033	–0.0033*	–0.0029	–0.0037**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.0057**	0.0037**	0.0039**	0.0037**	0.0032**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Adjusted R^2	0.021	0.004	0.004	0.002	0.006
F	1.84	1.22	1.29	1.51	1.61

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.B.3. Tests for the Day-of-the-Week Effect for Rotterdam Coal Futures

	Contract (i)				
	Dec-16	Mar-17	Jun-17	Sep-17	Dec-17
Tuesday	–0.0068	–0.0082*	–0.0069	–0.0067	–0.0068
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Wednesday	–0.0049	–0.0051	–0.0042	–0.0027	–0.0024
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Thursday	–0.0039	–0.0030	–0.0022	–0.0011	–0.00055
	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Friday	–0.0054	–0.0061	–0.0050	–0.0062	–0.0070
	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Constant	0.0072**	0.0068*	0.0058	0.0053	0.0052
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Adjusted R^2	–0.002	0.001	–0.003	0.001	0.004
F	0.70	0.99	0.72	1.04	1.30

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.B.4. Tests for the Day-of-the-Week Effect for Henry Hub Natural Gas Futures

	Contract (i)				
	Jan-17	Apr-17	Jul-17	Oct-17	Jan-18
Tuesday	–0.0045	–0.0045	–0.0045*	–0.0045*	–0.0041**
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Wednesday	0.0018	0.0004	0.0002	0.00003	0.00003
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Thursday	0.0025	0.0012	0.0010	0.0008	0.0006
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Friday	0.0017	0.0001	–0.0003	–0.0003	–0.0006
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)
Constant	0.0011	0.0019	0.0019	0.0019	0.0018
	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Adjusted R^2	0.006	0.009	0.015	0.015	0.018
F	1.28	1.40	1.62	1.67	1.87

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2.B.5. Tests for the Day-of-the-Week Effect for Ethanol Futures

	Contract (i)				
	Jan-17	Apr-17	Jul-17	Oct-17	Jan-18
Tuesday	–0.0078***	–0.0069***	–0.0068***	–0.0068***	–0.0075***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Wednesday	–0.0059**	–0.0050**	–0.0049**	–0.0049**	–0.0050**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Thursday	–0.0035	–0.0040*	–0.0040*	–0.0044*	–0.0046*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Friday	–0.0012	–0.0002	–0.0002	–0.0008	–0.0009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	0.0045**	0.0039**	0.0038**	0.0038**	0.0039**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.036	0.042	0.041	0.036	0.038
F	3.60	4.00	3.91	3.66	3.60

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Chapter 3

Coordinated Carbon Taxes or Tightened NDCs: Distributional Implications of Two Options for Climate Negotiations

Abstract

The Paris climate agreement represents a transition in international climate negotiations from a binding top-down model to a decentralized pledge-and-review agreement. The main advantage has been to achieve (quasi) unanimity around rather ambitious goals. It is unlikely, however, that the agreement will be able to achieve these goals without strengthening. One of the greatest obstacles to a stronger treaty comes from concerns about fairness among (and within) countries. The focus of this paper is to study the distributional implications of two different ways of strengthening the treaty, either by incorporating carbon pricing or through tightening of the nationally determined contributions (NDCs), which outline national goals for greenhouse gas emissions reductions. We quantify a number of different burden-sharing principles that have been proposed by representatives from various countries. Our results suggest that both carbon pricing and tightened NDCs are viable mechanisms that are less extreme and therefore more acceptable than grandfathering, which favors the most fossil-intensive economies, or equal per capita allocation, which favors low-income countries that use less fossil fuel.

This chapter is joint work with Thomas Sterner.

1. Introduction

The United Nations Framework Convention on Climate Change (UNFCCC) Conference of the Parties in 2015 (COP 21) was hailed as a great success by some who focused on the fact that we finally had a truly global agreement, aiming for quite radical goals (to keep global warming well below 2°C above preindustrial levels). On the other hand, critics argue the COP 21 was little more than a New Year's resolution, with lofty goals but no binding commitments.

The backdrop is that negotiations concerning the second period of the Kyoto Protocol stalled partly because some of the major economies were unable or unwilling to commit to legally binding quantitative restrictions. Many observers consider the Kyoto structure fatally flawed precisely because it did not sufficiently take into account the interests of the most powerful nations, did not ask anything of the non–Annex I countries, and lacked sufficient incentives to make parties want to stay in the agreement—in other words, it was not incentive compatible. Negotiations in Lima in 2014 therefore focused on a post-Kyoto framework in which all major polluters would contribute. However, China, India, and the United States all indicated their reluctance to ratify any treaty that committed them to legally binding emissions reductions.[1] The strength—and weakness—of the Copenhagen negotiations in 2009 (COP 15) was that they made explicit the costs and exposed fundamental conflicts about who should bear the costs of abatement.

The approach chosen to deal with this impasse was a "pledge and review" process, in which each country would propose its own target. This was an approach improvised in the face of negotiation failure in Copenhagen, formalized through agreements in Durban in 2011 (COP 17), and finally brought to fruition in Paris. In stark contrast to the Kyoto process, the Paris Agreement is a bottom-up approach built on the intended nationally determined contributions (INDCs).[2] Clearly it is in one sense a very weak approach. Public goods are not normally provided (in sufficient amounts, at least) by voluntary mechanisms (see Marwell and Ames 1981). A central problem of this approach is that the pledges will fall short of meeting ambitious goals. This is reinforced by the absence of any guarantee that even the weak NDCs will be fulfilled, since there is no compliance mechanism or penalty for noncompliance. Exactly this appears to have happened in Paris (see Boyd et al. 2015; Climate Action Tracker 2019; Robiou du Pont and Meinshausen 2018; UNEP 2018). Interpretations vary, but the NDCs are definitely not sufficiently ambitious to reach the 2°C target. They are also very vague, and there is thus consid-

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[1] Even though the Paris Agreement is voluntary and nonbinding, the United States only ratified the agreement through an executive order. This left open the possibility for another administration to withdraw without a vote in the Senate. On November 4, 2019, the Trump administration formally notified the UN that it would withdraw from the 2015 Paris climate agreement.

[2] Before the Paris climate agreement in December 2015, parties to the UNFCCC submitted plans to address climate change, known as intended nationally determined contributions (INDCs). These INDCs are the main instrument of the Paris Agreement. Upon ratification, they became nationally determined contributions (NDCs), and we use this latter term hereafter for simplicity.

erable disagreement about what temperature path they would lead to. According to a recent survey, studies point to somewhere in the range of 2.7°C–3.7°C (Levin and Fransen 2015). Clearly, this is a big improvement over the 4°C–5°C "business as usual" temperature range anticipated in the absence of any policy. However, it is also clear that it is not enough.

There are currently numerous suggestions of how to strengthen (or even replace) the Paris Agreement. Some of these go in the direction of speeding up technical progress (Wagner et al. 2015). Others suggest adding a "supply-side" approach (Asheim et al. 2019). This paper focuses on comparing the two main methods now being considered to ramp up international climate policy sufficiently to reach the Paris Agreement goals: either the NDCs need to be substantially tightened or a different mechanism—a price on carbon—needs to be introduced into the agreement.[3] The former is the official procedure that is negotiated within the UNFCCC; the latter is what most economists suggest as a necessary complement. This paper examines the distributional implications (in terms of country shares of the remaining carbon budget) of the two different ways of strengthening the treaty, either by incorporating carbon pricing or through tightening of the NDCs, which outline national goals for greenhouse gas emissions reductions.

We derive formulas for the different principles of allocating the remaining carbon budget that are widely mentioned in international climate negotiations by different groups of countries and in the literature (see Bretschger 2013; Lange et al. 2007; Mattoo and Subramanian 2012; Raupach et al. 2014; Ringius et al. 2002; Yu et al. 2011). We then determine each country's emissions allocation of the remaining carbon budget for the period 2015–2050 under five different principles. The carbon budget is derived from the 2°C target. The emissions shares are calculated under the following principles: equal emissions per capita, proportionality to income, equal percentage reductions (grandfathering), equal marginal cost of abatement (similar to harmonized carbon tax as proposed by Weitzman [2014]), and willingness to act (i.e., the "pledge and review" process within the Paris Agreement). We find that both carbon pricing and tightening the NDCs tend to be intermediate between grandfathering, which favors the most fossil-intensive economies, and equal per capita allocation, which favors low-income countries using less fossil fuel.

The contribution of our paper is related to Bretschger (2013) and Mattoo and Subramanian (2012), who derive carbon budgets for different countries under different equity principles. Bretschger and Mollet (2015) compare the carbon budgets derived from the equity principles laid out in Bretschger (2013) with carbon budgets derived using the egalitarian approach (BASIC experts 2011) and with a uniform global carbon tax similar to that proposed by Weitzman (2014). Mi et al. (2019) consider a carbon-trading scheme after initially allocating emissions permits for the period 2000–2100 using four different equity principles: ability

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[3] See "Economists' Statement on Carbon Pricing" at https://www.eaere.org/statement/.

to pay, egalitarianism, grandfathering, and historical responsibility. Historical responsibility as an allocation principle tends to be problematic, however, in that developed countries argue that emissions before anthropogenic climate change was identified as a problem should not count, since the atmosphere was universally believed to be an infinite resource then. Sheriff (2019), on the other hand, uses the mitigation targets within the NDCs to infer an equity principle consistent with the observed distribution of mitigation burden as given by the NDCs. Sheriff finds that the burden distribution embodied within the Paris pledges is consistent with the capability approach—countries that have a greater ability to finance the cost of mitigation present more ambitious targets.

In the current paper, we derive carbon budget shares for equal emissions per capita and harmonized carbon tax as in Bretschger and Mollet (2015), but we add to this analysis of allocation shares due to NDCs and grandfathering. We study in particular the distributional implications (in terms of emissions allocations) of an international regime based on coordinated national taxes compared with a regime based on negotiated or voluntary quantity targets (NDCs). We investigate the ambition within the current NDCs by comparing the resultant NDC shares with what each country would have received if equal emissions per capita, grandfathering, or a harmonized tax were used instead. To get a sense of the acceptability of harmonized taxes, we compare the tax shares with the allocations that would have emerged from using the other schemes.

The rest of the paper is organized as follows. Section 2 discusses the advantages of the two main proposals to strengthen the Paris Agreement: NDCs and carbon taxes. Section 3 outlines the different equity principles, discusses the difficulties of reaching a climate agreement based on grandfathering or equal emissions per capita, and highlights the ethical dilemma that often arises from the different equity principles. Section 4 describes the model used to derive the formulas for the different allocation principles, while Section 5 presents and discusses the quantitative results from the different allocation schemes. Section 6 concludes.

2. NDCs versus Carbon Taxes

One advantage of the NDCs is that they have a fair amount of legitimacy, since they have been formulated voluntarily by the countries concerned. The process of elaborating the NDCs was more constructive than the negotiating format, in which each country was just trying to maximize its share of global emissions. The preparation of the NDCs instead encouraged countries to think of a future, which in general included high welfare and growth aspirations, as well as to truly mobilize progressive environmental opinions and to envision radically new technologies. Elinor Ostrom wrote several influential pieces about how to get economic agents to collaborate in using common-pool resources (see, for example, Ostrom 2010). Writing about various cases, such as water management in California, she emphasized that the most difficult phase was often to get the stakeholders to come to the negotiating table and actually declare how much they use and how much they intend or hope to use in the future. In some sense, it was this step that was taken in Paris, and it may turn out to be essential.

Still, many, if not most, of the NDCs are quite vague, and it is a challenge to determine the specific figures that can be used for forecasting global emissions. Nevertheless, it is clear that aggregate emissions are much too high to meet ambitious goals such as a maximum of 2°C warming. To actually stabilize the climate and limit warming to 2°C would require making the NDCs binding, creating processes of verification, and establishing measures to deal with noncompliance, as well as making the targets within the NDCs much more restrictive. The question arises whether the current negotiating process can deliver such increased stringency without delay. Optimists might argue that negotiations will be easier because of the increased legitimacy of the NDCs.

Recently, a number of prominent researchers have suggested, partly in response to the negotiating difficulties and the lack of binding concrete results, that the world urgently needs a (minimum) carbon price. The exact instrument proposed varies somewhat among authors. Some argue more for actual taxes (Nordhaus 2015, 2013; Weitzman 2015, 2014), while others seem to favor a permit scheme but still put emphasis on the importance of a uniform price (Gollier and Tirole 2015b, 2015a). According to Nordhaus (2007, 42), "The tax would start relatively low and then, unless the outlook changes for better or worse, rise steadily over time to reflect the increasing prospective damages from global warming." Von Below (2012) suggests an opposite scenario in which the tax falls over time. Daniel et al. (2019), using an asset pricing model, have also suggested starting with a high tax that declines over time as technological change lowers the cost of mitigation and the benefits of mitigation decline.

Carbon taxes have long been presented as an efficient solution to the problem. However, the implementation would be complicated, not just because the underlying science of climate change is complicated (e.g., climate sensitivity, feedback effects, and the relative weights of different gases) but also because sovereign states must negotiate and because pollution is hard to monitor. Another complication is distributional issues, which arise regardless of the instrument used.

2.1 Arguments for Prices over Quantities

It is clear that there are a number of good arguments in favor of a tax-based negotiation.[4] Unless there are serious tipping points (which is possible), the damage

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[4] See Keohane (2009a, 2009b) and Gollier and Tirole (2015b) on the advantages of quantity-based instruments. Gollier and Tirole (2015b) argue that there is a possibility that "countries can put in place a carbon tax without fully enforcing it or mitigating its effect through subsidies or tax breaks." Bretschger and Mollet (2015) suggest that an international institution that monitors energy taxation and subsidies across countries may be necessary.

function would appear to be quite flat, while the abatement costs might be perceived to be steeper (Weitzman 1974). In this case, a carbon tax will be preferable on efficiency grounds. Weitzman (2014, 2015) argues that carbon taxes have a practical advantage in that negotiating "one number" is less demanding than *n* different quantities (one for each country). However, it should be noted that a carbon tax also introduces inflexibility by imposing a single tool to achieve emissions reductions, which may not be appropriate for some countries. At the same time, a treaty concerning quantities is more readily perceived as a zero-sum game, while an agreement about taxes will have winners and losers in each domestic constituency (due to reduction of other pollutants, cobenefits, double dividend or revenue recycling, and fiscal consolidation, among other things) (Nordhaus 2007; Weitzman 2014). Keohane (2009a), however, argues that carbon tax proposals often focus debate on the size of the tax and likely costs to the economy, making a tax less feasible in many countries.

In response to the seeming impasse concerning international negotiations over quantity reductions, a number of influential authors have suggested that the whole concept of coordinated emissions reductions be scrapped and replaced by price policies. Several different alternatives are possible. An international tax on carbon is often thought of as having the disadvantage of raising resources much too large for any international body to handle. Nordhaus (2007, 42) argues in favor of internationally coordinated but nationally levied carbon taxes and points to the advantages of this approach:

> *Many considerations enter the balance in weighing prices and quantities. One advantage of price-type approaches is that they can more easily and flexibly integrate economic costs and benefits of emissions reductions, whereas the approach in the Kyoto Protocol has no discernible connection with ultimate environmental or economic goals. This advantage is emphatically reinforced by the large uncertainties and the evolving scientific knowledge in this area. Emissions taxes are more efficient in the face of massive uncertainties because of the relative linearity of the benefits compared with the costs. A related point is that quantitative limits will produce high volatility in the market price of carbon under an emissions-targeting approach. In addition, a tax approach can capture the revenues more easily than quantitative approaches, and may add less to the distortion caused by existing taxes. The tax approach also provides less opportunity for corruption and financial finagling than quantitative limits, because it creates no artificial scarcities to encourage rent-seeking behavior.*

However, it is not enough that an allocation mechanism possesses some advantages. For a negotiation to be successful, *all* major parties need to be convinced. Since we will focus on the differences between rich and poor countries, it is particularly important to understand whether an agreement based on an international tax on carbon is in the interest of low-income countries. Clearly, it is not possible to force India to sign an agreement; nothing can easily be achieved against the will of such a large country.[5] The principle India argues for—equal emissions per capita—is a fairly reasonable intellectual principle from which it has little reason to back down. But under this scheme, the consequences would be greater for the richer countries, and thus it would be difficult to get richer countries to accept an agreement that not only reduces total emissions but also gives an equal share to all citizens.[6]

3. Quantity Policies from Top-Down Principles to Bottom-Up NDCs

During the period between the Kyoto Protocol in 1997 and COP 15 in Copenhagen in 2009, international climate discourse was focused on a top-down allocation of quantitative targets. The Kyoto Protocol established commitments for the reduction of various greenhouse gases (GHGs, including carbon dioxide (CO_2), methane, nitrous oxide, and others) produced by Annex I nations. The commitments for all other (non–Annex 1) countries were much vaguer, and one might say that they faced no effective limit.

The collapse of the negotiations at COP 15 in Copenhagen is often seen as the final failure for a coordinated top-down allocation of emissions. It is important to understand why the failure occurred. One of the main reasons was conflict concerning the perceived fairness of different allocation rules. In a top-down allocation, some principle has to be used to allocate to nations the right to use fossil fuel and emit CO_2 (and other greenhouse gases). Several ethical and practical proposals exist. In Section 3.1, we start by describing the allocation principles that could be easily defined quantitatively. We then discuss in Section 3.2 the difficulties involved in negotiating a treaty using two of the most extreme principles, grandfathering and equal emissions per capita allocation. In Section 3.3, we briefly address some of the ethical issues that arise from the different allocation principles.

3.1 Allocation Principles

Several different climate change mitigation burden-sharing schemes have been proposed, which entail different distributional consequences across countries (Carlsson et al. 2013; Mattoo and Subramanian 2012). Equity principles have generally been applied to emissions shares or reductions. In this paper, we work

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[5] Nordhaus (2007) reminds us that under the 1648 Treaty of Westphalia and the subsequent evolution of international law in Western Europe, no obligations can be imposed on any sovereign state without its consent.

[6] Note that we speak here of emissions allowances. Actual emissions can differ from allowance allocations if the latter are tradable.

with emissions allocation shares of the remaining carbon budget. Working with allocation shares is preferable because allocations can be made without reference to a baseline. However, both approaches should lead to similar results, since emissions allocations imply emissions reductions. Here we describe some of the burden-sharing schemes widely discussed in the literature, focusing on those that are easily estimable using publicly available data:

1. *Equal emissions per capita.* In this scheme, a country whose population amounts to *x*% of the global population should be allocated *x*% of the total emissions. This is also known as the *egalitarian rule*. This rule clearly benefits the countries with a large population as opposed to rules that base allocations on other variables (such as current or historical emissions or gross domestic product [GDP]). Therefore, it tends to be the preferred principle for countries that are poor and do not have large emissions. Another, more radical interpretation of this principle holds that the equality per capita should be applied to emissions that are accumulated over some period of time (or possibly all of history). This raises practical and logical questions such as how many years to use, whether emissions during the period of "excusable ignorance" count (Bell 2011), and how to address the fact that population numbers change over time. Sometimes this is referred to more vaguely as "historical responsibility," meaning that countries that emitted more CO_2 in the past should take on more responsibility. That formulation is not precise enough for our purposes, so we will consider only equality in current per capita emissions.
2. *Proportionality to income.* Under this rule, allocation is in proportion to income. This is the norm for all goods on all free markets, since one's ability to pay depends on one's income. Thus, as is well known, the market is a form of democratic vote—but the rich get more votes—and whether this is an ethical principle can be questioned. Proportionality to income is related to equal emissions per capita, but with the per capita share scaled by relative income.
3. *Equal percentage reductions (grandfathering).* This rule holds that future emissions rights should be in proportion to past emissions, which means that uniform percentage reductions are applied using emissions figures for the current year (or, to avoid manipulation, a couple of years ago) as an agreed baseline. This policy is sometimes promoted by saying that if every party makes the same percentage reduction, they all actually make the same effort. Critics of this principle argue, however, that it entitles those who consume a lot currently to continue consuming more in the future. It is somewhat similar to proportionality to income but benefits countries with low fossil fuel prices. It thus would benefit the large, rich, and wasteful economies.

4. *Equal marginal cost of abatement (harmonized tax).* This principle implies having the same price on carbon everywhere, which could be interpreted roughly as having a harmonized set of policies, such as taxes. Note, however, that this principle takes as its starting point proportionality to income (principle 2 above) and modifies it through making prices more or less harmonized so as to avoid the additional distortions that may occur if some countries have, for example, much lower fossil product prices.
5. *Willingness to act.* This can be interpreted as a "pledge and review" process through which countries' willingness to act is revealed. Thus the NDCs can be considered in this category.[7] It has the advantage that it is the result of a voluntary domestic process in each country, and one might assume that it therefore reflects national priorities when it comes to both development and climate damages and costs.

In addition to these five principles that have a quantitative interpretation and a rationale, other principles are sometimes evoked. People speak of "equal ability to pay" or similar principles, but it is not always clear if they mean equal marginal cost of abatement, as in our principle 4, or even domestic willingness to act, as in principle 5. Another principle that has been mentioned is "equal net benefit," which implies that the more vulnerable countries (low-lying countries that will be flooded, perhaps) should do more. This does not necessarily seem a convincing ethical principle, and it is also hard to quantify, since we do not know exactly what future damages will look like.

3.2 Grandfathering versus Equal Per Capita Allocation

In a regime of quantity restrictions, countries have to decide collectively on a set of emissions allowances (and thus implicitly abatement obligations) for each country. This does not mean that the actual emissions need to comply exactly with these numbers. If trade is allowed, then the emissions will occur where they are valued most highly. The market will allocate fossil fuel use and emissions. Allocation still plays an important role, since it forms the starting point for the trade. Countries with larger allowances than emissions will make significant gains through selling their permits. It is this potential that creates a conflict of interest around allocations.

One strong norm for setting individual country commitments has been grandfathering. Grandfathering is not ethically desirable or acceptable for all parties, however. It is, broadly speaking, in the interest of rich countries with large emissions, and thanks to the political influence of such countries, it has often been a

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[7] The NDCs are not equally ambitious and thus give rise to unequal contributions among countries (Bretschger 2017). A number of authors, including Joseph Stiglitz, Martin Weitzman, and Christian Gollier and Jean Tirole, have pointed out that the NDCs are inefficient because they do not equalize marginal abatement costs across countries and also do not meet the temperature target goal.

starting point for negotiations.[8] In these negotiations, low-income countries regularly ask for lower reductions or even increases in emissions to compensate for the fact that they have not yet reached some level of desirable "development." India has even suggested that historically accumulated emissions should be equalized. This would mean that countries that were early to industrialize, such as the UK and the United States, would already have used up their emissions rights. This is not acceptable to many developed economies, which argue that use before carbon emissions were identified to be a problem should not count.[9] Negotiations among countries with widely different income levels are bound to be very difficult. In fact, the impasse in past negotiations is perhaps evidence of this. To illustrate the difficulty in reaching consensus on a burden-sharing scheme, let us consider the two large countries with the most extreme positions: the United States and India.

Table 1 shows a "world" consisting of just two countries: the United States and India. The first two columns show the population and emissions levels for the United States and India in 2014, with total emissions of 5.25 and 2.24 gigatons of carbon dioxide (Gt CO_2), respectively. Now assume the "world" needs to cut total emissions by 50% within a few decades. With grandfathered rights, both countries would have to reduce their emissions by 50%, which would preserve the inequality, with the United States always emitting 70% and India 30% of global emissions, even though India has a much larger population. An alternative that would be desirable from India's viewpoint is to base reductions on equal per capita emissions. This gives almost the opposite allocation, since India has 80% of "world" population and the United States has 20%. India would be able to increase its emissions substantially, while the United States would have to reduce emissions by 86% rather than by the 50% required with grandfathering.

Table 1. Grandfathering or Equal Per Capita Allocation in a "World" of Two Countries

Country	Population (millions)	Emissions (Gt CO_2)	Population Proportion	Emissions Proportion	Grandfathering Allocation (Gt CO_2)	Equal Per Capita Allocation (Gt CO_2)
United States	318.62	5.25	0.20	0.70	2.63	0.74
India	1,293.86	2.24	0.80	0.30	1.12	3.01
Total	1,612.48	7.49	1.00	1.00	3.75	3.75

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[8] Under the Kyoto Protocol, industrialized countries are supposed to reduce their total GHG emissions by 5.2% compared with the base year of 1990. National limitations, however, range from 8% reductions for the European Union and some others, 7% for the United States, and 6% for Japan to 0% for Russia. Some countries, such as Australia and Iceland, were even allowed to increase emissions. Thus grandfathering was not applied in a strict manner, which would have meant exactly the same reductions for all. However, grandfathering still served as the norm or baseline from which some small adjustments were made.

[9] Based on the equitable per capita cumulative emissions right, Yu et al. (2011) show that most developed countries and several non–Annex I countries would get negative allocations because of their high past emissions. This affects the political acceptability of such an allocation scheme.

The United States and India are two polar cases, and focusing on these two cases is a pedagogical tool that clarifies the issues by somewhat exaggerating the effect, which would be extreme for the United States and India but not for most other countries, such as China or the EU nations. China and the EU have more average emissions intensities, and hence the different allocation principles would not result in such big differences in emissions reductions. When country positions are as far apart as those of India and the United States, the disparity can become a true impediment to dialogue, since it is almost better for each party to be disinterested in any discussion than to risk compromising its position in a negotiation. Earlier negotiations over global commons issues, such as the Law of the Sea, took many decades before the current laws were agreed on and codified.[10] The trouble is that with addressing climate change, we simply do not have decades to conduct negotiations, because it is urgent that countries start reducing emissions immediately. It is also clear that not reaching an agreement and hence experiencing drastic climate change will be unacceptably costly for all—not least the low-income countries such as India.

3.3 Ethical Considerations and Climate Negotiations

The fundamental difficulty in negotiating a strong centralized target with clearly delineated burdens for each country is that the stakes are high in allocating a fixed carbon budget, and country positions are far apart. International surveys have shown that perceived fairness is very important for political acceptance of climate deals. Thus there is an important link between perceptions of fairness and the possibility of negotiating any global climate policy. Citizens of various countries say that they are prepared to make bigger sacrifices for mitigation if burdens are shared *fairly* (Carlsson et al. 2012). However, they have dramatically different, even opposite, views of what "fairness" is. Different ethical positions have been discussed at length, but at the root of the difficulty in reaching agreement on what is a fair allocation scheme, we can clearly distinguish two groups: large (and rich) emitters, which have an interest in some form of grandfathering, and low-income countries that currently have low emissions (but harbor hopes for rapid economic growth), which are very worried that such an allocation scheme would stymie their much-coveted economic takeoff and growth. These countries would benefit instead from some form of per

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[10] It is important to point out that there are often many factors that interact in facilitating an agreement. In the case of the Montreal Protocol, Bretschger (2013) points out that the costs of protection were small and the benefits very large. For climate mitigation, perceived costs are substantial, since fossil fuels are still widely used in most countries. In addition, the negative effects of climate change are unevenly distributed across countries, and developed countries are better able to adapt. Therefore, the concern about climate change varies across countries.

capita allocation that would allow them to grow in the long run, while in the short run possibly giving them income from selling permits.[11]

Which allocation principle to use can be seen as an ethical choice, especially when countries deemed to be the most responsible for current warming are perceived to be unwilling to make reductions to the extent that they should. Most low-income countries argue against equal effort sharing on the basis that they are not responsible for the high historical emissions behind current global warming. Consequently, they believe it is unfair to demand that they drastically cut carbon emissions for the sake of future generations. Concern for future generations as a motivation for mitigation by poor countries is itself controversial, especially when many developed countries are already much richer than the poor countries are likely to become even in the midterm future. This means that schemes requiring low-income countries to drastically cut their emissions based on intergenerational equity arguments are likely to face resistance. Moreover, many of the rich countries that are the most responsible for historical emissions may turn out to be the least affected by climate change. They can also more easily adapt than can poor countries because of abundant capital and knowledge. This raises another ethical dilemma: adaptation requires huge financial resources and thus growth, yet low-income countries can no longer rely on the traditional fossil fuel energy-driven growth strategies used by the developed countries. Some people think it is unfair to demand that low-income countries forgo the option to develop through exploiting cheap fossil fuel energy as was done by the high-income countries. Given these issues, it is not surprising that burden-sharing principles such as historical responsibility and equal emissions per capita find support among low-income countries (BASIC experts 2011), which believe that developed countries should bear the greatest burden of addressing climate change.

The conflicts regarding which allocation principle to adopt at the global level can seem unsolvable, and the top-down approach broke down in Copenhagen. Note that the difference between grandfathering and equal per capita allocation could easily be a few hundred billion dollars per year with a carbon price such as Sweden's carbon tax of around $100/ton. By default, the top-down approach meant that countries had to focus on maximizing at the negotiating table their own share of the remaining carbon budget. The top-down approach seemed to focus attention on conflict, and thus the bottom-up approach was proposed to focus on the task of more creatively searching for constructive solutions. The Paris architecture avoided conflict by asking countries to determine their own contributions in the context of their national priorities, conditions, and capabilities. Astute observers must have realized that the contributions would be insufficient, but the Paris COP prioritized getting some consensus in hopes that countries would gradually increase the ambitiousness of their contributions later.

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[11] It was recognition of these concerns that led to the exception of non–Annex B countries from having any quantified reduction target, and in turn, the fact that major emitters such as China and India had no obligations made the protocol unacceptable for the United States.

In sum, the world now faces the choice between tightening the current NDCs and choosing a new direction: that of coordinated taxes. The choice set can also include a policy that combines both.

4. Modeling Carbon Allocation Principles

For a long period in which Kyoto has dominated our thinking, carbon taxes have been relegated to a secondary role. In light of the shortfalls of the NDCs, it might be time to start thinking seriously of taxes again. Since fairness was so critical in the breakdown of quantity-based negotiations, it is important to consider the distributional consequences of coordinated tax proposals. We want to explore the fairness and acceptability of carbon taxes from the viewpoint of international negotiations, particularly fairness from the viewpoint of nations with different income levels. To do this, we start by building a parsimonious model.

Let us assume country i has a population N_i, total income Y_i, and income per capita y_i. The corresponding world totals would be N, Y, and y. We assume there are two reasons for price variation: variation in local prices (P_i), such as for coal or gas, as well as variation due to local (climate and other) policies, which we denote T_i. In reality, there are multiple and more complex policies, but we argue that their ultimate effect is on the price the agents in the economy actually pay to consume carbon-emitting fossil fuels. For fuels that have a low transport cost, such as oil and gasoline, there is a rather homogeneous world market price. The formulas for this case are shown in Appendix 3.A. We assume the simplest possible model where carbon demand is given approximately by (1) at the national level and by (2) globally:

$$E_{it} = f(Y_{it}, P_{it}, T_{it}) \tag{1}$$

$$E_t = g(Y_t, P_t, T_t) \tag{2}$$

The indices i and t are for country and year. Equation (1) can be specified as log-linear:

$$E_{it} = \gamma_i Y_{it}^{\alpha} (P_{it} T_{it})^{\beta} \tag{1a}$$

where the local price in country i is $P_i T_i$, γ_i represents country characteristics, and α and β are the income and price elasticities, respectively. The log-linear specifications of equation (1) do not generally aggregate neatly into any simple functional form. In spite of this, empirical estimations of demand equations are often carried out with such functional forms at different geographical levels. If $\alpha = 1$, all βs are equal, and all prices and policies T_i were the same, then the function could be aggregated to

$$E_t = \gamma Y_t (P_t T_t)^{\beta} \tag{2a}$$

where $E_t = \sum E_{it}$; $Y_t = \sum Y_{it}$; $\gamma = \sum \gamma_i$. If the T_i were not the same, the aggregate T_i would presumably have to be interpreted as some kind of average world policy, but it would not necessarily be an actual average. The price elasticity β is negative, so countries with lower taxes emit more carbon, other factors being equal.[12] Carbon emissions are, however, also determined by country characteristics γ_i, which include a large number of other variables. We are thinking here of variables given by nature, such as local climate, since clearly this has some effect on the demand for heating or cooling energy. There are also variables that are partly given by nature and partly socioeconomic, such as population density and urban and regional spatial architecture, which clearly have an impact on such things as transport demand. Finally, cultural knowledge and habitual factors can also affect energy demand technology. For the purposes of simplifying the discussion, we will treat all these as nature-given and exogenous, and all the policy choices are subsumed in the variable T.

4.1 Quantifying Different Allocation Principles

We now quantify the first four allocation principles from Section 3.1. Willingness to act is already defined within the Paris Agreement and is thus not quantified here. For the sake of simplicity, we conduct this discussion in terms of shares E_i/E of a world total.

1. Equal emissions per capita allocation share for country i is given as $\sigma_{in} = N_i/N$.[13]
2. Proportionality to income is given as $\sigma_{iy} = Y_i/Y = N_i/N \cdot (y_i/y) = \sigma_{in} \cdot (y_i/y)$ (i.e., per capita share multiplied by relative income, so high-income coun-

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[12] If income elasticity were to vary among countries, then the countries with the highest income elasticity (such as possibly the middle-income countries) would actually get the highest allocation. If price elasticity also varied, then the countries with higher price elasticities would get smaller allocations. We assume that the price elasticities are the same. Surveys such as Basso and Oum (2007); Brons et al. (2008); Dahl (1995); Dunkerley et al. (2014); Goodwin et al. (2004); Graham and Glaister (2002); Hanly et al. (2002); and Huntington et al. (2019) suggest that elasticities do in fact vary depending on the data and models used, as well as on the country being studied. There is, however, quite a strong tendency of models to converge around unitary income elasticities (at least for middle- and high-income countries) and price elasticities in the range of –0.65 to –0.85, so the assumption of a common price elasticity is quite a reasonable simplification.

[13] Time subscripts on the country shares σ_i are suppressed throughout.

tries get more). Note that this is the same as harmonized emissions intensities (in the sense of emissions-to-GDP ratios).

3. Grandfathering means future user rights in proportion to consumption for the base year, which means that $\sigma_{ig} = E_{i,t-\tau} / E_{t-\tau}$. Grandfathering benefits those countries that have high historical use and tends to give more rights to those countries that have high intrinsic energy intensity because of tough climate conditions or low population density. This might be considered a desirable property of grandfathering. However, grandfathering also rewards countries that have been wasteful as measured by the variable T (they have not taxed carbon and perhaps subsidized it or had other wasteful policies). The counterpart to this is that proactive behavior by a country risks being penalized in negotiations based on grandfathering.
4. What physical allocation is the dual of a harmonized tax? We use the model introduced in equation (1a) to predict how much each country would use given the introduction of a harmonized tax T. It can be noted that in the special case where prices and taxes are totally harmonized, consumer prices would be the same everywhere.[14] If we assume that income elasticities are unitary, we can further simplify, and country shares will be given by

$$\sigma_{ip} = \frac{\gamma_i Y_{it} (P_{it} T_{it})^{\beta}}{\sum \gamma_i Y_{it} (P_t T_t)^{\beta}} = \frac{\gamma_i Y_{it}}{\sum \gamma_i Y_{it}} = \sigma_{iy} \cdot \frac{\gamma_i}{\gamma} \tag{3}$$

   since $P_i = P$ and $T_i = T$. From equation (3), we see that a harmonized tax will give the same share as what we described as proportionality to income but corrected by γ_i / γ (inherent country characteristics such as climate). In reality, carbon use and thus emissions are a function not just of the current carbon prices but also of historic pricing and other policies. If a country historically had low taxes, then carbon-intense habits and infrastructure are created. For a (limited and finite) transition period, countries that earlier had no policy (low or zero carbon taxes) would actually consume (and emit) more carbon than similar countries that have had high taxes in the past. However, assuming the harmonized tax is set at the right level, these countries will be emitting more, but the excess costs will be internalized in some way by the taxation, so the situation will not be so obviously beneficial for these countries. On the contrary, they might have a difficult period of adaptation.

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[14] Prices may vary for several reasons. For example, production (extraction and refinery) costs may vary. With free trade, however, absence of nontariff and other boundaries and low transport costs in proportion to product value will cause prices to be fairly similar across most countries. This applies to crude oil and refined products such as gasoline, where the variation in prices among major ports is small. Only in landlocked countries such as the Central African Republic are local transport and distribution costs so significant as to really distort the picture. For coal, gas, or electricity, the transport costs can be more significant, so in those cases—especially for coal—the assumption of local product prices being homogeneous is actually less well founded.

5. Numerical Comparison of Different Allocation Principles

In this section, we carry out a numerical exercise to compare some of the different allocation principles across countries. We make use of data on GDP, emissions, population, and gasoline prices to calculate the emissions allocation shares for each country. The country allocation shares are calculated for the following principles: grandfathering, equal emissions per capita, proportionality to income, willingness to act (NDCs), and harmonized tax allocation. We use 2014 data but also use 1990 as an alternative baseline for grandfathering. The year 1990 generally signifies the end of “excusable ignorance” regarding anthropogenic climate change. The numerical exercise is mainly illustrative and deliberately simplified. Because of data restrictions, it is based on CO_2 emissions and not all greenhouse gases. To do a full analysis, we would need detailed energy balance and energy demand models for each country, as well as real average weighted fuel prices. For ease of access, we use gasoline prices to proxy energy prices, and thus the results from the carbon tax should be taken as simply illustrative of the transport sector. In the following subsections, we discuss in detail the assumptions underlying the calculation of shares due to harmonized taxes and the NDCs.

5.1 Harmonized Tax Shares

In this subsection, we lay out the ingredients for calculating the carbon budget shares for each country using a harmonized tax similar to that proposed by Weitzman (2014). We consider a harmonized global tax in line with the 2°C target in the Paris Agreement. Meinshausen et al. (2009) calculates the remaining carbon budget for the period 2000 to 2050 that gives a 50% probability of warming exceeding the 2°C target. The harmonized tax should be of a magnitude such that it reduces the business-as-usual (BAU) cumulative emissions from 2015 to 2050 to within the remaining carbon budget. The latest emissions data we have are for 2014. The emissions in excess of the remaining carbon budget are thus calculated as the difference between total cumulative BAU emissions over the period 2015 to 2050 and the remaining carbon budget for the same period (see Table 2). To derive the harmonized tax, we require data on national energy prices and long-run price elasticities of energy demand. Demand elasticities allow us to derive the corresponding demand reductions associated with the harmonized tax. We assume the reduction in energy demand directly translates into a reduction in CO_2 emissions (we thus abstract from a number of additional options, such as carbon capture and sequestration or direct air capture). Based on the literature, we use –0.8 as the long-run price elasticity of demand for gasoline (see Flood et al. 2010).

Table 2. Parameter Values for Calculating Harmonized Tax

Description	Value (Gt CO_2)
Carbon budget 2000–2050	1,440
Realized emissions 2000–2014	462
Remaining carbon budget 2015–2050[a]	950
Average annual emissions[b]	33
Total projected emissions for 2015–2050	1,184
Emissions in excess of carbon budget	234
Average price of gasoline in US$	1.34
Gasoline tax per unit of energy	0.30
Liters of gasoline per 1 ton of CO_2 (conversion factor – *CF*)	432.63

Sources: The carbon budget data come from Meinshausen et al. (2009), and the emissions and gasoline prices data are from the World Bank.

[a] The remaining carbon budget is for 75 countries making up about 98% of CO_2 emissions.

[b] We assume that annual emissions stabilize at 2014 levels over the period 2015 to 2050.

For the purpose of calculating the harmonized tax shares, we consider the top 75 countries, which accounted for about 98% of total global emissions in 2014. Accordingly, the remaining carbon budget is scaled so that we work with the remaining budget for the 75 largest emitters. For illustrative purposes, we simplify by assuming annual emissions for each country stabilize at their 2014 levels.[15] The sum of BAU emissions from 2015 to 2050 would be 1,184 Gt CO_2 against a carbon budget of 950 Gt CO_2. The harmonized tax should thus lower emissions by 234 Gt CO_2 when imposed. The price per ton of CO_2 is then given as $P_{CO_2} = T \cdot CF$, where CF is the conversion factor used to calculate the quantity of gasoline corresponding to a ton of CO_2. Table 2 gives the values of the parameters used to calculate the harmonized tax and the emissions shares for each country. The harmonized tax associated with a 50% probability of warming exceeding the 2°C temperature target is 0.30, and this translates into a price per ton of CO_2 of $130.

5.2 Nationally Determined Contributions Shares

To calculate the shares resulting from the "pledge and review" process arising out of the Paris Agreement, we use data from Meinshausen and Alexander (2017), who translate the different NDCs submitted by the countries into comparable per capita emissions. We use these per capita emissions together with the 2030 population projections provided by the UN to get total emissions for each country. Summing the total emissions from each country's NDC gives us the total emissions from the NDCs in 2030, from which we can calculate the shares for each of the 75 countries.

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[15] In reality, for some countries emissions are yet to peak, while for other countries emissions are already falling. We assume here that on average, there will be no growth in global emission.

These 75 countries are responsible for 92% of the emissions reductions pledged in the NDCs. Since the NDCs are not compatible with the 2°C target, they can be tightened to be in line with the 2015–2050 carbon budget. In this paper, we consider tightening the NDCs proportionately to achieve the Paris climate target.

While percentage reductions from status quo, as in grandfathering, are grossly unfair for the poor, percentage reductions from the NDCs would be quite a different matter, and one could argue that these are much more fair. An important question is whether NDCs represent honest ambitions of the different countries. The NDCs have been criticized because some country contributions are more ambitious than others (Bretschger 2017).[16] Furthermore, the lack of convergence in past climate conferences suggests, according to Bretschger (2013), that countries do not view the "pledge and review" procedure as generating a fair burden sharing. One can argue, however, that if the degree of tactical dishonesty embedded within the NDCs is constant (think of an exaggeration factor ζ), then equal proportional reductions from the NDCs can be described as fair. If the tactical dishonesty varies across countries (the exaggeration factor is instead ζ_i), then countries with NDCs considered weaker would have to be asked to make proportionally larger reductions from the NDCs in order to meet the climate targets. This is clearly a potential problem, and we will try to cast some light on how big it is.

5.3 Quantitative Results of Different Allocation Principles

In this subsection, we present illustrative empirical results from the different allocation principles discussed. Table 3 shows country-level results for grandfathering (with 1990 and 2014 as base years), equal emissions per capita, allocations in proportion to income, and allocations from the NDCs. A first point to note is that grandfathering shares change significantly from 1990 to 2014. For instance (old) OECD countries typically see a decoupling of emissions to GDP. This may be due to ambitious climate policy or to structural changes with a bigger focus on services and a smaller share of traditional industry in GDP. Either way, the effect is a decrease of around 40% in allocation shares, while industrialized former Soviet economies such as Russia and Ukraine have even higher changes. In the latter case, inefficient industries appear to have been closed en masse once they were exposed to international competition.

Fast-growing countries such as China and India have grown tremendously, with grandfathering shares doubling or more (see Table 4). Countries with large fossil resources have tended to see stable or growing shares. These large changes suggest that it can be problematic to have any fixed share scheme, and certainly we understand why many countries were hesitant to agree to grandfathering based on 1990 values. A tentative conclusion is that grandfathering is not only problematic as an

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[16] See https://climateactiontracker.org/countries/ for a rating of the different NDCs in terms of their ambitions.

Table 3. Carbon Budget Allocations, 2015–2050 (gigatons)

Country	Rank	Grandfathering 1990	Grandfathering 2014	Equal Emissions Per Capita	Proportionality to Income	NDCs
United States	1	226.3	151.8	50.7	219.5	100.5
China	2	114.6	297.3	217.2	131.3	293.2
Russian Federation	3	97.5	49.3	22.9	25.9	62.8
Japan	4	51.4	35.1	20.3	60.8	20.1
Germany	5	43.6	20.8	12.9	48.9	11.4
Ukraine	6	29.6	6.6	7.2	1.7	11.1
India	7	29.0	64.7	206.0	25.5	100.7
United Kingdom	8	26.1	12.1	10.3	38.0	8.3
Canada	9	20.4	15.5	5.7	22.5	12.4
Italy	10	19.6	9.3	9.7	27.0	7.1
France	11	17.6	8.8	10.6	35.7	6.8
Poland	12	17.3	8.3	6.1	6.8	5.6
Mexico	13	14.9	13.9	19.8	16.5	11.5
South Africa	14	14.7	14.1	8.7	4.4	10.8
Australia	15	12.4	10.4	3.7	18.4	8.4
Kazakhstan	16	12.3	7.2	2.8	2.8	5.9
Korea, Rep.	17	11.6	17.0	8.1	17.7	10.3
Spain	18	10.3	6.8	7.4	17.3	5.8
Iran, Islamic Rep.	19	9.9	18.8	12.5	5.4	20.8
Brazil	20	9.8	15.3	32.5	30.8	22.3
Saudi Arabia	21	8.7	17.4	4.9	9.5	15.5
Romania	22	8.2	2.0	3.2	2.5	2.4
Netherlands	23	7.4	4.8	2.7	11.2	2.5
Indonesia	24	7.0	13.4	40.6	11.2	20.2
Turkey	25	6.8	10.0	12.3	11.7	18.7
Czech Republic	26	6.5	2.8	1.7	2.6	2.0
Venezuela, RB	27	5.7	5.4	4.9	6.0	7.3
Argentina	28	5.3	5.9	6.8	6.6	7.7
Uzbekistan	29	5.2	3.0	4.9	0.8	7.7
Belgium	30	5.0	2.7	1.8	6.7	1.8
Thailand	31	4.3	9.1	10.9	5.1	8.3
Belarus	32	4.1	1.8	1.5	1.0	1.9
Algeria	33	3.6	4.2	6.2	2.7	4.8
Egypt, Arab Rep.	34	3.6	5.8	14.6	3.8	9.1
Bulgaria	35	3.5	1.2	1.1	0.7	0.9
Greece	36	3.5	1.9	1.7	3.0	1.8
Hungary	37	3.3	1.2	1.6	1.8	1.2
Pakistan	38	3.2	4.8	29.5	3.1	9.3
Korea, Dem. People's Rep.	39	2.8	1.2	4.0		2.5
Austria	40	2.7	1.7	1.4	5.5	1.2

cont.

Table 3 cont.

Country	Rank	Grandfathering 1990	Grandfathering 2014	Equal Emissions Per Capita	Proportionality to Income	NDCs
Colombia	41	2.7	2.4	7.6	4.8	2.1
Malaysia	42	2.7	7.0	4.8	4.2	11.4
Azerbaijan	43	2.6	1.1	1.5	0.9	1.0
Serbia	44	2.5	1.1	1.1	0.6	1.4
United Arab Emirates	45	2.4	6.1	1.4	5.1	5.4
Sweden	46	2.4	1.3	1.5	7.2	1.0
Finland	47	2.4	1.4	0.9	3.4	1.0
Kuwait	48	2.4	2.8	0.6	2.0	3.3
Denmark	49	2.4	1.0	0.9	4.4	0.8
Iraq	50	2.2	4.9	5.6	2.9	4.9
Singapore	51	2.1	1.6	0.9	3.9	1.8
Slovak Republic	52	2.1	0.9	0.9	1.3	0.7
Switzerland	53	2.0	1.0	1.3	8.9	0.5
Portugal	54	2.0	1.3	1.7	2.9	1.3
Philippines	55	2.0	3.1	15.9	3.6	3.6
Nigeria	56	1.8	2.8	28.1	7.1	11.0
Syrian Arab Republic	57	1.8	0.9	3.1		2.3
Libya	58	1.7	1.6	1.0	0.5	2.6
Israel	59	1.7	1.9	1.3	3.9	1.5
Cuba	60	1.6	1.0	1.8	1.0	1.5
Chile	61	1.6	2.4	2.8	3.3	2.5
Turkmenistan	62	1.5	2.0	0.9	0.5	2.7
Norway	63	1.5	1.4	0.8	6.3	0.6
Ireland	64	1.5	1.0	0.7	3.2	0.9
Hong Kong SAR, China	65	1.3	1.3	1.2	3.7	
Estonia	66	1.1	0.6	0.2	0.3	0.2
New Zealand	67	1.1	1.0	0.7	2.5	1.4
Morocco	68	1.1	1.7	5.5	1.4	2.6
Lithuania	69	1.0	0.4	0.5	0.6	0.4
Vietnam	70	1.0	4.8	14.7	2.3	12.1
Peru	71	1.0	1.8	4.9	2.5	1.3
Moldova	72	1.0	0.1	0.6	0.1	0.2
Trinidad and Tobago	73	0.8	1.3	0.2	0.3	1.8
Ecuador	74	0.8	1.3	2.5	1.3	0.9
Croatia	75	0.8	0.5	0.7	0.7	0.5

Sources: The carbon budget data come from Meinshausen et al. (2009), while the data on CO_2 emissions and gasoline prices are from the World Bank.
Note: The countries are ranked according to 1990 CO_2 emissions. The columns shows each country's share of the remaining carbon budget using different allocation schemes. We show results for the 75 countries accounting for about 98% of global CO_2 emissions. The carbon budget shares are calculated using 2014 data.

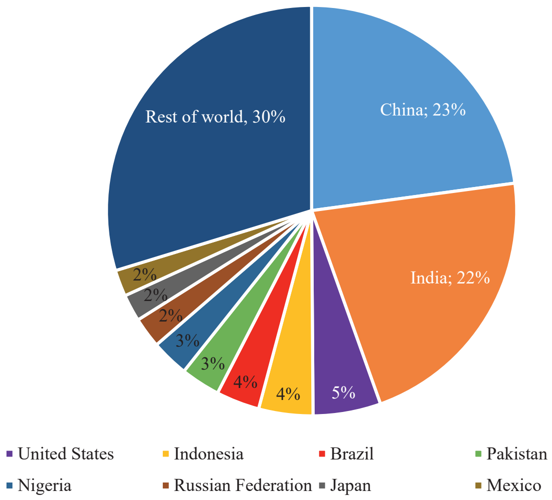
ethical principle but also fraught with likely gaming when it comes to selecting a base year.

Table 4. Grandfathering Allocation

Country	Share 1990 (%)	Share 2014 (%)
United States	23.82	15.98
China	12.06	31.30
Russian Federation	10.27	5.19
Japan	5.41	3.69
Germany	4.59	2.19
Ukraine	3.12	0.69
India	3.06	6.81
Mexico	1.57	1.46
South Africa	1.55	1.49
Australia	1.30	1.10
Iran	1.04	1.98
Brazil	1.03	1.61
Saudi Arabia	0.92	1.83
Rest of world	30.25	24.69

In contrast, we can consider the equal per capita allocation as it would be if strictly proportional to population numbers. Figure 1 shows the equal emissions per capita allocation, and we see that shares are dominated by China and India. Another handful of countries, such as the United States, Indonesia, Brazil, Pakistan, Nigeria, and Russia, also get a few percent each.

Figure 1. Equal Emissions Per Capita Allocation



A quite different allocation principle is proportionality to income, which would simply give shares in relation to GDP or some other agreed measure. This would give the largest allocation to the United States (see Figure 3.B.1 in Appendix 3.B) and in general give more allocation per capita to the countries with a higher income per capita. This is not, per se, an ethical principle that is often evoked. It is, however, of interest as a stepping-stone to the allocation that would be the consequence of harmonized taxes, which would be a function of three types of variables: a country's income; demographic, natural and social variables such as population density, temperature, and culture; and the price of fossil fuels and other relevant policy variables that shape the fuel choice in that country, such as a carbon tax or subsidies.

There are a number of ways to introduce a harmonized tax. All countries could be required to harmonize their tax levels to match the country with the highest tax levels today or to have the same final price. Such methods would have more drastic effects than the one we are looking at here, which is the addition of a new internationally harmonized carbon tax on top of observed current fuel prices in each country. Note that this principle means adding, say, 30 cents per liter of fuel both in countries where fuel is already expensive and in countries where it is very cheap. One can imagine protests from countries at both extremes. The countries with higher taxes might say they already have a tax. The countries with lower taxes might argue that taxes do not work in their country and may feel that the price increase will be relatively large. By way of illustration, consider Saudi Arabia, which has by far one of the lowest gasoline prices, at \$0.16/liter in 2014 against the world average price of \$1.34/liter. The country's CO_2 emissions in the same year were 0.6 Gt. Since we assume that country-level emissions from 2015 to 2050 stabilize at 2014 levels under BAU scenario, the country will thus emit a cumulative total of 21.64 Gt CO_2 from 2015 to 2050. From Table 2, $T = 0.30$ is the gasoline tax compatible with the 2°C temperature target over the period 2015 to 2050. Given the heavy subsidies and thus very low current gasoline price in Saudi Arabia, the gasoline tax would result in a price increase of 187.5% per liter of gasoline! With a price elasticity of demand of –0.8, this leads to a reduction in energy demand of 57%—one of the largest reductions.[17]

As mentioned earlier, the harmonized tax will result in an allocation that is, broadly speaking, proportional to GDP (and thus not very different from grandfathering using 2014 as base year; see Figure 3.B.2 in Appendix 3.B) but with an important correction that simply implies that countries that currently have low energy prices will see a larger reduction, as the model estimates what their demand would be with a harmonized carbon tax. Figure 2 shows one possible result of such a process (building as it does on just carbon emissions, gasoline prices as

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[17] It is, of course, not appropriate to use a constant price elasticity for such a large price change, but then again the calculations are intended only as illustrative. In reality, the Saudi Arabia elasticity might be lower, but it is clear that major policy changes would be needed and that there would be a large decrease in demand.

a proxy for all fossil prices, and the addition of a uniform carbon tax on top of all current local prices). The 10 countries shown in Figure 2 account for almost 70% of the shares due to harmonized taxes, the top 5 being China with 33%, the United States with 15%, India with 7%, Russia with 5%, and Japan with 4%. The others have 1%–2% each.

Figure 2. Harmonized Tax Allocation

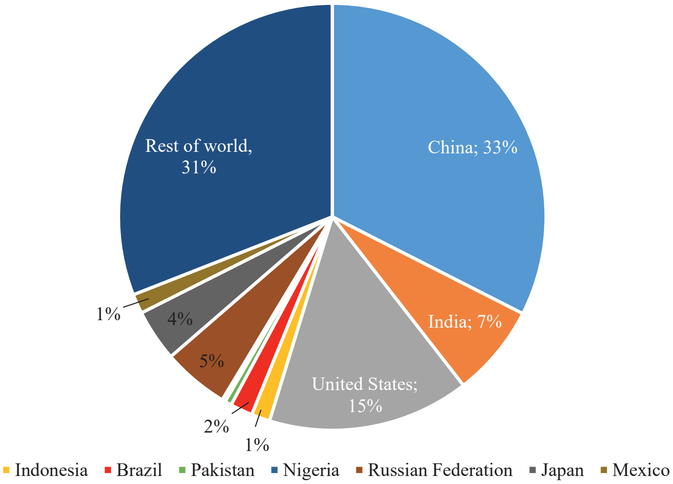

Table 3.B.1 in Appendix 3.B gives complete results for all the countries studied. From Table 3.B.1, we see that countries with low gasoline prices (mostly oil producers) face substantial increases in energy prices, and this is also associated with substantial reductions in their CO_2 emissions. This applies to the United States as well. For most low-income countries, the required increases in energy prices are modest—particularly for countries that are net importers of fossil fuels, which often already have stiff taxes for fuel imports. For quite a large number of countries, the differences between the allocation based on harmonized tax and that of grandfathering using 2014 as base year are relatively modest (in the range of ±10%; see Table 3.B.2 in Appendix 3.B). This applies in particular to many of the large countries, but it does not apply to the large fossil fuel exporters, since they heavily subsidize domestic consumption, so even the fairly modest carbon tax implies a large increase in local prices and thus a large decrease in fossil fuel demand.

Finally, we turn to the allocation implied by the NDCs. As shown in Figure 3, China as usual has around a third of the share, the United States and India have intermediate shares of just under 11% each, and Russia is the only other country with a sizable share.[18]

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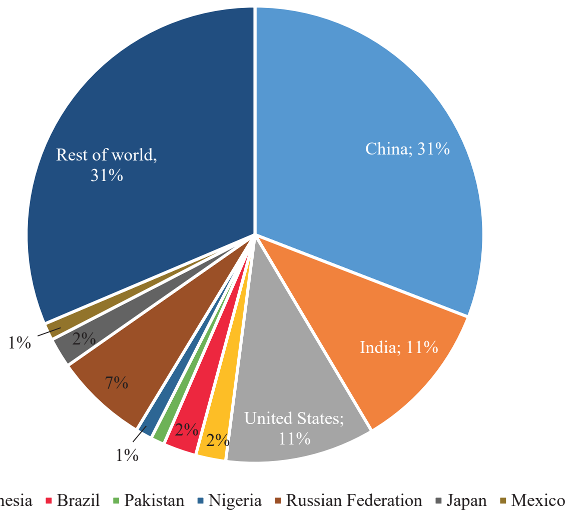
[18] We abstract for a moment from the difficulty in being sure what emissions an NDC actually does mean (the NDCs can be vague and it is not clear if they will be followed).

Figure 3. Allocations of NDCs



The most straightforward interpretation of the NDCs is that each country has made an honest effort to determine how much it really can abate (and thus the amount of emissions allocations it still needs) as a function of expected growth rates, costs, and other factors. If all the NDCs were drafted with the same level of serious good faith, they could be seen as an ideal allocation mechanism. The fact that the NDCs are voluntary and each country made commensurate efforts should satisfy at least some notion of fairness. If we discover that climate change is more serious than previously expected and there is a need to rapidly increase the stringency of international agreements on abatement, then a rapid and simple mechanism would be equal percentage reductions from the NDCs. We have argued that equal percentage reductions from current emissions (or emissions in some base year), or grandfathering, is unfair because it rewards those countries that have historically polluted the most. Equal percentage reductions from the NDCs would be quite different, if these NDCs could be interpreted as reflecting a similar level of abatement effort across countries. There is, of course, the risk that some countries have not made as much of an effort as others—or worse, that some possibly even tried to game the system to get a "good" baseline in terms of emissions allocations. We can get an indication of how ambitious the NDCs of various countries are by examining the amount of emissions implied by the NDCs compared with allocations based on grandfathering or equal emissions per capita.

Table 5 shows the ambitiousness of the NDCs for a selection of illustrative countries. (See Table 3.B.3 in Appendix 3.B for complete results for all the countries studied.) In a number of cases (Nigeria, India, Indonesia, Mexico, and Brazil), the NDC formulated gives the country substantially less than its equal per capita share (half in the case of India). Even if these countries get more than

Table 5. Ambitiousness of the NDCs

Country	NDC/GF14	NDC/PC	Rating of NDCs
Nigeria	3.97	0.39	—
India	1.56	0.49	2°C compatible (<2°C world)
Indonesia	1.51	0.50	Highly insufficient (<4°C world)
Mexico	0.83	0.58	Insufficient (<3°C world)
Brazil	1.46	0.69	Insufficient
United Kingdom	0.69	0.81	Insufficient
Germany	0.55	0.88	Insufficient
Japan	0.57	0.99	Highly insufficient
South Africa	0.76	1.24	Highly insufficient
United States	0.66	1.98	Critically insufficient (4°C+ world)
Canada	0.80	2.18	Insufficient
Australia	0.81	2.25	Insufficient
Russian Federation	1.27	2.74	Critically insufficient
Saudi Arabia	0.89	3.16	Critically insufficient

Note: GF14 is the grandfathering allocation with 2014 as base year, while PC denotes the equal emissions per capita allocation. Column 3 shows results for a subset of the 31 countries (including the EU) assessed by Climate Action Tracker (2019). The rating is in terms of the resultant global warming when a country's NDC is taken as a benchmark by other countries. Only the NDC of India is ambitious enough to keep the increase in global average temperature below 2°C. In the case of Australia, for example, global warming would be above 2°C and up to 3°C if all countries followed the same (low) level of ambition.

their actual emissions share in 2014 (Nigeria receives a large increase, and India gets more than the allocation implied by a harmonized carbon tax), it still seems reasonable to characterize these NDCs as having some degree of ambition in the sense of claiming less than their equal per capita share. Also, the NDCs that show substantial decreases compared with 2014 values could in some sense be seen as ambitious. There are, however, some cases such as the Russian Federation, where allocations from the NDCs are considerably higher than the allocations would be from grandfathering, equal emissions per capita, or other principles (including harmonized taxes). Such an NDC can hardly be characterized as ambitious. This is also the conclusion reached by Climate Action Tracker (2019), which rates NDCs. The Russian NDC is rated as critically insufficient and would lead to a warming of 4°C+ if all countries had a similarly low level of ambition (see Table 5 column 3). Unfortunately, some of the largest emitters have NDCs rated as critically insufficient.

6. Conclusions

This paper starts from the observation that the measures so far agreed will not be sufficient to attain the temperature goals stated in the Paris Agreement. There are, broadly speaking, two possible avenues to increase the level of ambition. One of these is through a gradual tightening of the national commitments, or NDCs. The other is to negotiate a carbon price as an ancillary mechanism, through for example, internationally coordinated but nationally enacted carbon taxes. The purpose of this paper is to examine these two mechanisms from the viewpoint of their distributional effects in terms of emissions shares of the remaining carbon budget.

Varying ethical standpoints can lead to the conclusion that different mechanisms, such as equal emissions per capita allocation or equal reduction from status quo (grandfathering), are fair. Rich countries with large current and historical emissions tend to argue for grandfathering, while countries with low emissions per capita tend to argue for equal emissions per capita. The difference in the resulting allocations can amount to hundreds of billions of dollars per year. However, neither equal emissions per capita nor grandfathering stands any chance of gathering the necessary support from enough countries.

The voluntary nature of the NDCs and the current lack of sanctions for not meeting targets present serious cause for concern. On the positive side, the NDCs have been formulated not in an adversarial setting to maximize local shares, but seemingly in an honest quest for what could be maximum reasonably achievable emissions reductions at the national level. A large number of NDCs do show some ambition. Many of them are below either the per capita or the grandfathering percentages, sometimes both. This gives some reason for hope. The sum of the NDCs is still far from sufficient to meet the desired targets, but if the NDCs are thought of as reasonably fair, they may function as a good starting point for equal percentage reductions. Whereas equal percentage reductions from the status quo are deeply unfair to those countries that have low per capita emissions today, equal percentage reductions from the NDCs may be thought of as increasing the pressure on all countries toward a common goal in a symmetric and thus fair way.

The final question is what role there might be for harmonized taxes. We know from economic theory that harmonizing prices will promote efficiency. Some research has also suggested that it may be easier to negotiate a harmonized price of carbon than country emissions quotas. We have shown that the introduction of a harmonized carbon tax will give an allocation that is not too different from grandfathering (using 2014 as base year) but with lower quotas for countries that today have very low prices of fossil fuel for domestic consumption. This does seem to be a positive result, although one should not underestimate the powerful lobbying that may come from fossil-rich nations.

As climate negotiations continue in the aftermath of the Paris COP, the focus is on whether to tighten the NDCs or increase the role of an internationally agreed (minimum) carbon price, or both. One tentative conclusion of our study is that the process of tightening NDCs may well be complementary to, and supported by, the introduction of a common harmonized carbon tax, the main effect of which would be to increase the profitability of fuel efficiency in the fossil-rich countries. There are many calls for countries to stop subsidizing fossil fuels. Striving to apply a reasonably high carbon price to all sectors and countries, after first having abolished all carbon fuel subsidies, may be an effective way of supporting the efforts to gradually tighten the ambition of the NDCs.

Appendix 3

3.A Modeling Carbon Allocation Principles

In the main paper, we present a model in which prices vary across countries. In this section, we consider a more restricted model with a homogeneous world market price (P_t) (which is more appropriate for the oil market). Carbon demand at both national and global levels are given by (3.A.1) and (3.A.2), respectively:

$$E_{it} = f(Y_{it}, P_t, T_{it}) \tag{3.A.1}$$

$$E_t = g(Y_t, P_t, T_t) \tag{3.A.2}$$

For gasoline, we assume a unitary income elasticity and a common price elasticity everywhere of β.

$$E_{it} = \gamma_i Y_{it} (P_t T_{it})^{\beta} \tag{3.A.1a}$$

$$E_t = \sum \gamma_i Y_{it} (P_t T_{it})^{\beta} \tag{3.A.2a}$$

Aggregating from equation (3.A.2a) is not trivial. If we have a general functional form, such as Cobb-Douglas, with different elasticities and constants in each country, there is simply no neat analytical way to aggregate. Still, it is common for analysts to estimate energy demand at different levels of aggregation with the same functional form as if this problem did not exist. For simplified cases with identical constants, common price and price elasticity, and a unitary income elasticity, the problem disappears. Otherwise, one could define an average effective world tax (and policy) variable, $\widetilde{T}$, and an average consumption constant γ that are defined such that they give an approximate representation:

$$E_t = \sum \gamma_i Y_{it} (P_t T_t)^{\beta} = \gamma Y_t (P_t \widetilde{T}_t)^{\beta}$$

where $E_t = \sum E_{it}$ and $Y_t = \sum Y_{it}$.

The grandfathering allocation can be expressed as

$$\sigma_{ig} = E_{i,t-\tau} / E_{t-\tau} = \frac{\gamma_i Y_i (P T_i)^{\beta}}{\gamma Y (P T)^{\beta}} \tag{3.A.3}$$

Equation (3.A.3) should be evaluated at time $t-\tau$ (the index was omitted for clarity of exposition). From equation (3.A.3), we note that grandfathering benefits not only those countries that have had high incomes but also countries that for a long time had low T_{it}, because these are the countries that have high consumption levels at time $t-\tau$, which implies that they claim high shares at time t.

We assume that we have a full harmonization of all policies everywhere. Then all countries face the same price $P_t T_t$. The harmonized tax shares are given as follows:

$$\sigma_{ip} = \frac{\gamma_i Y_{it} (P_t T_{it})^{\beta}}{\sum \gamma_i Y_{it} (P_t T_t)^{\beta}} = \gamma_i Y_{it} \Big/ \sum \gamma_i Y_{it} = \sigma_{iy} \cdot \frac{\gamma_i}{\gamma} \qquad (3.A.4)$$

since $T_i = T$.

3.B Figures and Tables

Figure 3.B.1. Proportionality to Income Allocation

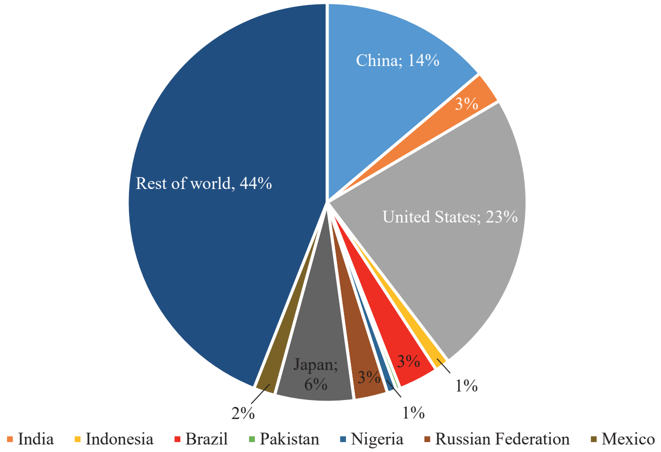


Figure 3.B.2. Grandfathering (2014) Allocation

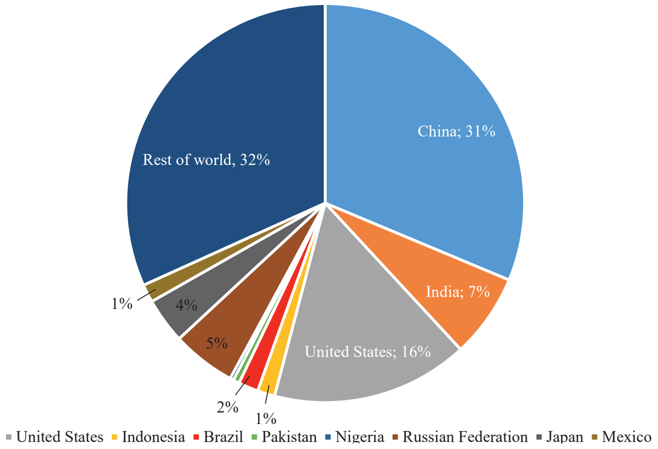


Table 3.B.1. Harmonized Tax Carbon Budgets

Country	Rank	Gasoline Price (US$/liter)	% Rise in Gasoline Price	% Reduction in Gasoline Demand	Gt CO_2 Reduction	Gt CO_2 Budget Share
United States	1	0.8	39.5	–23.4	–44.2	144.9
China	2	1.2	25.6	–16.7	–61.9	308.7
Russian Federation	3	0.8	37.0	–22.3	–13.7	47.7
Japan	4	1.4	21.7	–14.6	–6.4	37.3
Germany	5	1.8	16.7	–11.6	–3.0	22.9
Ukraine	6	1.2	25.6	–16.7	–1.4	6.8
India	7	1.1	27.3	–17.5	–14.1	66.4
United Kingdom	8	1.9	15.6	–11.0	–1.7	13.5
Canada	9	1.2	25.6	–16.7	–3.2	16.1
Italy	10	2.1	14.0	–10.0	–1.1	10.4
France	11	1.8	16.8	–11.7	–1.3	9.6
Poland	12	1.4	21.1	–14.2	–1.5	8.8
Mexico	13	1.0	29.1	–18.5	–3.2	14.1
South Africa	14	1.2	25.2	–16.5	–2.9	14.7
Australia	15	1.2	24.4	–16.0	–2.1	10.9
Kazakhstan	16	0.8	37.0	–22.3	–2.0	6.9
Korea, Rep.	17	1.6	19.4	–13.2	–2.8	18.3
Spain	18	1.6	18.4	–12.6	–1.1	7.4
Iran, Islamic Rep.	19	0.4	80.2	–37.6	–8.8	14.6
Brazil	20	1.3	23.6	–15.6	–3.0	16.1
Saudi Arabia	21	0.2	187.5	–57.0	–12.3	9.3
Romania	22	1.6	18.9	–12.9	–0.3	2.2
Netherlands	23	2.2	14.0	–9.9	–0.6	5.4
Indonesia	24	0.9	32.3	–20.0	–3.3	13.4
Turkey	25	2.1	14.6	–10.3	–1.3	11.2
Czech Republic	26	1.7	18.0	–12.4	–0.4	3.0
Venezuela, RB	27	0.0	2000.5	–91.2	–6.1	0.6
Argentina	28	1.5	19.7	–13.4	–1.0	6.4
Uzbekistan	29	1.0	29.4	–18.6	–0.7	3.1
Belgium	30	1.9	15.8	–11.1	–0.4	3.0
Thailand	31	1.3	23.3	–15.4	–1.8	9.6
Belarus	32	1.1	28.3	–18.1	–0.4	1.9
Algeria	33	0.3	111.1	–45.0	–2.4	2.9
Egypt, Arab Rep.	34	0.9	34.1	–20.9	–1.5	5.7
Bulgaria	35	1.5	20.1	–13.7	–0.2	1.3
Greece	36	2.0	15.2	–10.7	–0.3	2.2
Hungary	37	1.6	19.0	–13.0	–0.2	1.3
Pakistan	38	0.9	31.9	–19.9	–1.2	4.8
Korea, Dem. People's Rep.	39	0.9	31.9	–19.9	–0.3	1.2
Austria	40	1.6	18.8	–12.8	–0.3	1.8
Colombia	41	1.1	27.8	–17.8	–0.5	2.5

cont.

Table 3.B.1 cont.

Country	Rank	Gasoline Price (US$/liter)	% Rise in Gasoline Price	% Reduction in Gasoline Demand	Gt CO_2 Reduction	Gt CO_2 Budget Share
Malaysia	42	0.7	44.1	–25.4	–2.2	6.5
Azerbaijan	43	1.2	24.8	–16.2	–0.2	1.1
Serbia	44	1.6	19.4	–13.2	–0.2	1.2
United Arab Emirates	45	0.5	63.8	–32.6	–2.5	5.1
Sweden	46	1.8	16.5	–11.5	–0.2	1.4
Finland	47	1.9	15.9	–11.1	–0.2	1.5
Kuwait	48	0.2	136.4	–49.8	–1.7	1.7
Denmark	49	2.0	14.9	–10.5	–0.1	1.1
Iraq	50	0.4	69.8	–34.5	–2.1	4.0
Singapore	51	1.6	19.0	–13.0	–0.3	1.8
Slovak Republic	52	1.8	17.0	–11.8	–0.1	1.0
Switzerland	53	1.7	17.2	–12.0	–0.2	1.1
Portugal	54	1.9	15.9	–11.1	–0.2	1.4
Philippines	55	1.1	28.6	–18.2	–0.7	3.1
Nigeria	56	0.6	53.6	–29.1	–1.0	2.5
Syrian Arab Republic	57	0.8	36.2	–21.9	–0.2	0.9
Libya	58	0.1	250.1	–63.3	–1.3	0.8
Israel	59	1.9	16.0	–11.2	–0.3	2.1
Cuba	60	1.4	21.4	–14.4	–0.2	1.1
Chile	61	1.5	19.7	–13.4	–0.4	2.6
Turkmenistan	62	0.2	136.4	–49.8	–1.2	1.2
Norway	63	2.3	13.2	–9.5	–0.2	1.6
Ireland	64	1.9	15.6	–11.0	–0.1	1.1
Hong Kong SAR, China	65	2.1	14.6	–10.3	–0.2	1.5
Estonia	66	1.5	20.6	–13.9	–0.1	0.6
New Zealand	67	1.7	17.5	–12.1	–0.2	1.1
Morocco	68	1.4	21.7	–14.6	–0.3	1.8
Lithuania	69	1.6	19.1	–13.1	–0.1	0.4
Vietnam	70	1.0	28.9	–18.4	–1.1	4.9
Peru	71	1.5	20.6	–13.9	–0.3	1.9
Moldova	72	1.2	24.8	–16.2	0.0	0.1
Trinidad and Tobago	73	0.4	83.4	–38.4	–0.6	1.0
Ecuador	74	0.6	50.0	–27.7	–0.4	1.1
Croatia	75	1.7	18.1	–12.4	–0.1	0.5

Sources: The carbon budget data come from Meinshausen et al. (2009), and the CO_2 emissions, GDP, and population data are from the World Bank and UN.

Note: The countries are ranked according to 1990 CO_2 emissions. The last column shows each country's share of the remaining carbon budget using harmonized taxes. We show results for the 75 countries accounting for about 98% of global CO_2 emissions. The harmonized tax is calculated using 2014 data. The simulation is based on an overall target of 2°C, with 50% probability of warming exceeding the 2°C target. The simulated shares are based on adding a harmonized carbon tax to local carbon prices.

Table 3.B.2. Allocation Shares (%) Using Different Schemes

Country	Rank	GF90	GF00	GF10	GF14	PC	Income Prop	Tax	NDC
United States	1	23.82	24.6	17.5	15.98	5.34	23.11	15.26	10.58
China	2	12.06	14.71	28.46	31.3	22.86	13.83	32.49	30.87
Russian Federation	3	10.27	6.73	5.42	5.19	2.41	2.72	5.02	6.61
Japan	4	5.41	5.27	3.8	3.69	2.13	6.4	3.93	2.12
Germany	5	4.59	3.59	2.46	2.19	1.36	5.14	2.41	1.2
Ukraine	6	3.12	1.39	0.99	0.69	0.76	0.18	0.72	1.17
India	7	3.06	4.46	5.58	6.81	21.68	2.69	6.99	10.6
United Kingdom	8	2.75	2.34	1.6	1.28	1.08	4	1.42	0.88
Canada	9	2.15	2.31	1.73	1.63	0.6	2.37	1.7	1.3
Italy	10	2.06	1.95	1.31	0.97	1.02	2.84	1.09	0.74
France	11	1.86	1.56	1.14	0.92	1.11	3.76	1.02	0.72
Poland	12	1.82	1.29	1.03	0.87	0.64	0.72	0.93	0.59
Mexico	13	1.57	1.72	1.51	1.46	2.08	1.73	1.48	1.21
South Africa	14	1.55	1.64	1.54	1.49	0.91	0.46	1.55	1.14
Australia	15	1.3	1.42	1.27	1.1	0.39	1.93	1.15	0.89
Kazakhstan	16	1.29	0.51	0.81	0.76	0.29	0.29	0.73	0.63
Korea, Rep.	17	1.22	1.93	1.84	1.79	0.85	1.86	1.93	1.09
Spain	18	1.08	1.27	0.88	0.71	0.78	1.82	0.77	0.61
Iran, Islamic Rep.	19	1.04	1.61	1.86	1.98	1.31	0.57	1.54	2.19
Brazil	20	1.03	1.42	1.36	1.61	3.42	3.24	1.69	2.35
Saudi Arabia	21	0.92	1.28	1.68	1.83	0.52	1	0.98	1.63
Romania	22	0.86	0.39	0.26	0.21	0.33	0.26	0.23	0.25
Netherlands	23	0.78	0.75	0.59	0.51	0.28	1.18	0.57	0.26
Indonesia	24	0.74	1.14	1.39	1.41	4.28	1.18	1.41	2.13
Turkey	25	0.72	0.93	0.97	1.05	1.29	1.23	1.18	1.96
Czech Republic	26	0.68	0.54	0.36	0.29	0.18	0.27	0.32	0.21
Venezuela, RB	27	0.6	0.66	0.61	0.56	0.52	0.64	0.06	0.77
Argentina	28	0.55	0.61	0.61	0.62	0.72	0.69	0.67	0.81
Uzbekistan	29	0.55	0.53	0.34	0.32	0.52	0.08	0.32	0.81
Belgium	30	0.52	0.5	0.36	0.28	0.19	0.7	0.31	0.18
Thailand	31	0.45	0.78	0.91	0.96	1.15	0.54	1.01	0.88
Belarus	32	0.43	0.23	0.2	0.19	0.16	0.1	0.2	0.2
Algeria	33	0.38	0.38	0.39	0.44	0.66	0.28	0.3	0.51
Egypt, Arab Rep.	34	0.38	0.61	0.66	0.61	1.54	0.4	0.61	0.96
Bulgaria	35	0.37	0.19	0.14	0.13	0.12	0.07	0.14	0.1
Greece	36	0.37	0.4	0.27	0.2	0.18	0.31	0.23	0.19
Hungary	37	0.34	0.24	0.16	0.13	0.17	0.18	0.14	0.13
Pakistan	38	0.34	0.46	0.52	0.51	3.11	0.32	0.5	0.98
Korea, Dem. People's Rep.	39	0.29	0.3	0.22	0.12	0.42		0.12	0.27

cont.

Table 3.B.2 cont.

Country	Rank	GF90	GF00	GF10	GF14	PC	Income Prop	Tax	NDC
Austria	40	0.28	0.27	0.22	0.18	0.14	0.58	0.19	0.12
Colombia	41	0.28	0.25	0.25	0.26	0.8	0.5	0.26	0.22
Malaysia	42	0.28	0.54	0.71	0.74	0.51	0.45	0.69	1.2
Azerbaijan	43	0.28	0.13	0.1	0.11	0.16	0.1	0.12	0.1
Serbia	44	0.27	0.23	0.15	0.11	0.12	0.06	0.12	0.14
United Arab Emirates	45	0.26	0.49	0.52	0.64	0.15	0.53	0.54	0.57
Sweden	46	0.26	0.21	0.17	0.13	0.16	0.76	0.15	0.11
Finland	47	0.26	0.23	0.2	0.14	0.09	0.36	0.16	0.11
Kuwait	48	0.25	0.23	0.29	0.29	0.06	0.21	0.18	0.35
Denmark	49	0.25	0.22	0.15	0.1	0.09	0.47	0.11	0.08
Iraq	50	0.24	0.31	0.36	0.51	0.59	0.31	0.42	0.51
Singapore	51	0.22	0.21	0.18	0.17	0.09	0.41	0.19	0.19
Slovak Republic	52	0.22	0.16	0.12	0.09	0.09	0.13	0.1	0.07
Switzerland	53	0.21	0.17	0.13	0.11	0.14	0.94	0.12	0.05
Portugal	54	0.21	0.27	0.16	0.14	0.17	0.3	0.15	0.14
Philippines	55	0.21	0.32	0.28	0.32	1.68	0.38	0.33	0.38
Nigeria	56	0.19	0.33	0.3	0.29	2.96	0.75	0.26	1.16
Syrian Arab Republic	57	0.18	0.22	0.2	0.09	0.32		0.09	0.24
Libya	58	0.18	0.2	0.2	0.17	0.1	0.05	0.08	0.27
Israel	59	0.18	0.26	0.22	0.2	0.14	0.41	0.22	0.15
Cuba	60	0.16	0.11	0.12	0.11	0.19	0.11	0.11	0.16
Chile	61	0.16	0.25	0.23	0.25	0.3	0.34	0.27	0.26
Turkmenistan	62	0.16	0.16	0.19	0.21	0.09	0.06	0.13	0.28
Norway	63	0.16	0.17	0.19	0.14	0.09	0.66	0.16	0.07
Ireland	64	0.15	0.18	0.13	0.1	0.08	0.34	0.11	0.1
Hong Kong SAR, China	65	0.14	0.17	0.13	0.14	0.12	0.38	0.16	
Estonia	66	0.12	0.06	0.06	0.06	0.02	0.04	0.06	0.02
New Zealand	67	0.12	0.14	0.1	0.11	0.08	0.27	0.12	0.15
Morocco	68	0.12	0.15	0.18	0.18	0.58	0.15	0.19	0.27
Lithuania	69	0.11	0.05	0.04	0.04	0.05	0.06	0.04	0.04
Vietnam	70	0.11	0.23	0.46	0.51	1.55	0.25	0.52	1.28
Peru	71	0.1	0.13	0.19	0.19	0.52	0.27	0.2	0.14
Moldova	72	0.1	0.02	0.02	0.02	0.06	0.01	0.02	0.02
Trinidad and Tobago	73	0.08	0.1	0.16	0.14	0.02	0.04	0.11	0.19
Ecuador	74	0.08	0.09	0.12	0.13	0.27	0.13	0.12	0.09
Croatia	75	0.08	0.08	0.07	0.05	0.07	0.08	0.06	0.05

Note: The countries are ranked according to 1990 CO_2 emissions. The columns show each country's percentage share of the remaining carbon budget over the period 2015–2050. GF90, GF00, GF10, and GF14 denote the grandfathering shares using 1990, 2000, 2010, and 2014 as base years, respectively. PC denotes equal emissions per capita, and Income Prop represents proportionality to income.

Table 3.B.3. Ambitiousness of NDCs and Carbon Tax

Country	Tax/GF90	Tax/GF14	Tax/PC	Tax/NDC	NDC/GF90	NDC/GF14	NDC/PC	NDC/Tax
United States	0.64	0.95	2.86	1.44	0.44	0.66	1.98	0.69
China	2.69	1.04	1.42	1.05	2.56	0.99	1.35	0.95
Russian Federation	0.49	0.97	2.08	0.76	0.64	1.27	2.74	1.32
Japan	0.73	1.07	1.85	1.85	0.39	0.57	1.00	0.54
Germany	0.53	1.10	1.77	2.01	0.26	0.55	0.88	0.50
Ukraine	0.23	1.04	0.95	0.62	0.38	1.70	1.54	1.63
India	2.28	1.03	0.32	0.66	3.46	1.56	0.49	1.52
United Kingdom	0.52	1.11	1.31	1.61	0.32	0.69	0.81	0.62
Canada	0.79	1.04	2.83	1.31	0.60	0.80	2.17	0.76
Italy	0.53	1.12	1.07	1.47	0.36	0.76	0.73	0.68
France	0.55	1.11	0.92	1.42	0.39	0.78	0.65	0.71
Poland	0.51	1.07	1.45	1.58	0.32	0.68	0.92	0.63
Mexico	0.94	1.01	0.71	1.22	0.77	0.83	0.58	0.82
South Africa	1.00	1.04	1.70	1.36	0.74	0.77	1.25	0.74
Australia	0.88	1.05	2.95	1.29	0.68	0.81	2.28	0.77
Kazakhstan	0.57	0.96	2.52	1.16	0.49	0.83	2.17	0.86
Korea, Rep.	1.58	1.08	2.27	1.77	0.89	0.61	1.28	0.56
Spain	0.71	1.08	0.99	1.26	0.56	0.86	0.78	0.79
Iran, Islamic Rep.	1.48	0.78	1.18	0.70	2.11	1.11	1.67	1.42
Brazil	1.64	1.05	0.49	0.72	2.28	1.46	0.69	1.39
Saudi Arabia	1.07	0.54	1.88	0.60	1.77	0.89	3.13	1.66
Romania	0.27	1.10	0.70	0.92	0.29	1.19	0.76	1.09
Netherlands	0.73	1.12	2.04	2.19	0.33	0.51	0.93	0.46
Indonesia	1.91	1.00	0.33	0.66	2.88	1.51	0.50	1.51
Turkey	1.64	1.12	0.91	0.60	2.72	1.87	1.52	1.66
Czech Republic	0.47	1.10	1.78	1.52	0.31	0.72	1.17	0.66
Venezuela, RB	0.10	0.11	0.12	0.08	1.28	1.38	1.48	12.83
Argentina	1.22	1.08	0.93	0.83	1.47	1.31	1.13	1.21
Uzbekistan	0.58	1.00	0.62	0.40	1.47	2.53	1.56	2.53
Belgium	0.60	1.11	1.63	1.72	0.35	0.64	0.95	0.58
Thailand	2.24	1.05	0.88	1.15	1.96	0.92	0.77	0.87
Belarus	0.47	1.05	1.25	1.00	0.47	1.05	1.25	1.00
Algeria	0.79	0.68	0.45	0.59	1.34	1.16	0.77	1.70
Egypt, Arab Rep.	1.61	1.00	0.40	0.64	2.53	1.57	0.62	1.57
Bulgaria	0.38	1.08	1.17	1.40	0.27	0.77	0.83	0.71
Greece	0.62	1.15	1.28	1.21	0.51	0.95	1.06	0.83
Hungary	0.41	1.08	0.82	1.08	0.38	1.00	0.76	0.93
Pakistan	1.47	0.98	0.16	0.51	2.88	1.92	0.32	1.96
Korea, Dem. People’s Rep.	0.41	1.00		0.44	0.93	2.25	0.64	2.25
Austria	0.68	1.06	0.33	1.58	0.43	0.67	0.86	0.63

cont

Table 3.B.3 cont.

Country	Tax/GF90	Tax/GF14	Tax/PC	Tax/NDC	NDC/GF90	NDC/GF14	NDC/PC	NDC/Tax
Colombia	0.93	1.00	0.52	1.18	0.79	0.85	0.28	0.85
Malaysia	2.46	0.93	1.53	0.58	4.29	1.62	2.35	1.74
Azerbaijan	0.43	1.09	1.20	1.20	0.36	0.91	0.63	0.83
Serbia	0.44	1.09	2.00	0.86	0.52	1.27	1.17	1.17
United Arab Emirates	2.08	0.84	1.02	0.95	2.19	0.89	3.80	1.06
Sweden	0.58	1.15	0.20	1.36	0.42	0.85	0.69	0.73
Finland	0.62	1.14	0.44	1.45	0.42	0.79	1.22	0.69
Kuwait	0.72	0.62	0.86	0.51	1.40	1.21	5.83	1.94
Denmark	0.44	1.10	0.23	1.38	0.32	0.80	0.89	0.73
Iraq	1.75	0.82	1.35	0.82	2.13	1.00	0.86	1.21
Singapore	0.86	1.12	0.46	1.00	0.86	1.12	2.11	1.00
Slovak Republic	0.45	1.11	0.77	1.43	0.32	0.78	0.78	0.70
Switzerland	0.57	1.09	0.13	2.40	0.24	0.45	0.36	0.42
Portugal	0.71	1.07	0.50	1.07	0.67	1.00	0.82	0.93
Philippines	1.57	1.03	0.87	0.87	1.81	1.19	0.23	1.15
Nigeria	1.37	0.90	0.35	0.22	6.11	4.00	0.39	4.46
Syrian Arab Republic	0.50	1.00		0.38	1.33	2.67	0.75	2.67
Libya	0.44	0.47	1.60	0.30	1.50	1.59	2.70	3.38
Israel	1.22	1.10	0.54	1.47	0.83	0.75	1.07	0.68
Cuba	0.69	1.00	1.00	0.69	1.00	1.45	0.84	1.45
Chile	1.69	1.08	0.79	1.04	1.63	1.04	0.87	0.96
Turkmenistan	0.81	0.62	2.17	0.46	1.75	1.33	3.11	2.15
Norway	1.00	1.14	0.24	2.29	0.44	0.50	0.78	0.44
Ireland	0.73	1.10	0.32	1.10	0.67	1.00	1.25	0.91
Hong Kong SAR, China	1.14	1.14	0.42					
Estonia	0.50	1.00	1.50	3.00	0.17	0.33	1.00	0.33
New Zealand	1.00	1.09	0.44	0.80	1.25	1.36	1.88	1.25
Morocco	1.58	1.06	1.27	0.70	2.25	1.50	0.47	1.42
Lithuania	0.36	1.00	0.67	1.00	0.36	1.00	0.80	1.00
Vietnam	4.73	1.02	2.08	0.41	11.64	2.51	0.83	2.46
Peru	2.00	1.05	0.74	1.43	1.40	0.74	0.27	0.70
Moldova	0.20	1.00	2.00	1.00	0.20	1.00	0.33	1.00
Trinidad and Tobago	1.38	0.79	2.75	0.58	2.38	1.36	9.50	1.73
Ecuador	1.50	0.92	0.92	1.33	1.13	0.69	0.33	0.75
Croatia	0.75	1.20	0.75	1.20	0.63	1.00	0.71	0.83

Note: GF90 and GF14 denote the grandfathering shares using 1990 and 2014 as base years, respectively, while PC denotes equal emissions per capita.

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