Measuring the Impact of Climate Policy Risk

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Abstract

I estimate the impact of the risks associated with climate policy action on oil production, the spot price of oil, and asset prices. Using an event study analysis I show that events corresponding to an upward shift in the likelihood of significant future climate policy action lead to an increase in the returns of sector portfolios that are more exposed to climate policy risk, while a downward shift leads to increased returns. I then construct a climate policy index measure to estimate the impact of climate policy events on oil production and oil prices over the times series. In reduced form estimation, I find that in the recent, policy-relevant time period increases in the likelihood of future climate policy action increase oil production and decrease oil prices, as well as oil firm values. Finally, using a structural VAR framework I find evidence that in the recent, policy-relevant time period climate policy likelihood shocks that increase the likelihood of significant future climate policy action not only increase oil production and decrease the price of oil, but do so in a dynamic and persistent manner.

Keywords: Asset Pricing, Oil Prices, Climate Change, Climate Policy, Stranded Assets

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1 Introduction

Climate change, and its potential physical consequences, has become one of the most significant issues currently facing governments, institutions, and individuals around the world. These concerns have led policymakers to propose significant policy actions in an attempt stave off the possible long-term economic damages of climate change. Yet, these policy actions have generated additional risk that comes not only from the uncertainty about when or if such climate policies will ever be implemented, but also from the far-reaching implications of such policies for the profitability of significant sectors of the economy and the significant possibility of important natural resources becoming stranded or unusable. Understanding the effects of these climate policy risks is therefore essential for understanding the full economic and financial consequences of climate change.

This paper focuses on empirically estimating how changes in climate policy risk affects economic and financial outcomes. The empirical analysis is motivated by a number of key predictions from a simplified version of the general equilibrium, production-based asset pricing model of Barnett (2019). The model incorporates climate change, as well as climate policy that carries significant risk due to the fact that it restricts the use of oil and has an unknown arrival time. The key predictions of this model are as follows: the risk associated with climate policy leads to dynamically increasingly oil production to avoid having reserves become stranded; the risk of stranded assets from climate policy and the run on oil that causes lead to dynamic reductions in the price of oil; the value of oil firms decreases substantially due to the lower expected usable reserves that stranded assets risk implies and because of the shift in oil production and price that this risk generates.

I test these model predictions through variety of empirical estimation techniques. I first do this using an event-study analysis of climate policy events that shift the likelihood of future climate policy actions taking place. For events that imply a downward shift in the likelihood of future climate policy occurring, such as the 2016 US presidential election or the US Supreme Court decision to put a stay on the Clean Power Plan, the model would predict these events should increase the value of firms with high climate policy risk exposure, such as oil firms, and also increase the price of oil. The opposite should hold for events that increase the likelihood of future climate policy actions, such as the announcements of the Clean Power Plan and the UN's Paris Climate Accord. I estimate the effect of shifts in the likelihood of future climate policy due to climate policy events by regressing sectors' cumulative abnormal returns after the event on their exposure to climate policy risk, proxied for by exposure to oil price shocks as motivated by the model prediction. I find sectors with the highest climate policy risk exposure experienced the largest increases in cumulative abnormal returns for events that decreased the likelihood of future climate policy action and the largest decreases in cumulative abnormal returns for events that increased the likelihood of future climate policy actions, consistent with the model predictions.

Finally, I construct a climate policy event index from realized climate policy, energy sector, and climate-related events to estimate the dynamic impact of changes in climate policy shocks. In estimated reduced-form regressions, I find that increases in the likelihood of major climate policy measured by my index lead to increased global and regional oil production. I also find that positive climate policy shocks lead to increasingly negative returns for the US oil sector and the spot price of oil. Finally, I estimate a structural VAR for the global oil market that includes the climate policy index, and calculate impulse response functions for a shock to climate policy. The results suggest that increases in the likelihood of significant climate change policy leads to long-term and permanent increases in crude oil production and a statistically significant decreases in the oil spot price, consistent with the dynamic predictions of my model. For each index-based empirical test, the statistical and economic significance are greater during the more recent, policy-focused time period (1996-2017) than for the entire available time sample (1973-2017), further validating the temperature dependence of outcomes implied by the model and the dynamic effect of climate policy risk the model predicts. Finally I extend the VAR estimates by using returns from a type of factor-mimicking portfolio for the impacts climate policy event interacted with the climate policy index. Using this measure of shocks to the likelihood of future climate policy action, designed to better capture the magnitude and dynamics of these shocks, I find dynamic and persistent impacts on oil prices and oil production consistent the previous results that are even more significant.

2 Examples of Climate Policy Events

To highlight the effect I am interested in identifying, I outline a number of important climate policy events that have a signaled a shift in the expectation of future significant climate policy action with implications for the use of fossil fuels. In the US, a number of such policy events have occurred. The Energy Policy Conservation Act set the first fuel economy goals in the US, leading to the development of unleaded gas and catalytic converters. The Clean Air Act gave air pollution and vehicle emissions standards for the future while providing technical and financial assistance to state and local governments. The Diesel Emissions Reduction Act, part of the Energy Policy Act which was enacted in 2005, established diesel engine emissions standards for the future which have led to innovations in diesel engine technology from companies like Cummins. The passing of the Energy Independence and Security Act established the Corporate Average Fuel Economy standards regulating vehicle emissions in the future which motivated the development of hybrid and electric vehicles like the Prius, Leaf, and Tesla. The critical features of these policy events for my analysis are that they established expectations for future outcomes, with clear implications for the usability of fossil fuels and fossil fuel dependent goods, while containing uncertainty about how and if such policy actions would remain in place or be implementable in the future because of their long-term nature.

Renewable Portfolio Standards (RPS) are another type of policy action with similar implications that have been used in the US and internationally. RPS policies set required standards for future power and electricity production. These standards typically require an increased fraction of power and electricity to be produced by renewable and green sources, and thus a sizeable reduction coming from fossil fuels. Over half the states in the US, the European Union, Germany, Japan, China, the UK, and numerous other countries and regions have implemented or tried to implement Renewable Portfolio Standard-type policies. Implementation or proposal of such policies again have two significant effects that are central to my analysis. First, these policy events shift expectations about the likelihood of strict future policy requirements and the future use of fossil fuels as signification restriction of use of fossil fuels will be required to meet such targets. Second, with this type of long-term policy action there is no certainty that these targets will be achieved or enforced by future policymakers because, even when these targets are put in to law and carry significant financial penalties for being violated, they may not be economically feasible or in line with future political consensus.

A prime example of the risk implications I focus on in my analysis can be seen with the implementation of the Clean Power Plan and the related climate policy events connected to this regulation. The Clean Power Plan was established by US President Barack Obama in conjunction with the 2015 Paris Climate Accord to reduce greenhouse gas emissions and by setting future renewable portfolio standards requiring increases in the fraction of energy and electricity produced from low-emission and renewable resources while phasing out high-emissions sources like coal and oil. While this policy clearly has significant implications for restriction of the use of fossil fuels in the future, numerous policy actions since then have put in doubt whether the policy will ever be implemented. On February 9, 2016 the US Supreme ruled to put a stay on the policy regulation until a lower court could determine whether the EPA was legally allowed to implement thus type of policy action. Furthermore, the election of Donald Trump to be the President of the United States came with policy promises such as repealing the Clean Power Plan. Thus the Clean Power Plan, as well the follow-up policy events of the US Supreme Court ruling and election of Donald Trump, are events that shift the likelihood of future climate policy restrictions given the forward-looking ramifications of these events.

The aforementioned Paris Climate Accord is another key policy example with global implications. This agreement is the result of the UN Framework Convention on Climate Change to limit change in the global mean temperature (GMT). The agreement was seen as a significant step toward limiting climate change, and likely limiting the use of fossil fuels in the future, but also carries substantial uncertainty about when and if the necessary policy actions to achieve this target will occur. There is no centralized enforcement mechanism holding countries accountable for meeting contribution targets, and furthermore countries contributions are self-determined and self-reported. In addition, some countries have already proposed or suggested they would propose withdrawing from the agreement, such as the US and Brazil in conjunction with the elections of Donald Trump and Jair Bolsonaro, while others have yet to set any concrete plans to reach the proposed goal.

These policy events demonstrate the potential risks of climate policy action tied to their implementation and future impact that I study in this paper. Through the use of event-study analysis around individual climate policy related events such as these, and through reduced form and structural vector autoregression estimates using the time series of these types of climate policy related events, I empirically measure the impact of climate policy risk on oil production, the spot price of oil, and asset prices. By focusing on these three outcomes, I can capture the real and financial implications of these risks, as well as the interaction of these effects. Furthermore, I am able to study both cross-sectional and dynamic implications related to the risk of climate policy actions these events embody.

3 Related Literature

This paper builds on and contributes to various areas of work in economics, finance, and climate change. The first area is the literature focusing on the interaction between economics and climate change. Stern (2007), Nordhaus (2014), Golosov et al. (2014), Acemoglu et al. (2016), Pindyck and Wang (2013), Hambel et al. (2015), and Cai et al. (2015) are recent examples of theoretical frameworks that examine the social cost of carbon and optimal carbon taxation, directed technological change, and other key climate-economic elements using theoretical models. Kelly and Kolstad (1999), Crost and Traeger (2011), Lemoine and Traeger (2012), Anderson et al. (2016), Brock and Hansen (2017), and Barnett et al. (2018) focus on elements of uncertainty related to risk, ambiguitiy, and misspecification related to climate change and climate models. Deschenes and Greenstone (2007), Dell et al. (2012), Hsiang et al. (2017), and Burke et al. (2018) empirically estimate climate damages in different economic sectors and regions and the impact of climate change on economic growth. McGlade and Ekins (2015) and the Grantham Research Institute study the potential magnitude of stranded assets for fossil fuels based on proposed temperature ceiling policies using least-cost analysis and implications for a potential "carbon bubble," or possible overvaluation of oil firms from not accounting for stranded assets risk, respectively. The Green Paradox, a theory proposed by Sinn (2007) and recently extended by Kotlikoff et al. (2016), suggests the possibility that climate policy intended to mitigate climate change on the demand side may cause firms to alter the timing of their fossil fuel production in a possibly harmful way. This paper builds on elements from these areas and extends this work by motivating critical features of the climate economic models and the potential for stranded assets from climate policy risk to motivate the empirical estimation that examines the dynamic implications of climate policy risk for real and financial outcomes in the oil sector

This paper also contributes to important areas in the asset pricing literature. The interaction between government and asset prices has been studied by Santa-Clara and Valkanov (2003), Pastor and Veronesi (2012), Belo et al. (2013), and Kelly et al. (2016), which focus election and political uncertainty for asset prices, exploiting differential exposures to these types of risk. Sialm (2006) and Koijen et al. (2016) are two examples closely related to this paper that study the impacts of policy risk related to taxes and healthcare on asset prices, whilePástor and Veronesi (2009) provides an important example of the asset pricing impacts that arise from a shift in the production function, in their case due to learning about and adopting a new technology, similar to the impact of the policy events in my model. There is a growing recent literature about climate change and asset prices that my paper adds to. Examples here include Giglio et al. (2015), Bansal et al. (2016), Dietz et al. (2017), Hong et al. (2016), Barnett (2017), and Engle et al. (2019). These papers explore the term structure of long-run discount rates and their interaction with climate change mitigation efforts, the impact of climate change and long-run risk on the social cost of carbon and asset prices, the elasticity of climate damages, the reaction of stock prices in the food sector to climate change, the cross-sectional and time series implications of climate change and climate model uncertainty on economic and asset pricing outcomes, and the ability to hedge climate risk, respectively. My paper provides an important contribution here by empirically studying the impacts of climate policy risk on production and asset prices.

This paper contributes to the expansive work on oil prices and extraction. Hotelling (1931) and Dasgupta and Heal (1974) provide the foundations for the literature on natural resource extraction, while Hamilton (2005), Hamilton (2008), Kilian (2008), Kilian and Park (2009), Kilian (2009), and Baumeister and Hamilton (2019) provide estimates for the link between oil prices and economics and financial shocks. Carlson et al. (2007), Casassus et al. (2009), Kogan et al. (2009), David (2015), Ready (2015), and Bornstein et al. (2017) provide model frameworks to explain varying stylized facts of oil prices and identify important model mechanisms required to match those outcomes. This paper provides estimates for measuring the impact of climate policy risk on oil production and oil prices, a previously unexplored channel in this literature.

Finally, this paper is connected to the narrative approach empirical work of Romer and Romer (2010), Ramey (2011), and Mertens and Ravn (2014). These papers use narrative records to construct an index of relevant policy shocks and then use this index as a proxy for these shocks in their empirical estimation strategy. The climate policy index I construct is similar to this strategy of constructing a policy shock proxy from the text of narrative records by hand-collecting key events from lists of significant climate policy related events that I sign based on the expected impact on the likelihood of future policy. Furthermore, I extend this analysis by interacting my narrative-style climate policy index with a type of factor-mimicking portfolio to capture magnitude and dynamic implications of the climate policy shocks my index is designed to capture.

4 Modelling the Impact of Dynamic Climate Policy Risk

To motivate the empirical tests in my analysis, consider the implications from a simplified version of the model from Barnett (2019). I provide details for this simplified model in the appendix, and direct the reader to Barnett (2019) for full details and a more rich theoretical analysis of climate policy risk. The model consists of households, final output and oil good production, and climate and climate policy components. The solution to this model which includes the risk of climate policy that could strand oil reserves and has a climate-dependent arrival rate λ_t is given by the following proposition:

Proposition 1. *With dynamic climate policy risk where the arrival rate of policy is given by the climate-dependent function λ_t and where oil use is restricted after the policy shock, the optimal extraction, spot price of oil, and oil firm value are given by*

$$O_t = a_n \frac{v}{v_R - v_{CC}}, \quad P_{O,t} = \nu \tilde{Y}_t O_t^{-1}, \quad S_t^O = a_O \frac{v_R R}{v} \tilde{Y}_t$$

Note v is the solution to the HJB equation characterizing the planner's problem (given in the appendix), v_R is the marginal value of oil reserves and $-v_{CC}$ is the marginal cost of climate change. The constants a_n, a_O are functions of the model parameters only (also given in the appendix), ν is the oil input demand share and $\tilde{Y}_t$ is final output net of climate damages.

Without the dynamic climate policy risk, this model behaves like a standard Hotelling-type model where the effects of climate change are internalized through an optimal tax. As oil reserves decrease, the marginal value of holding reserves increases in order to produce in future periods. The internalized climate impact would further diminish oil production because of the climate damages resulting from carbon emissions that increase atmospheric temperature. However, dynamic climate policy risk importantly alters the key forces that drive these results. Directly, temperature impacts climate damages and the likelihood of climate policy occurring, but now in a way that the temperature-related adjustment to extraction and the subjective discount rate adjustment depend on the state of climate change. Indirectly, temperature has greater influence on the marginal value of reserves because the value function is no longer separable.

Though the production and asset pricing impacts associated with oil reserves and temperature can only be determined numerically, we know the impact of climate policy will matter because of the expressions for oil extraction, the spot price of oil, and the oil firm value given above. The key impact of the climate-linked policy risk, through both the direct and indirect effects, is that it creates a dynamic, climate-related feedback mechanism in the model. The risk of a policy shock that restricts the use of oil leads to an increased level of oil extraction. This is true whether λ is constant or temperature dependent. However, as the arrival rate is state dependent, increased oil extraction caused by the stranded asset risk leads to increased climate change. This further exacerbates the stranded assets risk, by increasing the likelihood of a policy shock, and thus provides motivation for oil firms to further increase their oil extraction. The link between climate change and climate policy that strands oil reserves generates a feedback loop that can lead to a dynamic increase in oil production, not simply a level shift up. This can occur even as oil reserves are decreasing and temperature is increasing.

The expression for the spot price of oil clearly demonstrate the inverse relationship between oil production and the spot price of oil. As a result, the forces in play generating a run on oil production will lead to a drop in oil spot prices because of the significant supply of oil in the market. This drop is a dynamic effect, amplified over time through the dynamic feedback loop that alters the optimal path of oil extraction over time.

Finally, the price of the oil firm incorporates two features. The first is that the firm price includes the damage-scaled final output. Therefore, forces related to the impact of climate damages and the impact of the run on oil production for the damage-scaled final output that impact the final output firm and green energy firm prices still matter here. However, the second feature is that the price of the oil firm is also scaled by the marginal value of reserves v_R. Thus, the oil firm has an additional force impacting its price. We know from the macroeconomic outcomes that the risk of stranded assets from a climate policy shock will cause the marginal value of oil reserves to decrease over time as reserves diminish and climate change increases. Therefore, we expect that the price of the oil firm will be lower than without the temperature-dependent risk of climate policy, due to the reduced value of holding oil reserves in this setting. Moreover, we also expect that the price will decrease dynamically due to the increasing likelihood of policy occurring that is driving the run on oil extraction.

5 Empirical Analysis

The solution to the model outlined above provides a number of important predictions that I will now examine empirically. The first prediction of the model is that the dynamic risk of climate policy generates a run on oil, meaning the production of oil dynamically increases with increases in climate change which correspond to increases in the likelihood of a climate policy shock. The model also predicts that the temperature-dependent climate policy risk depresses the spot price of oil due to the increased oil production. Empirically, these outcomes correspond to an observed increase in the likelihood of future climate policy leading to an increase in current and future oil production and a decrease in current and future oil spot prices. The model further predicts that the value of oil firms decreases due to the risk of stranded assets leading to expectations that not all oil reserves held by firms can be used and because the run on oil depresses oil prices. Lastly, the model predicts that the value of the final output firm will increase due to decreased oil prices and policy expectations. These final two predictions can be re-stated as empirically observed increases in the likelihood of future climate policy occurring should lead to oil firms and firms with the highest climate policy risk exposure experiencing decreased returns and non-oil firms and firms with the lowest climate policy risk exposure experiencing increased returns.

I examine these predictions using the following empirical exercises. The first exercise examines the impact of individual events that shift the likelihood of future climate policy action occurring. Estimating cross-sectional regressions for returns of US sector portfolios on a proxy for climate policy exposure shows sectors with greater climate policy exposure experienced larger increases in returns from climate policy events that decreased the likelihood of future climate policy action and larger decreases in returns from climate policy events that increased the likelihood of future climate policy action. Thus, the post-event outcomes provide evidence that the shift in expectations for future climate policy did impact asset prices as my model predicts.

I then extend this event-type analysis of the model predictions by exploring the impact of the time series of climate policy related events. I construct an index of the time series of climate policy events by aggregating lists of key climate- and energy-related events from non-partisan, informational websites. With this time-series index of relevant events, I first test the model predictions using reduced-form regressions of the impact of climate policy shocks on oil production in different regions, returns of US oil sector firms, and returns of the oil spot price. The second approach focuses on the dynamic impact of climate policy shocks by estimating a vector autoregression that incorporates the climate policy events index into a standard global oil market model to examine the impact of climate shocks on current and future oil production and oil prices. Results from each of these exercises again appear to be consistent with the model predictions. Finally, to better capture the dynamics and magnitudes of the effect of the climate policy events in my index I augment the index. I do this by constructing a type of factor-mimicking portfolio, based on the climate policy risk exposure measures used in the event study analysis, and weight the climate policy index by the returns of the portfolio. Repeating the VAR analysis with this return weighted index, I find amplified effects, consistent in direction with the previous estimates, on production and the price of oil for shocks to the likelihood of future climate policy actions.

5.1 Data Sources

The data I use for oil production and oil prices comes from the US Energy Information Administration (EIA). I use global atmospheric temperature as the variable for climate change, which is available from NOAA and NASA. Data on returns for the oil sector and the market come from Ken French's website and the Compustat/CRSP merged database available from WRDS. Macroeconomic variables such as GDP growth, deflators, and other indicators come from FRED, the BEA, Lutz Kilian's website, and James Hamilton's website. Additional oil spot price data come from FRED and the CME's End of Day database, made available to me through the University of Chicago Booth School of Business Fama-Miller Center. Finally, I construct a proxy for changes in the probability of climate policy occurring in my model by compiling a time series of significant climate, climate policy, and energy events (major fossil fuel and alternative energy events, IPCC meetings, US presidential election results, and lists of major climate policies and US energy policies) from non-partisan government, academic, and non-profit informational websites (ProCon.org, IPCC website, and Wikipedia.org). Table 8 shows the list of events since 1997, though the full list extends back to match the full range of dates available from the EIA (1973). As indicated in the table, events can either be positive or negative policy shocks in terms of an increased or decreased likelihood, respectively, of a shift to the production function. The variable contains values of 0 for no event, 1 for a positive event, or -1 for a negative event at the daily level that are then aggregated to a monthly count for the empirical analysis. Section 5.3 provides further details on the index.

5.2 Climate Policy Event Study Analysis

The first empirical exercise I do estimates the impact of individual events that in expectation would shift the likelihood of future climate policy action occurring on stock returns for different sectors in the US economy based on their estimated exposure to climate policy. I focus on events which signal changes in expectations for future policy outcomes as these events more directly test the mechanism related to the likelihood of future climate policy action that my analysis is focused on. Within the context of the model, these events can be compared to comparative statics in the model where λ_t is shifted up or down. Moreover, the more unexpected the shock to the value of λ_t, the more cleanly we can identify the impact as a comparative static shock rather than a more prolonged response to an expected outcome. Such shocks have clear implications in the model: a shock that increases (decreases) the likelihood of future climate policy action should lead to increased (decreased) oil production, negative (positive) realized returns for the oil sector, and negative (positive) realized returns for the spot price of oil due to increased (decreased) stranded assets risk.

To formalize this exercise using an event-study analysis, I estimate the impact of the unexpected shift in climate policy risk expectations on cumulative abnormal returns after the a climate policy event by exploiting the cross-sectional variation in climate policy risk exposure across different sectors. To estimate this cross-sectional regression, I use daily returns for the 49 sector portfolios provided on Ken French's website. I derive abnormal returns as unexplained differences with respect to the market portfolio, or the CAPM model. I estimate the following regression for each sector i using daily returns for the year leading up to the event date to estimate abnormal returns:

$$R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \epsilon_{i,t}$$

The residual for this regression $\epsilon_{i,t}$ is then the abnormal return. I aggregate these residuals for each sector in order to get the cumulative abnormal returns:

$$CAR_{i,t} = \sum_{0}^{t} \epsilon_{i,t} = \sum_{0}^{t} (R_{i,t} - \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}))$$

Next, I derive a measure of climate policy risk exposure. The model predicts that changes in climate-policy expectations influence oil prices and oil production, as well as firm values. Therefore, the model predictions suggest a sector's exposure to climate policy risk can be proxied for by the sector's exposure to oil price innovations or oil production innovations. Given that oil prices are available at a daily frequency, are in direct units of comparison, and are closely linked to oil production, I use exposure to oil price returns as the proxy for exposure to climate policy risk. I estimate this exposure as the beta for oil price returns from the following regression for each sector i over the full available time series of oil prices:

$$R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,OilPrice} R_{OilPrice,t} + \varepsilon_{i,t}$$

To estimate the impact on returns of climate policy risk exposure after the event, I run the following cross-sectional regression:

$$CAR_{i,event} = \delta_0 + \delta_1 \frac{\beta_{i,OilPrice}}{\sigma(\beta_{i,OilPrice})} + e_i$$

Because I normalize the climate policy risk beta by the cross-sectional standard deviation of the beta estimates ($\sigma(\beta_{i,OilPrice})$), the coefficient δ_1 can be interpreted as the percent change in cumulative abnormal returns due to a one-standard deviation increase in the climate policy risk beta resulting from the change in climate policy expectations from the event outcome.

Table 1 provides estimates for a number of recent climate policy-related events. The estimates are the cumulative abnormal return response one day and 4 weeks after the policy events for value- and equal-weighted sector portfolios with t-stats for the heteroskedastic-robust standard errors and the z-stats for the bootstrapped standard errors for the two-stage estimation to account for the inclusion of a generated regressor. Events in the table are those recent events where the impact on returns was statistically significant. Other events tested (such as other US presidential elections since 1996 and the Kyoto Protocol) provided null results.

In each case with significant estimates, the results are consistent with the model predictions. For events that increased the likelihood of future climate policy (the publication of the Clean Power Plan and date of the Paris Climate Agreement) there is a negative CAR response for sectors with higher climate policy exposure. For the events that decreased the likelihood of future climate policy action (the Trump Presidential elections, the announcement date of the US plan to withdraw from the Paris Climate Agreement, and the US Supreme Court ruling to put a hold on implementing the Clean Power Plan) there is a positive CAR response for sectors with higher climate policy exposure.

Focusing on a couple of key events, figures 1-4 provide the one-day and four-week cumulative abnormal return responses for the value- and equal-weighted sector portfolios, sorted by climate policy risk exposure beta, and the estimated climate policy risk exposure impact slope coefficient δ_1 (with the t-statistic and z-statistic for the estimate) for two events that I want to highlight briefly. The first event was the 2016 US presidential election. This event was a surprise shift down in the likelihood of future climate policy action given President Trump's campaign statements about supporting the coal and oil sectors, withdrawing from the Paris Climate Agreement, removing emissions regulations policies such as the Clean Power Plan, and doubting the impact of human behavior on the climate. After the election, for the value-weighted (equal-weighted) portfolios a one-standard deviation increase

Table 1: Event Study Analysis of Significant Climate Policy-Related Events

	1-Day, VW	4-Weeks, VW	1-Day, EW	4-Weeks, EW
Clean Power Plan	**−1.08**	**−0.77**	**−1.01**	**−2.08**
T-Stat: Robust SE	−4.62	−1.14	−2.64	−1.80
Z-Stat: Bootstrap SE	−4.56	−0.98	−2.63	−1.51
Paris Climate Accord	**−0.68**	**−0.39**	**−0.79**	**−1.03**
T-Stat: Robust SE	−2.49	−0.35	−5.30	−2.48
Z-Stat: Bootstrap SE	−2.49	−0.32	−4.50	−1.55
USSC Hold on CPP	**0.55**	**4.49**	**0.42**	**6.82**
T-Stat: Robust SE	2.38	2.17	0.48	8.84
Z-Stat: Bootstrap SE	1.89	2.12	0.46	6.96
Trump 2016 Election	**1.24**	**2.06**	**1.11**	**2.81**
T-Stat: Robust SE	3.05	1.82	1.96	1.99
Z-Stat: Bootstrap SE	2.47	1.57	1.93	1.90
US Paris Withdrawal	**0.71**	**0.30**	**0.71**	**−0.07**
T-Stat: Robust SE	4.25	0.43	5.52	−0.22
Z-Stat: Bootstrap SE	3.91	0.41	4.42	−0.16

Table 1 shows the relationship between the cumulative abnormal returns of sectors after a given climate policy related event and their standardized exposure to climate policy risk. The events are major recent events which had significant responses for cumulative abnormal. The regression specification is given by $R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,OilPrice}R_{OilPrice,t} + \varepsilon_{i,t}$. Cumulative abnormal returns are normalized to zero at the election date, and are estimated with respect to the value-weighted excess market return. Estimates are for value- and equal-weighted sector portfolio cumulative abnormal returns one day and 4 weeks after the election. I provide the t-state for the coefficient for heteroskedasticity-robust standard errors and the z-state for bootstrapped standard errors of the two-stage estimation procedure to account for the use of a generated regressor. See text for full definition of variables.

in climate policy risk beta would have resulted in a 1.24% (1.11%) increase in cumulative abnormal returns after one day and a 2.06% (2.81%) increase in cumulative abnormal return after four weeks. For the value-weighted portfolio estimates, both estimates are statistically significant using heteroskedasticity-robust standard errors (t-statistic), while only the one-day cumulative abnormal return response is statistically significant for the bootstrapped standard errors (z-statistic). For the equal-weighted portfolio estimates, both estimates are statistically significant using heteroskedasticity-robust standard errors (t-statistic) and bootstrapped standard errors (z-statistic).

The second event was the 2016 US Supreme Court decision to put a stay on the Clean Power Plan. This event was also a surprise decrease in the likelihood of future climate policy action given the lower courts had yet to rule on the constitutionality of the policy. After the court decision, for the value-weighted (equal-weighted) portfolios a one-standard deviation increase in climate policy risk

Figure 1: Election Impact on Returns by Climate Policy Exposure - Value-Weighted

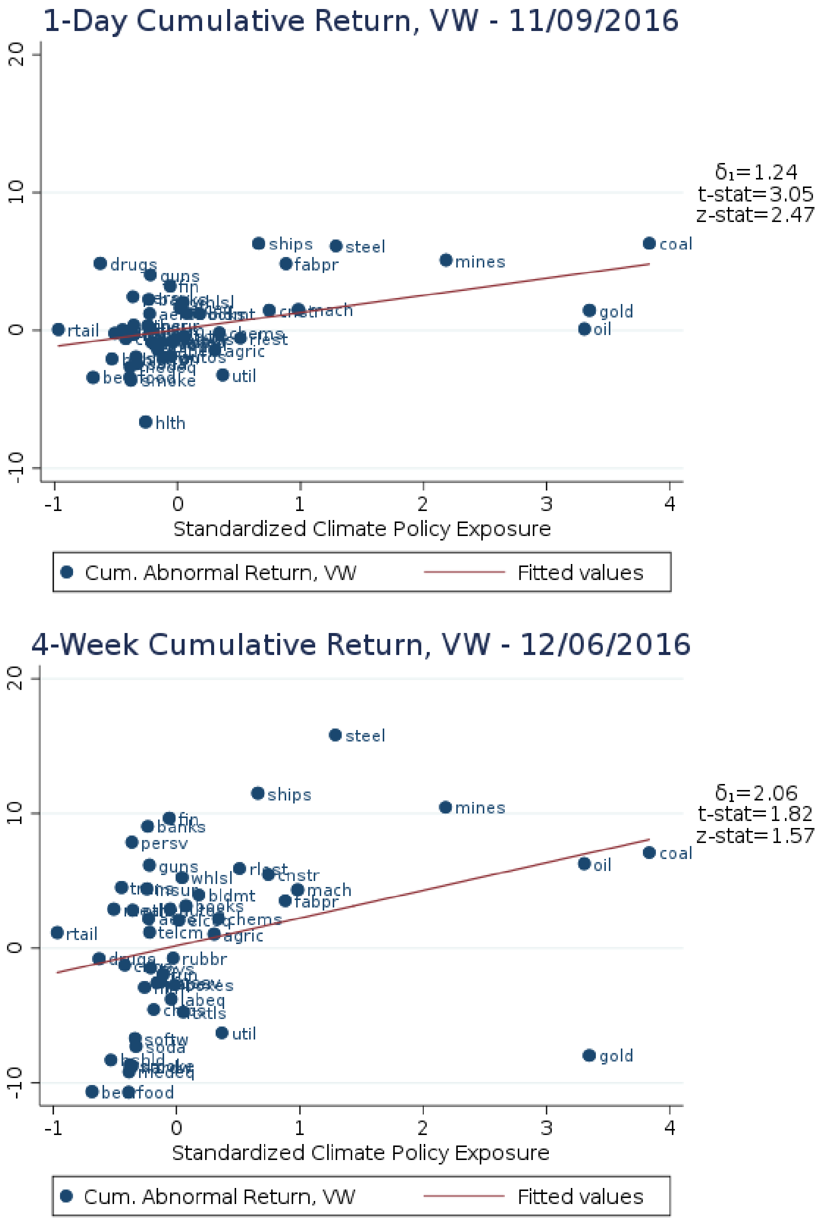


Figure 1 shows the relationship between the cumulative abnormal returns of sectors after the 2016 US presidential election and their standardized exposure to climate policy risk. The regression specification is given by $R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,OilPrice} R_{OilPrice,t} + \varepsilon_{i,t}$. Cumulative abnormal returns are normalized to zero at the election date, and are estimated with respect to the value-weighted excess market return. The top panel are estimates for cumulative abnormal returns one day after the election, and the bottom panel are estimates for cumulative abnormal returns four weeks after the election. See text for full definition of variables.

beta would have resulted in a 0.55% (0.42%) increase in cumulative abnormal returns after one day and a 4.49% (6.82%) increase in cumulative abnormal return after four weeks. For the value-weighted portfolio estimates, both estimates are statistically significant using heteroskedasticity-robust stan-

Figure 2: Election Impact on Returns by Climate Policy Exposure - Equal-Weighted

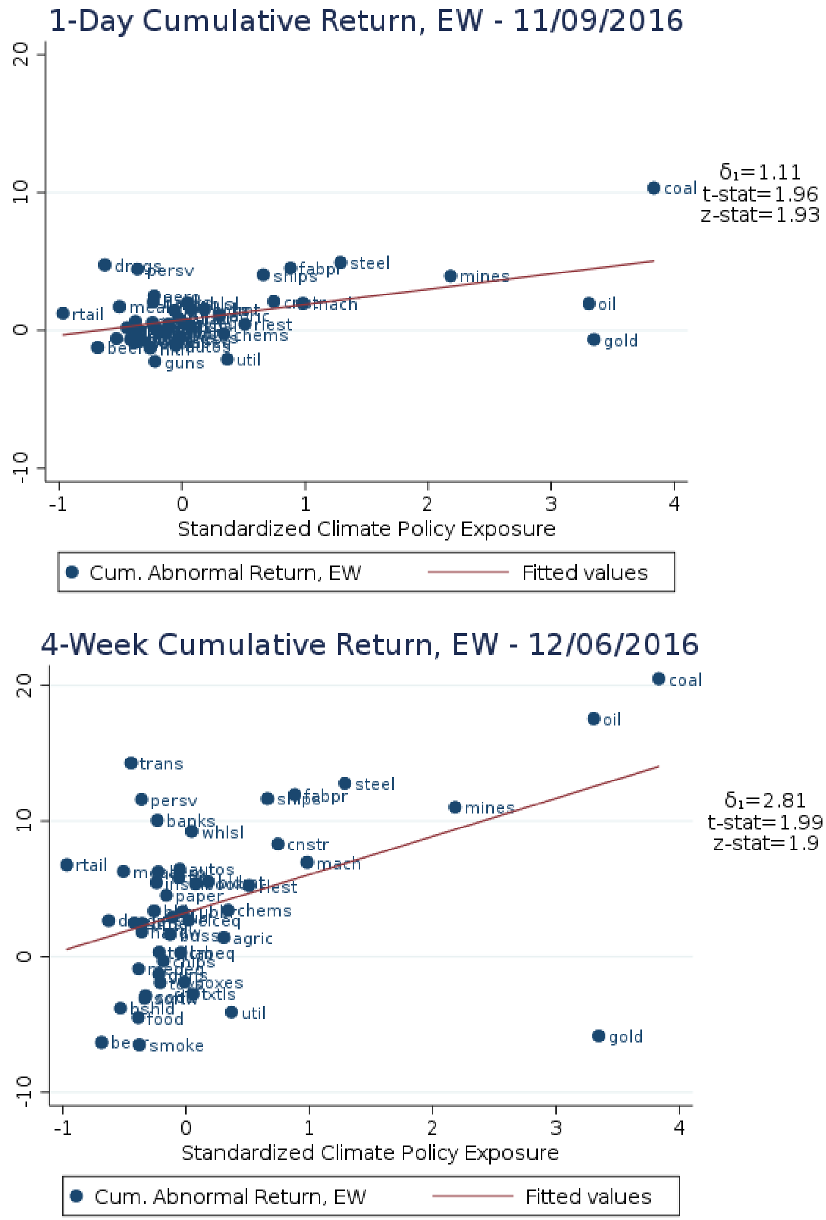


Figure 2 shows the relationship between the cumulative abnormal returns of sectors after the 2016 US presidential election and their standardized exposure to climate policy risk. The regression specification is given by $R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,OilPrice}R_{OilPrice,t} + \varepsilon_{i,t}$. Cumulative abnormal returns are normalized to zero at the election date, and are estimated with respect to the value-weighted excess market return. The top panel are estimates for cumulative abnormal returns one day after the election, and the bottom panel are estimates for cumulative abnormal returns four weeks after the election. See text for full definition of variables.

dard errors (t-statistic) and the bootstrapped standard errors (z-statistic). For the equal-weighted portfolio estimates, only the 4-week estimated impacts are statistically significant, for both the heteroskedasticity-robust standard errors (t-statistic) and bootstrapped standard errors (z-statistic).

Figure 3: Court Impact on Returns by Climate Policy Exposure - Value-Weighted

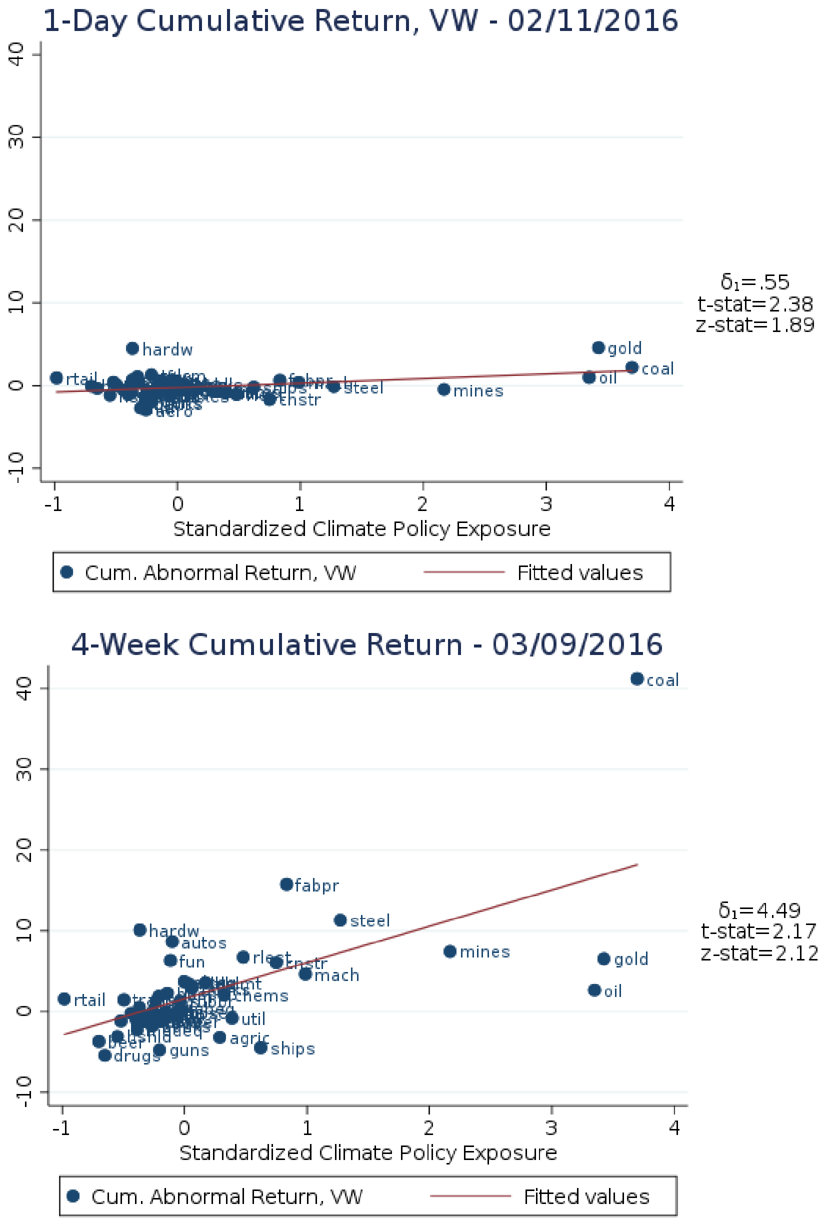


Figure 3 shows the relationship between the cumulative abnormal returns of sectors after the 2016 US Supreme Court decision to put a stay on the Clean Power Plan and their standardized exposure to climate policy risk. The regression specification is given by $R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,OilPrice}R_{OilPrice,t} + \varepsilon_{i,t}$. Cumulative abnormal returns are normalized to zero at the election date, and are estimated with respect to the value-weighted excess market return. The top panel are estimates for cumulative abnormal returns one day after the election, and the bottom panel are estimates for cumulative abnormal returns four weeks after the election. See text for full definition of variables.

I highlight these two examples as they help link the observed outcomes to the model. First, these two events are arguably two of the more unanticipated outcomes listed, meaning the estimates are more likely to capture the full impact of the event whereas the other events being more anticipated

Figure 4: Court Impact on Returns by Climate Policy Exposure - Equal-Weighted

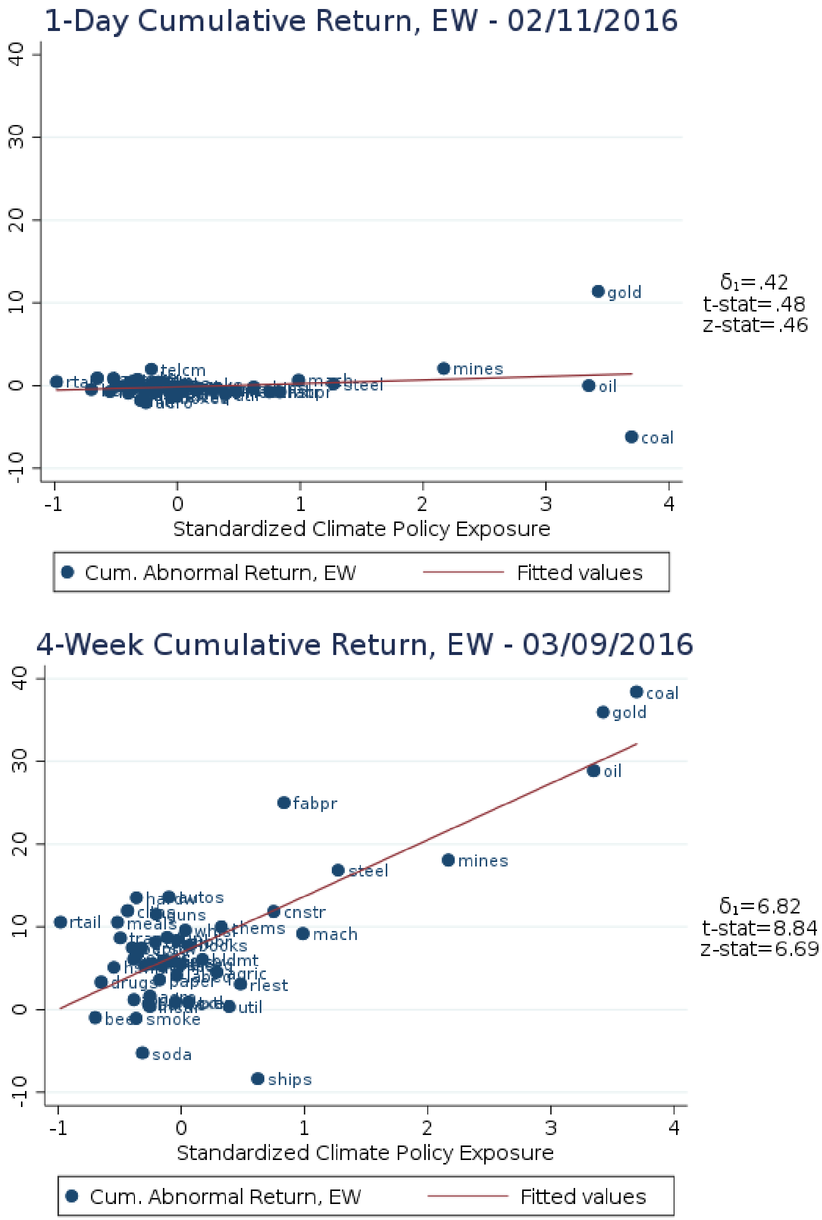


Figure 4 shows the relationship between the cumulative abnormal returns of sectors after the 2016 US Supreme Court decision to put a stay on the Clean Power Plan and their standardized exposure to climate policy risk. The regression specification is given by $R_{i,t} = \alpha_i + \beta_{i,Mkt}(R_{Mkt,t} - R_{f,t}) + \beta_{i,OilPrice}R_{OilPrice,t} + \varepsilon_{i,t}$. Cumulative abnormal returns are normalized to zero at the election date, and are estimated with respect to the value-weighted excess market return. The top panel are estimates for cumulative abnormal returns one day after the election, and the bottom panel are estimates for cumulative abnormal returns four weeks after the election. See text for full definition of variables.

mean that the estimates are likely lower bounds on the estimated event impacts. This corresponds with the fact that these events had the largest estimated impacts on cumulative returns. Second, these events also saw dynamic effects that played out for up to four weeks that were statistically significant.

While the use of the climate policy risk exposure measure based on oil prices and production is one way that helps link these outcomes to my specific model, the dynamic responses, corresponding to the dynamic responses related to production and pricing impacts my model predicts, provide further formal evidence consistent with my model mechanism in the direction of the impact and dynamics.

5.3 Climate Policy Events Index

I now extend the empirical analysis to the time series of climate policy related shocks. To identify the impact of climate policy shocks to oil production and oil sector returns, I first estimate reduced-form regressions focused on the link between changes in the probability of climate policy occurring, as measured by climate- and climate-policy-related events, and oil production decisions, oil sector returns for US firms, and oil spot price returns. The climate policy shocks measure is labeled as $ClimPol$, the index variable tracking different climate related events discussed previously. For example, events in $ClimPol$ include the establishment of the Paris Accord in 2015, as well as the election of Donald Trump as the President of the United States in 2016. The Paris Accord is considered a positive shock to the arrival rate of a significant climate policy action and so a positive one in the index and the election of Trump is considered a negative shock and so a negative one in the index. I identify these events at a daily level, and then aggregate them up to monthly values for my analysis.

The goal of this exercise is to identify whether events related to changes in the likelihood of future climate policy action lead to changes in production and prices consistent with the model predictions. The model predicts that a positive shock to the arrival rate should cause an increase in oil production and negative oil firm returns and oil price returns, whereas a negative shock to the arrival rate should lead to a decrease in oil production and increase in oil firm returns and oil price returns.

The reduced-form regression approach provides a estimate of how climate policy driven demand shocks influence economic and financial outcomes. To determine whether the empirical outcomes from this simple analysis are consistent with the model, I focus on the signs and statistical significance of the estimates, and compare those with the qualitative results of the model. Furthermore, I will estimate each regression on the full time sample (1973-2017) and on a shorter, more recent subsample (1996-2017). The recent sub-sample I refer to as the policy-relevant sample. I choose 1996 as the starting year for this sample as it is near the time when major climate policy begins to take place, such as the Kyoto Protocol, which was an early global climate agreement similar to the recent Paris Climate Accord. The model would predict that impacts estimated in the policy relevant subsample should be higher as temperature has increased and the likelihood of climate policy occurring is higher.

5.3.1 Oil Production

I begin by focusing on the impact of climate policy on oil production. To estimate the effect of climate policy shocks, I estimate the following regression:

$$Y_t = \alpha + \beta_Y Y_{t-1} + \phi_{ClimPol} ClimPol_t + \epsilon_t$$

where Y_t is crude oil production, Y_{t-1} is the one-period lag of crude oil production, and $ClimPol$ is the index for the climate events mentioned above. I exploit the time series and panel dimensions of the data by estimating this regression using information from the changes in the dependent variable across time for different regions of interest. Tables 2 and 3 show the results for oil production across four different regions using the full time sample (1973-2017), and the bottom table shows the results for oil production across four different regions using the more recent, policy-focused time sample (1996-2017).

Table 2: Climate Policy Impact on Oil Production (1973-2017)

	OPEC	US	Non-OPEC	World
ClimPol	-0.022	0.026	0.099	0.069
S.E.	(0.034)	(0.063)	(0.012)	(0.072)
# Obs.	536	536	536	536
R^2	0.995	0.979	0.991	0.988

Table 3: Climate Policy Impact on Oil Production (1996-2017)

	OPEC	US	Non-OPEC	World
ClimPol	0.035	0.041	0.141	0.176
S.E.	(0.055)	(0.015)	(0.047)	(0.074)
# Obs.	260	260	260	260
R^2	0.980	0.972	0.988	0.987

Tables 2 and 3 show the impact of climate policy events as measured by the *ClimPol* index on oil production for the Non-OPEC, OPEC, US, and World regions. The top table are estimates using the full time sample of data (1973-2017), and the bottom table are estimates using the policy-relevant time subsample (1996-2017). The regression specification is given by $Y_t = \alpha + \beta_Y Y_{t-1} + \phi_{ClimPol} ClimPol_t + \epsilon_t$. I omit the constant and lag variable coefficients from the table. See text for full definition of variables.

Controlling for the lag value, meant to capture relevant market conditions and current market effects or trends, oil production increases for the US, non-OPEC countries, and globally for an event that increases the likelihood of climate related policy. The effect is larger and more statistically significant in the recent policy-focused time period estimates. Climate policy events have essentially no impact on the production of the OPEC-countries region, though the estimate goes from negative to positive when comparing the full time sample to the policy-relevant time sample. These results are in line with two predictions of the model. First, they are consistent with the result of a run on oil occurring for an increased likelihood in climate policy occurring, at least for all regions that are not exclusively the OPEC region. Second, the increased magnitude for the most recent time period is consistent with the prediction that an increased likelihood of climate policy, tied to higher temperatures, should generate larger impacts on production.

5.3.2 Oil Sector and Oil Price Returns

Next, I test the model implication for the impact of climate policy on oil sector returns and oil price returns. To do this, I estimate whether shocks to climate policy predict negative changes to oil sector returns by estimating the following regression:

$$r_{i,t+1,t+h} = a_i + b_i X_t + c_i ClimPol_t + \varepsilon_{i,t}$$

where $r_{i,t+1,t+h}$ are 1-, 6-, 12-, 18-, and 24-month ahead cumulative returns, i is for cumulative excess returns for the oil sector portfolio or cumulative returns for the WTI oil price, $ClimPol_t$ is the climate policy dummy, and X_t includes non-contemporaneous controls for the market portfolio, economic productivity, spot price and sector returns, oil production innovations, and log OECD industrial production innovations. Tables 4 through 7 show the results across the five different cumulative return scenarios using the full time sample (1973-2017), and the results across the five different cumulative return scenarios using the more recent, policy-focused time sample (1996-2017).

After including controls to capture relevant market and macroeconomic conditions and trends, I find that shocks to climate policy have a negative impact on oil sector and oil price returns, as can be seen across the different horizons and time samples used for estimation. The coefficients are negative or insignificant for all horizons of cumulative returns. The effect is more negative and is statistically significant for the estimates based on the more recent time period sample at the 18- and 24-month horizons. The magnitude of the impact and predictability are also increasing with the horizon of the cumulative returns, as the coefficients become more negative and the R^2's become larger. These results are in line with three more predictions of the model. First, the results are consistent with the prediction that shocks to climate policy that lead to an oil run also depress oil sector firm values and oil prices. Second, the impact has a dynamic effect on outcomes as the negative returns persist

Table 4: Climate Policy Impact on Oil Sector Returns (1973-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol	0.000	0.005	−0.009	−0.035	−0.027
S.E.	(0.005)	(0.013)	(0.020)	(0.026)	(0.036)
# Obs.	534	529	523	517	511
R^2	0.004	0.016	0.014	0.028	0.013

Table 5: Climate Policy Impact on Oil Sector Returns (1996-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol	−0.002	−0.002	−0.034	−0.072	−0.085
S.E.	(0.007)	(0.015)	(0.024)	(0.032)	(0.038)
# Obs.	260	260	260	260	260
R^2	0.021	0.017	0.016	0.045	0.041

Tables 4 and 5 show the impact of climate policy events as measured by the *ClimPol* index on returns for the value-weighted US Oil sector portfolio. The regression specification is given by $r_{i,t+1,t+h} = a_i + b_i X_t + c_i ClimPol_t + \varepsilon_{i,t}$. $r_{i,t+1,t+h}$ is the k-month cumulative return for the value-weighted US Oil sector portfolio. X_t is a vector of control variables that includes the lagged values for the value-weighted market portfolio return, the value-weighted oil sector portfolio return, lagged oil production innovations, lagged oil spot price returns, and lagged real economic activity innovations. The top panel are estimates using the full time sample of data (1973-2017), and the bottom panel are estimates using the policy-relevant time subsample (1996-2017). I omit the constant and control coefficients from the table. See text for full definition of variables.

and increase in magnitude over the longer cumulative return horizons explored. Finally, as was seen with oil production, the increased magnitude over the most recent time period as compared to the full time period estimates is consistent with an increased impact of climate policy as temperature increases and the likelihood of significant climate policy occurring increases.

5.3.3 Climate Policy*Temperature Interaction Estimates

To strengthen the validity of the climate policy index analysis and further connect the estimated results to the model, I augment these regressions by using a climate policy index and temperature interaction term. The model specifies that the likelihood of climate policy is tied to increases in temperature, and therefore increases in temperature should amplify the impact of climate policy risk. The use of the climate policy index interacted with temperature directly tests this link, while also still testing the impact that policy and climate have on oil production, oil sector returns, and oil

Table 6: Climate Policy Impact on Oil Price Returns (1973-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol	-0.002	0.042	0.050	0.018	0.017
S.E.	(0.008)	(0.026)	(0.042)	(0.045)	(0.047)
# Obs.	534	529	523	517	511
R^2	0.045	0.021	0.022	0.016	0.021

Table 7: Climate Policy Impact on Oil Price Returns (1996-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol	-0.004	0.021	-0.001	-0.076	-0.099
S.E.	(0.011)	(0.033)	(0.045)	(0.048)	(0.050)
# Obs.	260	260	260	260	260
R^2	0.013	0.020	0.029	0.043	0.047

Tables 6 and 7 show the impact of climate policy events as measured by the *ClimPol* index on returns for the WTI spot price of oil. The regression specification is given by $r_{i,t+1,t+h} = a_i + b_i ClimPol_t + c_i X_t + \varepsilon_{i,t}$. $r_{i,t+1,t+h}$ is the k-month cumulative return for the WTI spot price of oil. X_t is a vector of control variables that includes the lagged values for the value-weighted market portfolio return, the value-weighted oil sector portfolio return, lagged oil production innovations, lagged oil spot price returns, and lagged real economic activity innovations. The top panel are estimates using the full time sample of data (1973-2017), and the bottom panel are estimates using the policy-relevant time subsample (1996-2017). I omit the constant and control coefficients from the table. See text for full definition of variables.

price returns. Though I have previously proposed that the increased effects seen when comparing the subsample of recent, policy relevant data are related to increases in temperature and increases in policy concern, these interaction estimates help verify whether or not this is the case.

I continue to include the same lag values and controls as before in the regression equations. The key difference is that the dependent variable of interest is now an interaction variable of the climate policy index and the one year moving average of global mean temperature, $ClimPol * Temp$. More precisely, the regression specifications for the production, oil return, and oil price returns estimates are respectively given by

$$
\begin{aligned}
Y_t &= \alpha + \beta_Y Y_{t-1} + \phi_{ClimPol*Temp} ClimPol_t * Temp_t + \epsilon_t \\
r^e_{t+1,t+h} &= a + bX_t + c_{ClimPol*Temp} ClimPol_t * Temp_t + \varepsilon_t \\
r^{spot}_{t+1,t+h} &= a + bX_t + c_{ClimPol*Temp} ClimPol_t * Temp_t + \varepsilon_t
\end{aligned}
$$

Table 8: Climate Policy Impact on Oil Production (1973-2017)

	OPEC	US	Non-OPEC	World
ClimPol*Temp	0.061	0.053	0.200	0.236
S.E.	(0.095)	(0.023)	(0.070)	(0.117)
# Obs.	536	536	536	536
R^2	0.995	0.979	0.991	0.988

Table 9: Climate Policy Impact on Oil Production (1996-2017)

	OPEC	US	Non-OPEC	World
ClimPol*Temp	0.035	0.062	0.210	0.264
S.E.	(0.055)	(0.024)	(0.075)	(0.116)
# Obs.	260	260	260	260
R^2	0.980	0.973	0.988	0.987

Tables 8 and 9 show the impact of climate policy events as measured by the *ClimPol* index on oil production for the Non-OPEC, OPEC, US, and World regions. The top table are estimates using the full time sample of data (1973-2017), and the bottom table are estimates using the policy-relevant time subsample (1996-2017). The regression specification is given by $Y_t = \alpha + \beta_Y Y_{t-1} + \phi_{ClimPol*Temp} ClimPol_t * Temp_t + \epsilon_t$. I omit the constant and lag variable coefficients from the table. See text for full definition of variables.

Tables 8-13 provide the estimated coefficients and I outline briefly here the estimation results. For oil production, an increase in the interaction term leads generally to an increase in oil production as it did before. Also similar to before, the impacts are increasing in magnitude and significance for the more recent subsample of data. However, the interaction term for climate policy and temperature is now positive and statistically significant for the US, Non-OPEC, and World regions in the 1973-2017 sample of date. Thus we see an enhanced effect by accounting for temperature within the impact of the climate policy risk, which is in line with the models prediction of increased effects from increased temperature and the proposed justification for increased effects seen in the more recent, policy-relevant and higher temperature subsample of data.

The estimated effects of the interaction term for oil sector and oil price returns also line up with the previous results. An increase to the interaction term has a negative impact on oil sector and oil price returns. The effect is more negative and is statistically significant for the estimates based on the more recent time period sample at the 18- and 24-month horizons, and the magnitude of the impact and predictability are also increasing with the horizon of the cumulative returns. However, again with

Table 10: Climate Policy Impact on Oil Sector Returns (1973-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol*Temp	-0.003	-0.005	-0.058	-0.119	-0.131
S.E.	(0.010)	(0.023)	(0.037)	(0.048)	(0.060)
# Obs.	534	529	523	517	511
R^2	0.004	0.016	0.019	0.037	0.023

Table 11: Climate Policy Impact on Oil Sector Returns (1996-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol*Temp	-0.003	-0.015	-0.077	-0.153	-0.177
S.E.	(0.011)	(0.025)	(0.040)	(0.051)	(0.063)
# Obs.	260	260	260	260	260
R^2	0.021	0.019	0.023	0.059	0.052

Tables 10 and 11 show the impact of climate policy events as measured by the $ClimPol$ index on returns for the value-weighted US Oil sector portfolio. The regression specification is given by $r^e_{t+1,t+h} = a + bX_t + c_{ClimPol*Temp}ClimPol_t * Temp_t + \varepsilon_t$. $r_{i,t+1,t+h}$ is the k-month cumulative return for the value-weighted US Oil sector portfolio. X_t is a vector of control variables that includes the lagged values for the value-weighted market portfolio return, the value-weighted oil sector portfolio return, lagged oil production innovations, lagged oil spot price returns, and lagged real economic activity innovations. The top panel are estimates using the full time sample of data (1973-2017), and the bottom panel are estimates using the policy-relevant time subsample (1996-2017). I omit the constant and control coefficients from the table. See text for full definition of variables.

these estimates there are key main differences from the previous results. First, the estimated impact of the interaction term on the oil sector returns is now monotonically increasing in magnitude and statistical significance, and are statistically significant for the 18- and 24-month cumulative return horizons for the 1973-2017 data sample estimates. And though the impact on oil price returns is not statistically significant for 1973-2017 data sample estimates, the impacts are now all negative and monotonically increasing in magnitude and significance for longer horizons. This results again validates that there is an enhanced effect by accounting for temperature within the impact of the climate policy risk as the model implies, as now even the full sample of data estimates are significant, and further confirms the impacts on oil production and prices estimated in the previous regressions that are consistent with the model implications for climate policy risk.

Table 12: Climate Policy Impact on Oil Price Returns (1973-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol*Temp	-0.009	0.040	0.010	-0.071	-0.083
S.E.	(0.017)	(0.052)	(0.075)	(0.081)	(0.088)
# Obs.	534	529	523	517	511
R^2	0.051	0.018	0.018	0.018	0.023

Table 13: Climate Policy Impact on Oil Price Returns (1996-2017)

	$r_{oil,t+1}$	$r_{oil,t+6}$	$r_{oil,t+12}$	$r_{oil,t+18}$	$r_{oil,t+24}$
ClimPol*Temp	-0.009	0.028	-0.013	-0.145	-0.176
S.E.	(0.017)	(0.028)	(0.078)	(0.079)	(0.081)
# Obs.	260	260	260	260	260
R^2	0.017	0.026	0.030	0.046	0.048

Tables 12 and 13 show the impact of climate policy events as measured by the *ClimPol* index on returns for the WTI spot price of oil. The regression specification is given by $r^{spot}_{t+1,t+h} = a + bX_t + c_{ClimPol*Temp} ClimPol_t * Temp_t + \varepsilon_t$ is the k-month cumulative return for the WTI spot price of oil. X_t is a vector of control variables that includes the lagged values for the value-weighted market portfolio return, the value-weighted oil sector portfolio return, lagged oil production innovations, lagged oil spot price returns, and lagged real economic activity innovations. The top panel are estimates using the full time sample of data (1973-2017), and the bottom panel are estimates using the policy-relevant time subsample (1996-2017). I omit the constant and control coefficients from the table. See text for full definition of variables.

5.4 Vector Autoregression Analysis

To further the empirical estimation of the dynamic effects of the risk of climate policy shocks on oil sector quantity and price outcomes, I estimate a structural vector autoregression (VAR) for the global oil market. Augmenting the global oil market VARs proposed and used by Kilian and Park (2009), Baumeister and Hamilton (2017), and others, I estimate:

$$y_t = \nu + \sum_j A_j y_{t-j} + u_t$$

where the vector of endogenous state variable vector y_t is defined by

$$y_t = [ClimPol_t, \Delta prod_t, rea_t, \Delta p^{oil}_t]'$$

$ClimPol$ is the climate policy index measure I mentioned previously. $\Delta prod$ is the percent change in global oil production available from the EIA. REA is a measure of real economic activity given by innovations in the log OECD industrial production index suggested in recent work by James Hamilton. r_t^{mkt} is log differences in the real West Texas Intermediate (WTI) monthly closing price for crude oil.

I use a Cholesky decomposition of the estimated variance-covariance matrix for identification of the structural shocks. This identification strategy imposes a recursive interpretation of the impact of the shocks. The general representation and interpretation of this identification is as follows:

$$u_t = B \left[\epsilon_{\text{climate policy}}, \quad \epsilon_{\text{oil supply}}, \quad \epsilon_{\text{aggregate demand}}, \quad \epsilon_{\text{oil-specific demand}} \right]'$$

where B is the lower triangular matrix derived from the Cholesky decomposition of the estimated variance covariance matrix $\hat{\Sigma}$, i.e., $BB' = E_t[u_t' u_t] = \hat{\Sigma}$. I outline the specific interpretation and identification of each shock in what follows.

$ClimPol_t$, the focus of this exercise, captures changes in the likelihood of future climate policy that restricts oil use, that is changes in λ_t from the model. Although long-run temperature directly maps to the likelihood of significant climate policy action in the model, in practice this link is less precise. Figure 9 in the appendix, which shows the US temperature anomaly time series over the annual $ClimPol$ index measure, demonstrates this relationship. The time series for the two variables are positively correlated, but the correlation is obviously not one. For this reason, I use the more direct measure of $ClimPol$ to capture changes in the likelihood of future climate policy that restricts the use of oil.

This ordering assumes the likelihood of significant climate policy is contemporaneously predetermined with respect to oil sector shocks and the oil sector is contemporaneously influenced by shifts to the likelihood of future climate policy. This assumption is intuitive and maintains consistency with the model in that the likelihood of significant climate policy responds only with a lag to oil sector shocks as a result of emissions from oil production impacting the climate policy arrival rate. Recent climate science work by Matthews et al. (2009), Ricke and Caldeira (2014), and Zickfeld and Herrington (2015) has shown that impacts on temperature from carbon emissions can take many years or even decades to fully realize, which further validates this restriction. The order for the remaining variables follows the setting of Kilian (2009). Thus, this interpretation of the structure fits this setting as well: 1.) a vertical short-run supply curve and downward sloping demand curve; and 2.) oil demand and supply shocks imply immediate changes in the real oil price.

To further highlight the consistency of the VAR model with the theoretical model, consider the following. The supply shocks and real aggregate demand shocks can be interpreted as the shocks to oil reserves and shocks to capital in the model. As in the model, supply and policy shocks are important determinants of oil supply or production, along with temperature shocks, which are correlated with climate policy likelihood. Combined with capital shocks, and the preferences of agents, these shocks then determine oil prices. These effects together then pin down asset prices in the model. The link

Figure 5: ClimPol Shock IRF - 1973-2017 vs. 1996-2017 Time Samples

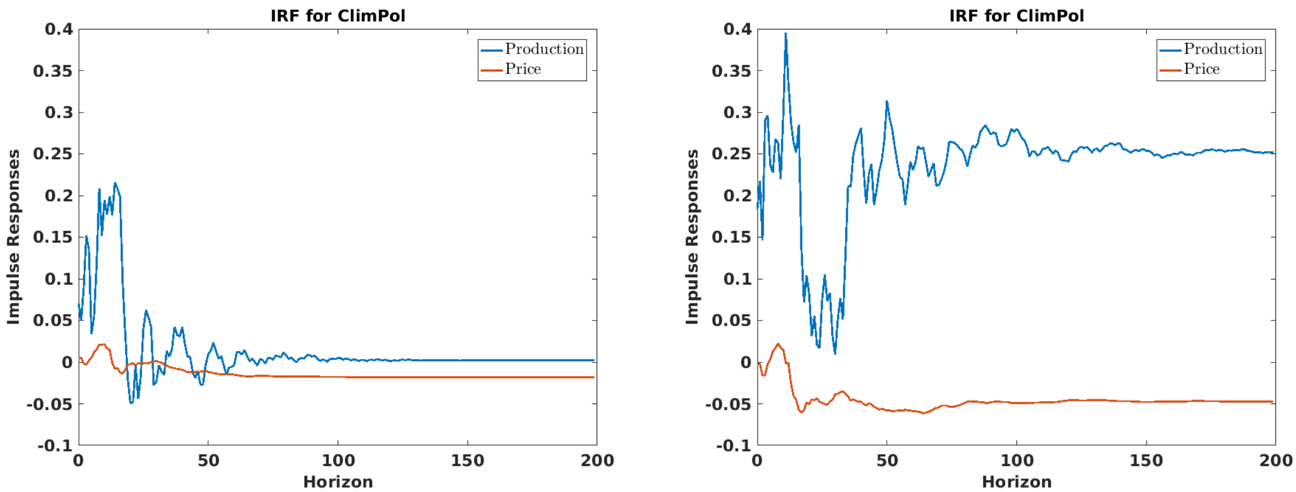


Figure 5 shows estimated impulse response functions for global oil production and the WTI spot price of oil for a shock to the *ClimPol* index. The left panel are estimates using the full time sample of data (1973-2017), and the right panel are estimates using the policy-relevant time subsample (1996-2017). See text for the full VAR specification used and definition of variables. The VAR is estimated using 24 lags.

between the climate and the economy in the model comes through how emissions from oil produced impact temperature and then how temperature influences climate damages and the climate policy likelihood, which feed into the determination of the economic and financial outcomes of interest. Thus, the variables included in the VAR and the ordering of the variables in the recursive decomposition is consistent with the theoretical model framework.

From the VAR estimates and the recursive identification structure, I derive impulse response functions (IRFs), or the cumulative responses to a given structural variable shock, which are the results I use to examine the validity of the model mechanism. To understand how the IRFs generated from the VAR estimation can help validate the model, consider first the expected IRFs from alternative model settings. In the setting without any anticipated risk of a policy shock, a shift in climate policy corresponding to an increased carbon tax would lead to a decrease in oil production and an increase in the spot price of oil, and no change in outcomes if the event did not directly change the carbon tax. In the policy setting where the arrival rate is climate-independent and constant, a shock to the climate policy variable should lead to an increase in oil production and decrease in the spot price of oil, but this effect would not persist because of the lack of temperature dependence and the prevailing Hotelling-type forces. However, in the dynamic climate policy risk setting with a climate-dependent arrival rate, a shock to the likelihood of significant climate policy occurring leads to an increase in oil production and a decrease in the oil spot price. Furthermore, the impacts of a shock to the likelihood of significant climate policy occurring should produce impacts that are persistent and potentially increasing in magnitude dynamically for these outcomes, two defining features of what I have termed

Figure 6: ClimPol Shock IRF - 1996-2017 Time Sample w/ C.I.s

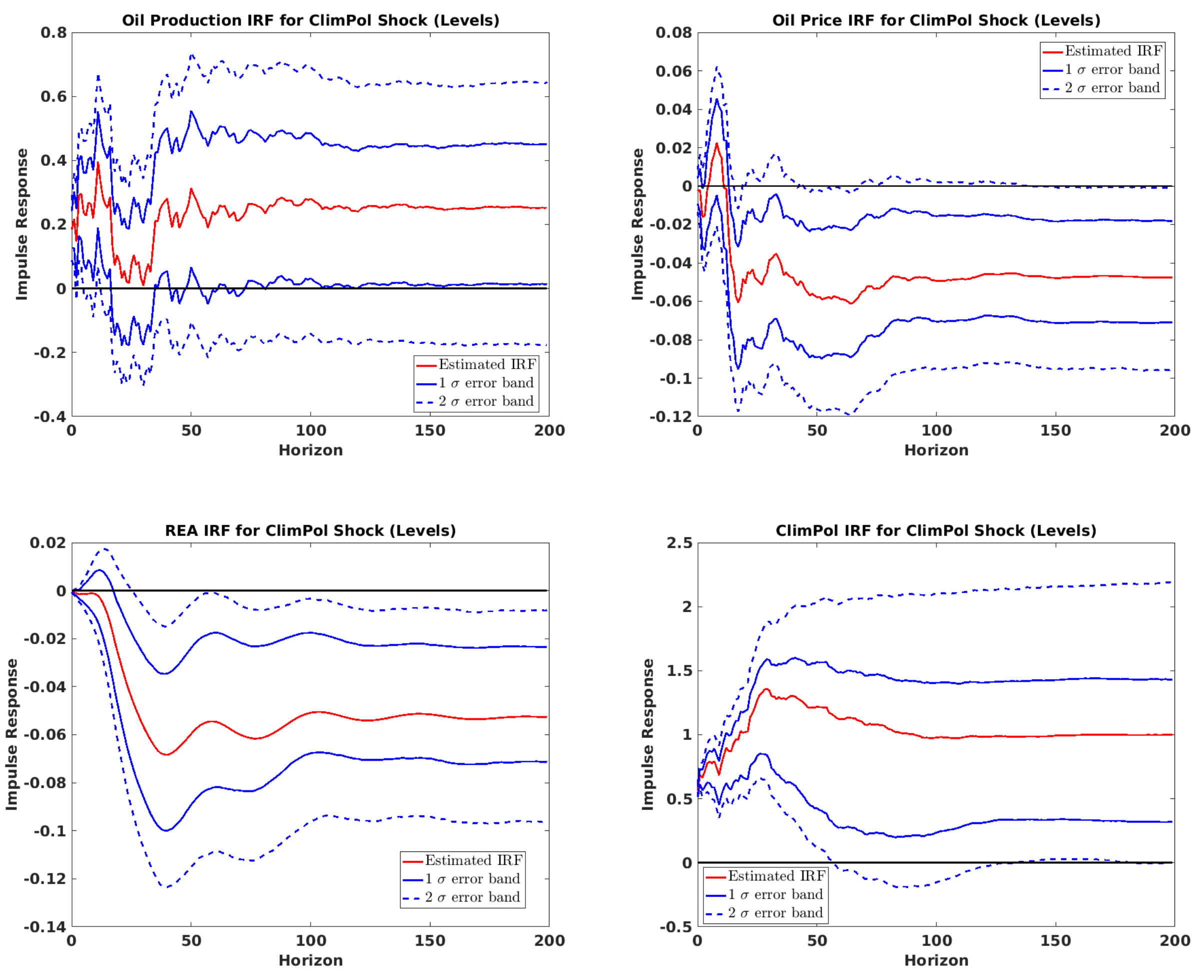


Figure 6 shows the estimated impulse response functions for global oil production, the WTI spot price of oil, real economic activity, and the *ClimPol* climate policy index measure for a shock to the likelihood of climate policy measured by the *ClimPol* index. The red line is the estimated IRF, the solid blue lines represent the on-standard deviation error bands, and the blue dashed lines represent the two standard deviation error bands. Error bands are estimated using boostrapping. The estimates use the policy-relevant time subsample (1996-2017). See text for the full VAR specification used and definition of variables. The VAR is estimated using 24 lags.

a run on oil. Therefore, one can "test" the validity of the model proposed in this paper by looking at the sign and dynamics of the IRFs for oil production and oil spot prices resulting from a shock to the likelihood of significant climate policy occurring.

Figure 5 shows the cumulative level impulse response functions of oil production and oil prices for a shock to the likelihood of significant climate policy occurring. The left plot is for the VAR estimated using the full time sample (1973-2017) and the right plot for the VAR estimated using the more recent, policy-focused time sample (1996-2017). Figure 6 shows the individual impulse response functions with bootstrapped standard errors for the policy focused time sample (1996-2017), where the solid blue lines are for the one-standard deviation confidence interval, the dashed blue lines are for the two-standard deviation confidence interval, and the red line is for the estimated IRF.

The impulse response functions further confirm the results seen previously in the reduced-form estimates. For the impulse response functions generated from the full time sample VAR estimates, the responses are substantially muted and quite close to zero. However, focusing on the impulse responses generated from the VAR estimates using the policy-focused time sample, we see results that correspond to the model predictions. A shock to climate policy leads to an increase in oil production and a decrease in the spot price of oil. Moreover, these impacts grow in magnitude and persist over time. Though only the impact on the spot price of oil is statistically significant for the two variables of interest, as seen in Figure 6, the direction and dynamics of these results taken together are consistent with the key predictions of the model and the other empirical exercises.

5.5 Return-Weighted Climate Policy Index

Finally, I provide an extension of the VAR analysis which uses return-weighted climate policy index measures. The purpose of this extension is to account for the magnitude and dynamics of the effects of the climate policy events on the oil price and production of oil by incorporating the forward-looking information of relevant asset price returns into my climate policy index. This extension ties the asset pricing and production implications into a single analysis to provide a more complete test of the model implications. The results of this extension are not only consistent with the results given above, but in fact identify larger and more significant impacts by exploiting the informational value of asset prices and accounting for policy magnitudes and dynamic implications.

A natural asset price measure of the magnitude of the impact of climate policy events follows from the event study analysis done previously. Each event in the event study analysis required estimating a climate policy risk exposure measure for the cross-section of sector portfolios. These climate policy risk exposure measures provide a weighting scheme for a type of factor-mimicking portfolio that captures not only the realization of climate policy events, but the also the magnitude of the impacts of these events. Furthermore, this method will also capture the dynamic implications of the events through the return response as we saw with the event study analysis. Thus this extension should allow me to determine not only the effect of a climate policy event realization, but also the magnitude and dynamics of the effects of the climate policy events on the oil price and production of oil.

I implement this method as follows. First, I focus on a particular event to estimate the climate policy risk exposures from exposure to oil price innovations for each sector. Given these estimate exposure measure, I rescale the exposures to sum to one to provide a portfolio weighting scheme. These event-study estimated weights are then used to calculate a factor-mimicking portfolio from the sector portfolios. I focus on the equal weighted portfolios for simplicity. With this factor-mimicking portfolio, I can implement the analysis in two ways. The first is to incorporate the factor mimicking portfolio returns directly into the VAR in place of the climate policy event index as a continuous measure of responses to climate policy events. The second is to use an interaction term of the climate policy event index dummy used originally with the factor-mimicking portfolio that I have constructed. The interaction term will highlight directly the events as given by the climate policy event index, while also incorporating magnitudes through the return measure. This analysis ties the asset pricing and production implications into a single analysis to test the full model implications. I will first focus on the weights generated from the Supreme Court hold on the Clean Power Plan, and for robustness will test portfolio weightings based on different dynamic response times and different events.

Figure 7 shows the cumulative level impulse response functions of oil production and oil prices for a shock to the likelihood of significant climate policy occurring using these alternative climate policy indices. All the plots are for the VAR estimated using the more recent, policy-focused time sample (1996-2017). Each plot include includes the the estimated IRF (red line), the one-standard deviation bootstrapped confidence interval (solid blue line), and the two-standard deviation bootstrapped confidence interval (dashed blue line).

The top two plots show the results for the factor mimicking portfolio returns used as the climate policy risk likelihood measure. Here the results are quite similar to the original ClimPol IRFs. A shock to climate policy leads to an increase in oil production and a decrease in the spot price of oil. Moreover, these impacts grow in magnitude and persist over time. As before, the direction and dynamics of these results are consistent with the key predictions of the model. While again only the impact on the spot price of oil is statistically significant, the significance is even greater in this setting.

The bottom two plots show the results for the factor mimicking portfolio returns interacted with the original ClimPol index used as the climate policy risk likelihood measure. Again, a shock to climate policy leads to an increase in oil production and a decrease in the spot price of oil, and these impacts grow in magnitude and persist over time. There are a number of key differences in this setting. First, the magnitude of the IRFs is greater for the impact on both oil prices and oil production. Second, the impact on the spot price of oil and oil production is statistically significant. This setting shows that previous results that do not account for magnitude likely understate the measured impact from before, as well as show the value of using asset prices to study the impact of climate policy risk.

Figure 7: ClimPol Shock IRF - 1996-2017 Time Sample w/ C.I.s

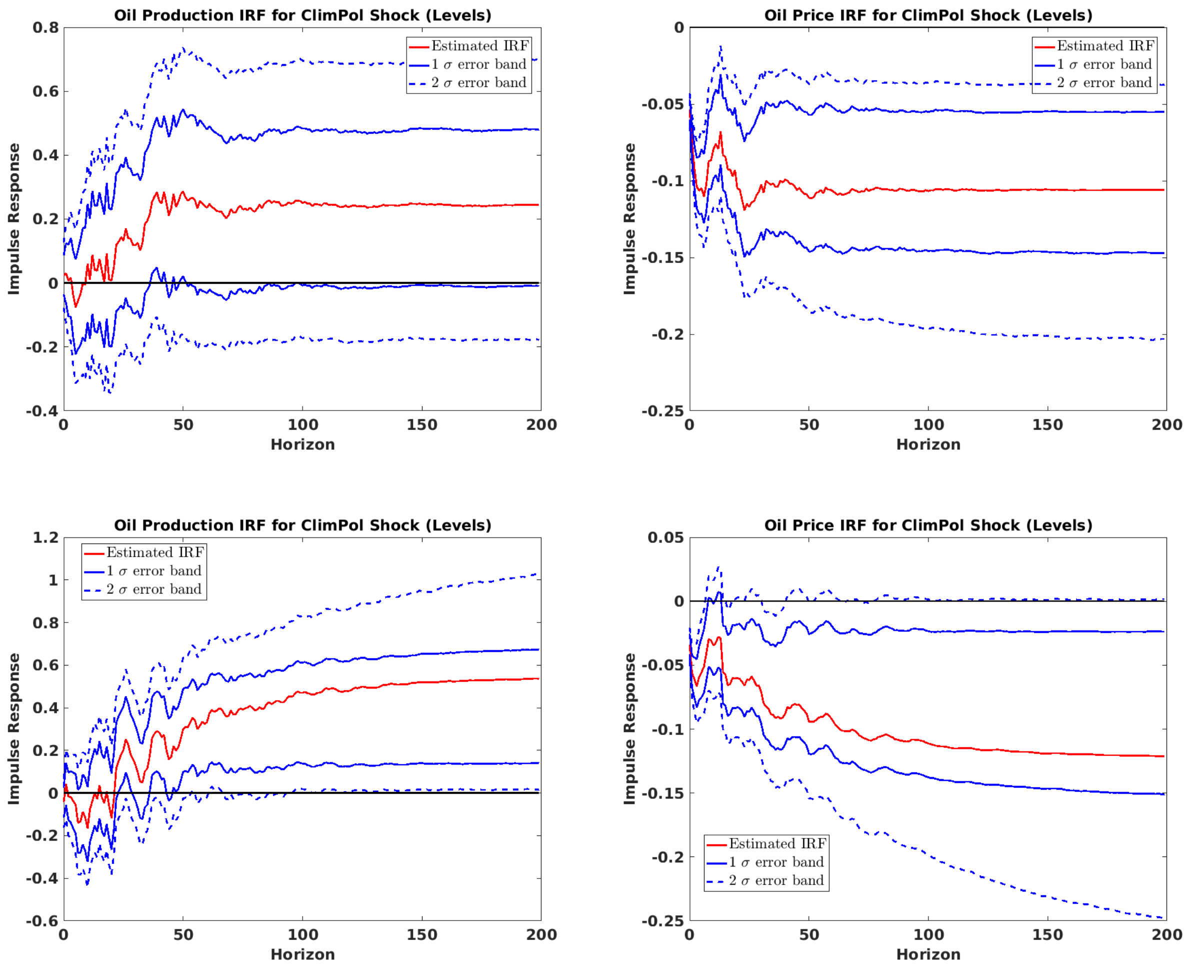


Figure 7 shows the estimated impulse response functions for global oil production, the WTI spot price of oil, real economic activity, and variations of the *ClimPol* climate policy index measure for a shock to the likelihood of climate policy. The first variation uses the returns of the factor mimicking portfolio created from sector portfolios weighted by their normalized climate policy risk exposure estimated value. The second variation uses the returns for this same factor mimicking portfolio, but is interacted with the original ClimPol index. The red line is the estimated IRF, the solid blue lines represent the on-standard deviation error bands, and the blue dashed lines represent the two standard deviation error bands. Error bands are estimated using boostrapping. The estimates use the policy-relevant time subsample (1996-2017). See text for the full VAR specification used and definition of variables. The VAR is estimated using 24 lags.

6 Conclusions

In this paper I have empirically estimated the impact of climate policy risk on real and financial outcomes. The empirical analysis examines the predicted effects of the risk of future climate policy action that could strand fossils fuels that come from a simplified version of the model developed by Barnett (2019). These predictions are that an increased likelihood of future climate policy regulation leads to a dynamic run-up in oil production, a dynamically decreasing spot price of oil due to the increasing supply generated by the run on oil, and significant decreases in the value of oil firms, or firms with high exposure to climate policy risk, because of the decreased expected level of usable oil reserves and the decreased expected value of those usable oil reserves.

I test these model predictions through variety of empirical estimation techniques. I first do an event-study analysis of climate policy events that shift the likelihood of future climate policy actions taking place. I estimate the effect of shifts in the likelihood of future climate policy due to climate policy events by regressing sectors' cumulative abnormal returns after the event on their exposure to climate policy risk, proxied for by exposure to oil price shocks as motivated by the model prediction. I find sectors with the highest climate policy risk exposure experienced the largest increases in cumulative abnormal returns for events that decreased the likelihood of future climate policy action and the largest decreases in cumulative abnormal returns for events that increased the likelihood of future climate policy actions, consistent with the model predictions.

I then construct a "climate policy" event index from realized climate policy, energy sector, and climate-related events to estimate the dynamic impact of changes in climate policy shocks. In estimated reduced-form regressions, I find that increases in the likelihood of major climate policy measured by my index lead to increased global and regional oil production. I also find that positive climate policy shocks lead to increasingly negative returns for the US oil sector and the spot price of oil. Finally, I estimate a structural VAR for the global oil market that includes the climate policy index, and calculate impulse response functions for a shock to climate policy. The results suggest that increases in the likelihood of significant climate change policy leads to long-term and permanent increases in crude oil production and a statistically significant decreases in the oil spot price, consistent with the dynamic predictions of my model. For each index-based empirical test, the statistical and economic significance are greater during the more recent, policy-focused time period (1996-2017) than for the entire available time sample (1973-2017), further validating the temperature dependence of outcomes implied by the model and the dynamic effect of climate policy risk the model predicts.

I leave for future work a number of interesting empirical tests related to my current analysis. In particular, examining the term structure implications of shocks to the likelihood of future climate policy action as observed oil options and oil futures is a particularly interesting area of continued work that would provide insight into the long-run implications of climate policy risk. Exploring the impact of climate policy risk at the firm and country level would provide valuable understanding of the cross-sectional differences in the impacts of this type of risk. Finally, focusing on alternative financial instruments, alternative measures of climate policy risk, and additional real outcomes would provide further depth into the implications of the climate policy risk I focus on here. Each of these would offer additional insight to help us understand the impacts of climate change and the dynamic risk associated with climate policy.

Appendix A Model Details and Derivations

A.1 Households

Households have recursive preferences of the Duffie-Epstein-Zin type, given by

$$h(C,V) \quad = \quad \rho(1-\xi)V(\log C - \frac{1}{1-\xi}\log((1-\xi)V))$$

where ρ is the subjective discount rate, ξ is risk aversion, V is the value function or continuation value, and C_t is consumption. These preferences allow for the separation of risk aversion and the elasticity of intertemporal substitution (EIS) and incorporate agents' concerns about the resolution of future uncertainty into the decision-making process. Given this preference structure, the household maximizes discounted lifetime utility subject to their budget constraint:

$$\begin{aligned} V &= \max_{C_t} E[\int_0^\infty \rho(1-\xi)V(\log C_t - \frac{1}{1-\xi}\log((1-\xi)V))dt] \\ \text{subject to} & \\ C_t &\leq \Pi_t + \mathcal{T}_t \end{aligned}$$

where Π_t are profits from the household-owned firms and $\mathcal{T}_t$ are taxes rebated to households.

A.2 Production

A.2.1 Final Output

The final output firm produces the consumption good using a Cobb-Douglas technology:

$$Y_t = AK_t^{1-\nu_t}O_t^{\nu_t}$$

where A is total factor productivity (TFP), K_t is capital, O_t is oil energy, and ν is the factor input share of oil. Climate policy governs the value of ν_t and I assume, for simplicity, there are only two possible values of ν_t, ν in the pre-policy state and 0 in the post-policy state. When $\nu_t = \nu$ it represents loose climate policy and a high demand for oil in final good production, and when $\nu_t = 0$ it represents strict climate policy where final good production can only be done without oil. The process for policy change is governed by a state-dependent arrival rate characterized in section A.3.

The final output sector is perfectly competitive, and so firms in this sector maximize discounted, expected lifetime profits by optimally choosing investment, labor, and energy inputs subject to state variable evolution, market clearing, and taking prices as given:

$$\begin{aligned} V_C &= \max_{O,I} E \int \pi_t(\tilde{Y}_t - P_{I,t}I_t - P_{O,t}O_t)ds \\ \text{subject to} & \\ dK_t &= K_t(\ln B + \delta_1 \ln I_t - \delta_2 \ln K_t)dt + \sigma_K K_t dB_K \end{aligned}$$

Note that $\tilde{Y}_t$, used in the firm problem above, is final output after accounting for climate change damages, which I explain in section A.3. The stochastic discount factor (SDF), π_t, provides the necessary discounting across time and states of nature in order to derive firm values, which I derive and elaborate on in section A.6.1. The evolution of the capital stock is subject to a specific case of the adjustment costs used by Jermann (1998) and others, highlighted in recent work by Anderson and Brock (2017), which are empirically indistinguishable from other common forms used in the literature for observable outcomes in the data and allows for tractability when solving the model.

A.2.2 Oil Input

The oil firm produces using the linear technology

$$O_t = N_t$$

where O_t is the oil used for final output production and N_t is oil extracted. Oil firms maximize discounted expected lifetime profits by choosing extraction subject to evolution of state variables and market clearing:

$$\begin{aligned} V_O &= \max_{N} E \int \pi_t(P_{O,t}N_t)ds \\ \text{subject to} & \\ dR_t &= (-N_t)dt + \sigma_R R_t dB_R \\ dT_t &= \varphi N_t dt + \sigma_T dB_T \end{aligned}$$

Again π_t is the SDF used for discounting firm profits. T_t is atmospheric temperature, discussed in section A.3. The evolution of reserves is determined by extraction of oil and shocks to supply. There are no explicit costs of extraction. However, because oil firms take into account the shadow value of holding reserves, this implicit cost limits extraction done at any given time. I assume a competitive oil sector so that oil firms take prices as given.

A.3 Climate and Climate Policy

Atmospheric temperature in excess of pre-industrial levels evolves as

$$dT_t = \varphi N_t dt + \sigma_T dB_T$$

where φ is the carbon-climate response (CCR) to emissions from oil. This climate process is a stochastic version of the relationship estimated by Matthews et al. (2009), Matthews et al. (2012), and MacDougall and Friedlingstein (2015). I use the "Matthews approximation" in place of more complex climate dynamics for tractability and because of the longer-run nature of the approximation that is designed for climate change fluctuations that I am focusing on in my analysis.

The damage function $D(T_t)$, which captures how climate change impacts economic outcomes, multiplicatively scales final good output. Furthermore, the damage function has the properties $D(T_t) \in [0,1] \forall T_t$, $D(0) = 1$, $D(\infty) = 0$, and $\frac{dD}{dT} < 0$. The functional forms for the damage function and consumable final output are given by

$$D(T_t) = exp(-\eta T_t) \quad \text{and} \quad \tilde{Y}_t = D(T_t) Y_t$$

Change in policy is modeled by a permanent jump in the energy input share of oil, ν_t, which occurs according to a Poisson jump process. This critical feature of the model generates the key mechanism for the results in the model related to the impact of climate policy, which includes an uncertain arrival time and the risk of stranded assets, on oil production, oil prices, and the oil firm value. The arrival rate of the shock to ν_t, or climate policy shock, is given by

$$\lambda_t = \lambda(T_t) = \psi(1 - exp(-\varpi T_t^p))$$

The arrival rate is importantly dependent on the endogenously evolving level of climate change due to emissions generated by oil use. One can interpret this as an increasing likelihood of significant climate policy being enacted as climate change becomes more pronounced either by increases in temperature, or, as functional form is quite similar to the damage function, as observed climate damages increase.

A.4 Planner Outcomes

A.4.1 Climate and Climate Policy

The planner's problem can be solved by the pre-policy First Order Conditions (FOC)

$$
\begin{aligned}
N &= \frac{\rho(1-\xi)V(1-C_1)^{-1}\nu}{V_R - \varphi_T V_T} \\
I &= \frac{V_K K \delta_1}{\rho(1-\xi)V + V_K K \delta_1} exp(-\eta T) A K^{1-\nu} (N)^{\nu}
\end{aligned}
$$

the post-policy First Order Conditions (FOC)

$$
I = \frac{V_K K \delta_1}{\rho(1-\xi)V + V_K K \delta_1} exp(-\eta T) A K
$$

and by guessing and verifying that the pre- and post-policy value functions are given by

$$
V_{pre} = K^{c_1} v(R,T) \qquad V_{post} = \tilde{c}_0 K^{c_1} exp(c_3 T)
$$

where the coefficients of the value functions are given by

$$
\begin{aligned}
\tilde{c}_0 &= \frac{1}{1-\xi} exp(\frac{1}{\rho}\{\rho(1-\xi)\log(A(1-C_1)) + c_3^2 \frac{1}{2}\sigma_T^2 \\
&\quad + c_1(\log B + \delta_1 \log(AC_1)) + \frac{\sigma_K^2}{2} c_1(c_1-1)\}) \\
c_1 &= \frac{\rho(1-\xi)(1-\nu)}{\rho - (1-\nu)\delta_1 + \delta_2} \\
c_3 &= -\frac{\eta(1-\xi)(\rho+\delta_2)}{\rho - \delta_1(1-\nu) + \delta_2} \\
C_1 &= \frac{c_1\delta_1}{\rho(1-\xi) + c_1\delta_1}
\end{aligned}
$$

The remaining differential equation v solves

$$
\begin{aligned}
0 &= \rho(1-\xi)v(\log(exp(-\eta T)A(N)^{\nu}(1-C_1)) \\
&\quad - \frac{1}{(1-\xi)} \log((1-\xi)v)) + v_R(-N) + \varphi N v_T \\
&\quad + v c_3(\ln B + \delta_1 \ln(exp(-\eta T)AC_1)) \\
&\quad + \frac{1}{2}\sigma_R^2 R^2 v_{RR} + \frac{1}{2}\sigma_T^2 v_{TT} + \frac{1}{2}\sigma_K^2 v c_1(c_1-1) + \lambda(T)[\tilde{c}_0 exp(c_3 T) - v]
\end{aligned}
$$

A.5 Decentralized Outcomes

A.5.1 Household

The household optimization problem is given by

$$\begin{aligned} V &= \max_{C} E\int \rho(1-\xi)V(\log C - \frac{1}{1-\xi}\log(1-\xi)V)dt \\ s.t.\quad & W_t \geq \int \pi C \end{aligned}$$

The SDF is given by

$$\pi = exp(\int h_V)\rho(1-\xi)VC^{-1}$$

and

$$\begin{aligned} h_C &= \rho(1-\xi)VC^{-1} \\ h_J &= \rho(1-\xi)\log C - \rho\log((1-\xi)V) - \rho \end{aligned}$$

A.5.2 Final Output

The final output firm's profit maximization problem is given by

$$\begin{aligned} V_F &= \max_{I,O} E\int \pi(exp(-\eta T)AK^{1-\nu}O^{\nu} - P_I I - P_O O)ds \\ s.t.\quad & dK = K(\ln B + \delta_1 \ln I - \delta_2 \ln K) \end{aligned}$$

The FOC are given by

$$\begin{aligned} P_I &= \lambda_K K\delta_1\pi^{-1}I^{-1} \\ P_O &= \nu exp(-\eta T)AK^{1-\nu}O^{\nu-1} \end{aligned}$$

Taking the SDF and value function as given, by definition the Langrangian multiplier λ_K is given by the discounted marginal value of another unit of capital, i.e., $\lambda_K = exp(\int h_V)V_K$, and so

$$\frac{c_1\delta_1}{\rho(1-\xi)+c_1\delta_1}\tilde{Y} = I$$

given $h_C = \rho(1-\xi)VC^{-1}$, $V = K^{c_1}v(R,T)$, and $P_I = 1$.

A.5.3 Oil Firm and Optimal Tax

From the oil firm's profit maximization problem, which includes a tax on the oil extraction piece of output only as that is the only piece contributing to emissions, we see

$$\begin{aligned} V_O &= \max_n E \int \pi(P_O R((1-\tau_{opt})n))ds \\ s.t. &\ \ dR/R = -ndt + \sigma_R dB \\ &\ \ dT = \varphi_T nRdt + \sigma_T dB \end{aligned}$$

The FOC for extraction is given by

$$P_O = \lambda_R R(1-\tau)^{-1}\pi^{-1}$$

Taking P_O, the SDF, and the value function as given previously, and by definition the Langrangian multiplier λ_R is the discounted marginal value of another unit of oil, i.e., $\lambda_R = exp(\int h_V)V_R$. Plugging in these expressions we find

$$n = \frac{\rho(1-\xi)vY(C)^{-1}\nu(1-\tau)}{v_R}$$

Note that the Social Planner's FOC derived from the HJB equation are given by

$$n = \frac{\rho(1-\xi)v(1-C_1)^{-1}\nu}{v_R - \varphi_T v_T}$$

Equating the SP and decentralized FOCs provides a system of equations from which the optimal tax can be derived as

$$(1-\tau_{opt}) = \frac{v_R}{v_R - \varphi_T v_T}$$

A.6 Asset Pricing Outcomes

A.6.1 The Stochastic Discount Factor (SDF)

Note that the intertemporal marginal rate of substitution (IMRS) or stochastic discount factor (SDF) following Duffie and Skiadas (1994) is

$$\pi_t = exp(\int_0^t h_J(C,V)ds)h_C(C,V)$$

As shown by Duffie and Skiadas (1994), Ito's Lemma then gives $\frac{d\pi_t}{\pi_t} = h_J dt + \frac{\mathcal{D}h_C}{h_C}$ and the risk prices are the loadings on the Brownian motions and jump process for the SDF evolution:

$$\begin{aligned}
\sigma_{\pi,K} &= (1-\nu-c_1)\sigma_K \\
\sigma_{\pi,R} &= \{\nu\frac{O_R}{O} - \frac{v_R}{v}\}\sigma_R R \\
\sigma_{\pi,T} &= \{\nu\frac{O_T}{O} - \frac{v_T}{v} - \eta\}\sigma_T \\
\Theta_\pi &= \{1 - \frac{v_{post}\tilde{Y}_{post}^{-1}}{v_{pre}\tilde{Y}_{pre}^{-1}}\}
\end{aligned}$$

A.6.2 Firm Prices

To derive firm prices, I apply the envelope theorem to the social planner's Lagrangian. This follows the methodology used by Papanikolaou (2011) for example. Note for the final output firm we have

$$\begin{aligned}
\pi_t S_t^C &= E_t \int_t^\infty \pi_s(exp(-\eta T)AK^{1-\nu}O^\nu - P_O O - I)ds \\
&= E_t \int_t^\infty \pi_s(exp(-\eta T)AK^{1-\nu}O^\nu(1-\nu) - i^* K)ds \\
&\Longrightarrow \\
S_t^C &= E_t \int_t^\infty exp(\int_t^s h_V)\frac{h_{C,s}}{h_{C,t}}(exp(-\eta T)AK^{1-\nu}O^\nu(1-\nu) - i^* K)ds
\end{aligned}$$

For the oil firm, plugging in the socially optimal choices, we have

$$\begin{aligned}
\pi_t S_t^O &= E_t \int_t^\infty \pi_s(P_O R((1-\tau)n - i_R)ds \\
&\Longrightarrow \\
S_t^O &= E_t \int_t^\infty exp(\int_t^s h_V)\frac{h_{C,s}}{h_{C,t}} P_O R(n^* - i_R^*)ds
\end{aligned}$$

Note the Lagrangian for the social planner's problem is given by

$$\mathcal{L} = E_t \int_t^\infty \{h(C,V) - \pi_s(C - exp(-\eta T)AK^{1-\nu}O^\nu + iK) - P_O\pi_s(O - nR)\}ds$$

Therefore, by application of the envelope theorem we know that

$$\frac{\partial \mathcal{L}}{\partial K} = \frac{\partial V}{\partial K} \quad , \quad \frac{\partial \mathcal{L}}{\partial R} = \frac{\partial V}{\partial R}$$

Furthermore, we also know that

$$\frac{\partial K_s}{\partial K_t}K_t = K_s \quad , \quad \frac{\partial R_s}{\partial R_t}R_t = R_s$$

Calculating derivatives of Lagrangian and comparing I find that

$$
\begin{aligned}
S_t^C &= \frac{1}{h_C}\frac{\partial V}{\partial K}K = c_1\frac{(1-C_1)}{\rho(1-\xi)}\tilde{Y}_t \\
S_t^O &= \frac{1}{h_C}\frac{\partial V}{\partial R}R = \frac{(1-C_1)}{\rho(1-\xi)}\frac{v_R R}{v}\tilde{Y}_t
\end{aligned}
$$

Therefore, the firm prices for each sector in the model are given by

$$
S_t^C = c_1\frac{(1-C_1)}{\rho(1-\xi)}\tilde{Y}_t, \quad S_t^O = \frac{(1-C_1)}{\rho(1-\xi)}\frac{v_R R}{v}\tilde{Y}_t
$$

Appendix B Climate Policy Index Details

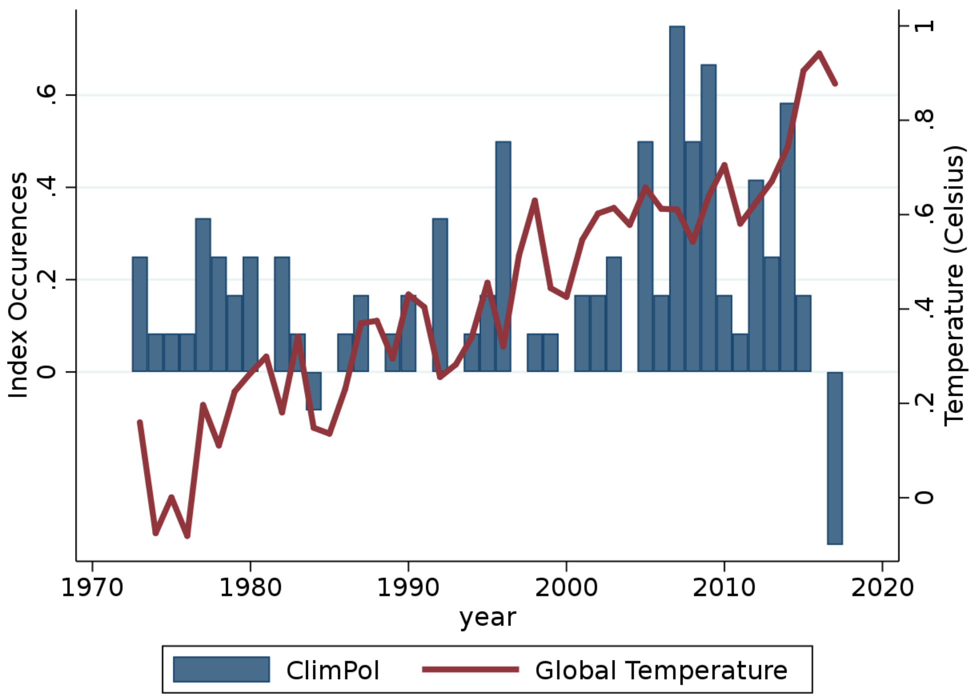
Figure 8: Climate Policy Index List, 1996-Present

Date	Event	Shock Sign	Source
5-Jun-96	Solar Two Plant Demonstrates Low Cost Method of Storing Solar Energy	+	ProCon.org
18-Jul-96	COP 2, Geneva, Switzerland	+	IPCC
9-Oct-96	Hydrogen Future Act of 1996 Is Passed to Further Expand Hydrogen Power Development	+	ProCon.org
29-Oct-96	European Union adopts target of a maximum 2 °C rise in average global temperature	+	Wikipedia
5-Nov-96	Bill Clinton Elected POTUS	+	U.S. Presidential Elections
5-Dec-96	EV1 Electric Car Is Made Available to the Public For Lease; Lease Program and EV1 Later Dismantled by GM	+	ProCon.org
25-Jun-97	US Senate passes Byrd–Hagel Resolution rejecting Kyoto	-	Wikipedia
11-Dec-97	COP 3, The Kyoto Protocol on Climate Change	+	Wikipedia/IPCC
14-Nov-98	COP 4, Buenos Aires, Argentina	+	IPCC
5-Nov-99	COP 5, Bonn, Germany	+	IPCC
7-Nov-00	George W. Bush Elected POTUS	-	U.S. Presidential Elections
25-Nov-00	COP 6, The Hague, Netherlands	+	IPCC
28-Mar-01	President George W. Bush withdraws from the Kyoto negotiations	-	Wikipedia
27-Jul-01	COP 6, Bonn, Germany	+	IPCC
29-Sep-01	IPCC Third assessment report	+	IPCC
10-Nov-01	COP 7, Marrakech, Morocco	+	IPCC
13-May-02	Farm Security and Rural Investment Act	+	Wikipedia
1-Nov-02	COP 8, New Delhi, India	+	IPCC
6-Feb-03	President Bush Unveils the Hydrogen Fuel Initiative	+	ProCon.org
27-Feb-03	Plans Announced to Build Worlds First Zero Emissions Coal Power Plant	+	ProCon.org
12-Dec-03	COP 9, Milan, Italy	+	IPCC
2-Nov-04	George W. Bush Elected POTUS	-	U.S. Presidential Elections
17-Dec-04	COP 10, Buenos Aires, Argentina	+	IPCC
1-Jan-05	EU Emissions Trading Scheme is launched, the first such scheme	+	Wikipedia
16-Feb-05	Kyoto Protocol comes into force (not including the US or Australia)	+	Wikipedia
8-Jul-05	31st G8 summit discusses climate change, relatively little progress made	+	Wikipedia
8-Aug-05	Energy Policy Act	+	Wikipedia
9-Nov-05	US House Prevents Drilling for Oil in the Arctic National Wildlife Refuge	+	ProCon.org
9-Dec-05	COP 11/CMP 1, Montreal, Canada	+	Wikipedia/IPCC
30-Oct-06	The Stern Review is published	+	Wikipedia
17-Nov-06	COP 12/CMP 2, Nairobi, Kenya	+	IPCC
16-Feb-07	February 2007 Washington Declaration	+	IPCC
7-Jun-07	33rd G8 summit	+	IPCC
31-Jul-07	2007 UN General Assembly plenary debate	+	IPCC
3-Aug-07	September 2007 Washington conference	+	IPCC
31-Aug-07	2007 Vienna Climate Change Talks and Agreement	+	IPCC
24-Sep-07	September 2007 United Nations High-Level-Event	+	IPCC
17-Nov-07	IPCC Fourth assessment report	+	IPCC/ProCon.org
17-Dec-07	COP 13/CMP 3, Bali, Indonesia	+	IPCC
19-Dec-07	Energy Independence and Security Act	+	Wikipedia
30-Jan-08	First Commercial Cellulosic Ethanol Plant Goes Into Production	+	ProCon.org
22-May-08	Food, Conservation, and Energy Act	+	Wikipedia
7-Oct-08	National Biofuel Action Plan Unveiled	+	ProCon.org
4-Nov-08	Barack Obama Elected POTUS	+	U.S. Presidential Elections

12-Dec-08	COP 14/CMP 4, Poznań, Poland	+	IPCC
22-Dec-08	Worst Coal Ash Spill in US History in Kingston, Tennessee	+	ProCon.org
17-Feb-09	ARRA (2009) Contains Funding for Renewable Energy	+	ProCon.org/Wikipedia
22-Apr-09	First Framework for Wind Energy Development on the US Outer Continental Shelf Announced	+	ProCon.org
5-May-09	President Obama Issues Presidential Directive to USDA to Expand Access to Biofuels	+	ProCon.org
27-May-09	US Announces Funding in Recovery Act Funding for Solar and Geothermal Energy Development	+	ProCon.org
26-Jun-09	US House of Representatives passes the American Clean Energy and Security Act (Waxman)	+	Wikipedia
22-Sep-09	September 2009 United Nations Secretary General's Summit on Climate Change	+	IPCC
27-Oct-09	US Invests $3.4 Billion to Modernize Energy Grid	+	ProCon.org
18-Dec-09	COP 15/CMP 5, Copenhagen, Denmark	+	IPCC
20-Apr-10	BP Oil Rig Explodes & Causes Largest Oil Spill in US History	+	ProCon.org
10-Dec-10	COP 16/CMP 6, Cancún, Mexico	+	IPCC
11-Mar-11	Earthquake off Coast of Japan Damages Six Powerplants at Fukushima	+	ProCon.org
1-Sep-11	Solar Power Company Solyndra Declares Bankruptcy	-	ProCon.org
9-Dec-11	COP 17/CMP 7, Durban, South Africa	+	IPCC
9-Feb-12	US Nuclear Regulatory Commission (NRC) Approves New Nuclear Power Plants	+	ProCon.org
27-Mar-12	EPA Announces First Clean Air Act Standard for Carbon Pollution from New Power Plants	+	ProCon.org
17-Apr-12	EPA Issues First Ever Clean Air Rules for Natural Gas Produced by Fracking	+	ProCon.org
6-Nov-12	Barack Obama Elected POTUS	+	U.S. Presidential Elections
7-Dec-12	COP 18/CMP 8, Doha, Qatar	+	IPCC
25-Jun-13	President Obama Releases His Climate Action Plan	+	ProCon.org
20-Sep-13	EPA Issues New Proposed Rule to Cut Greenhouse Gas Emissions from Power Plants	+	ProCon.org
23-Nov-13	COP 19/CMP 9, Warsaw, Poland	+	IPCC
13-Feb-14	Ivanpah, the World's Largest Concentrated Solar Power Generation Plant, Goes Online	+	ProCon.org
9-May-14	President Obama Announces Solar Power Commitments and Executive Actions	+	ProCon.org
2-Jun-14	EPA Proposes First Ever Rules to Reduce Carbon Emissions from Existing Power Plants	+	ProCon.org
22-Sep-14	Rockefellers and over 800 Global Investors Announce Fossil Fuel Divestment	+	ProCon.org
23-Sep-14	Climate Summit 2014	+	IPCC
1-Nov-14	IPCC Fifth assessment report	+	IPCC
12-Dec-14	COP 20/CMP 10, Lima, Peru	+	IPCC
3-Aug-15	President Obama Announces Clean Power Plan (finalized Oct. 23, 2015; Active December, 22, 2015)	+	ProCon.org
12-Dec-15	COP 21/CMP 11, Paris, France	+	Wikipedia/IPCC
8-Nov-16	Donald Trump Elected POTUS	-	U.S. Presidential Elections
18-Nov-16	COP 22/CMP 12/CMA 1, Marrakech, Morocco	+	IPCC
28-Mar-17	President Trump Signs Executive Order to Begin Reversal of President Obama' Clean Power Plan	-	ProCon.org
1-Jun-17	President Donald Trump withdraws the United States from the Paris Agreement	-	Wikipedia
31-Jul-17	Two Nuclear Power Reactors in South Carolina Abandoned Before Construction Completed	-	ProCon.org
22-Dec-17	Tax Bill Opens Arctic National Wildlife Refuge for Oil Drilling	-	ProCon.org
9-May-18	Solar Power to Be Required on All New California Homes by 2020	+	ProCon.org

*Events come from ProCon.org Fossil Fuel and Alternative Energy timeline, IPCC/UNFCC Meetings, U.S. Presidential Election outcomes, and Wikipedia.org Selective historical timeline of significant climate change political events and List of United States energy acts

Figure 9: ClimPol Index and Annual Global Mean Temperature



References

Acemoglu, D., U. Akcigit, D. Hanley, and W. Kerr (2016). Transition to clean technology. *Journal of Political Economy 124*(1), 52–104.

Anderson, E. W. and W. A. Brock (2017). Logarithmic depreciation. *SSRN Workin Paper 1*(1), 1.

Anderson, E. W., W. A. Brock, and A. Sanstad (2016). Robust consumption and energy decisions.

Bansal, R., M. Ochoa, and D. Kiku (2016). Climate change and growth risks. Technical report, National Bureau of Economic Research.

Barnett, M. (2017). Climate change and uncertainty: An asset pricing perspective. *Working Paper*.

Barnett, M. (2019). A run on oil: Climate policy, stranded asets, and asset prices. *Working Paper*.

Barnett, M., W. Brock, and L. P. Hansen (2018). Pricing uncertainty induced by climate change. *Working Paper. In-principle acceptance of RFS Climate Finance registered report, completion in progress.*.

Baumeister, C. and J. D. Hamilton (2019). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. *American Economic Review 109*(5), 1873–1910.

Baumeister, C. J. and J. D. Hamilton (2017). Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. Technical report, National Bureau of Economic Research.

Belo, F., V. D. Gala, and J. Li (2013). Government spending, political cycles, and the cross section of stock returns. *Journal of Financial Economics 107*(2), 305–324.

Bornstein, G., P. Krusell, and S. Rebelo (2017). Lags, costs, and shocks: An equilibrium model of the oil industry. Technical report, National Bureau of Economic Research.

Brock, W. A. and L. P. Hansen (2017). Wrestling with uncertainty in climate economic models.

Burke, M., W. M. Davis, and N. S. Diffenbaugh (2018). Large potential reduction in economic damages under un mitigation targets. *Nature 557*(7706), 549.

Cai, Y., K. L. Judd, and T. S. Lontzek (2015). The Social Cost of Carbon with Economic and Climate Risks. *Working Paper*.

Carlson, M., Z. Khokher, and S. Titman (2007). Equilibrium exhaustible resource price dynamics. *The Journal of Finance 62*(4), 1663–1703.

Casassus, J., P. Collin-Dufresne, and B. R. Routledge (2009). Equilibrium commodity prices with irreversible investment and non-linear technologies.

Crost, B. and C. P. Traeger (2011). Risk and aversion in the integrated assessment of climate change.

Dasgupta, P. and G. Heal (1974). The optimal depletion of exhaustible resources. *The review of economic studies 41*, 3–28.

David, A. (2015). Exploration activity, long run decisions, and the risk premium in energy futures.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Deschenes, O. and M. Greenstone (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *The American Economic Review 97*(1), 354–385.

Dietz, S., C. Gollier, and L. Kessler (2017). The climate beta. *Journal of Environmental Economics and Management*.

Duffie, D. and C. Skiadas (1994). Continuous-time security pricing: A utility gradient approach. *Journal of Mathematical Economics 23*(2), 107–131.

Engle, R. F., S. Giglio, H. Lee, B. T. Kelly, and J. Stroebel (2019). Hedging climate change news. *Available at SSRN 3317570*.

Giglio, S., M. Maggiori, J. Stroebel, and A. Weber (2015). Climate change and long-run discount rates: Evidence from real estate. Technical report, National Bureau of Economic Research.

Golosov, M., J. Hassler, P. Krusell, and A. Tsyvinski (2014). Optimal Taxes on Fossil Fuel in General Equilibrium. *Econometrica 82*(1), 41–88.

Hambel, C., H. Kraft, and E. Schwartz (2015). Optimal carbon abatement in a stochastic equilibrium model with climate change. Technical report, National Bureau of Economic Research.

Hamilton, J. D. (2005). Oil and the macroeconomy. *The New Palgrave Dictionary of Economics 2*.

Hamilton, J. D. (2008). Understanding crude oil prices. Technical report, National Bureau of Economic Research.

Hong, H., F. W. Li, and J. Xu (2016). Climate risks and market efficiency. Technical report, National Bureau of Economic Research.

Hotelling, H. (1931). The economics of exhaustible resources. *Journal of political Economy 39*(2), 137–175.

Hsiang, S., R. Kopp, A. Jina, J. Rising, M. Delgado, S. Mohan, D. Rasmussen, R. Muir-Wood, P. Wilson, M. Oppenheimer, et al. (2017). Estimating economic damage from climate change in the united states. *Science 356*(6345), 1362–1369.

Jermann, U. J. (1998). Asset pricing in production economies. *Journal of Monetary Economics 41*(2), 257–275.

Kelly, B., L. Pástor, and P. Veronesi (2016). The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance*.

Kelly, D. L. and C. D. Kolstad (1999). Bayesian learning, growth, and pollution. *Journal of economic dynamics and control 23*(4), 491–518.

Kilian, L. (2008). Exogenous oil supply shocks: how big are they and how much do they matter for the us economy? *The Review of Economics and Statistics 90*(2), 216–240.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review 99*(3), 1053–69.

Kilian, L. and C. Park (2009). The impact of oil price shocks on the us stock market. *International Economic Review 50*(4), 1267–1287.

Kogan, L., D. Livdan, and A. Yaron (2009). Oil futures prices in a production economy with investment constraints. *The Journal of Finance 64*(3), 1345–1375.

Koijen, R. S., T. J. Philipson, and H. Uhlig (2016). Financial health economics. *Econometrica 84*(1), 195–242.

Kotlikoff, L. J., A. Polbin, and A. Zubarev (2016). Will the paris accord accelerate climate change? Technical report, National Bureau of Economic Research.

Lemoine, D. M. and C. P. Traeger (2012). Tipping points and ambiguity in the economics of climate change. Technical report, National Bureau of Economic Research.

MacDougall, A. H. and P. Friedlingstein (2015). The origin and limits of the near proportionality between climate warming and cumulative co2 emissions. *Journal of Climate 28*(10), 4217–4230.

Matthews, H. D., N. P. Gillett, P. A. Stott, and K. Zickfeld (2009). The proportionality of global warming to cumulative carbon emissions. *Nature 459*(7248), 829–832.

Matthews, H. D., S. Solomon, and R. Pierrehumbert (2012). Cumulative carbon as a policy framework for achieving climate stabilization. *Phil. Trans. R. Soc. A 370*(1974), 4365–4379.

McGlade, C. and P. Ekins (2015). The geographical distribution of fossil fuels unused when limiting global warming to 2 degrees c. *Nature 517*(7533), 187–190.

Mertens, K. and M. O. Ravn (2014). A reconciliation of svar and narrative estimates of tax multipliers. *Journal of Monetary Economics 68*, S1–S19.

Nordhaus, W. (2014). *A question of balance: Weighing the options on global warming policies*. Yale University Press.

Papanikolaou, D. (2011). Investment shocks and asset prices. *Journal of Political Economy 119*(4), 639–685.

Pástor, L. and P. Veronesi (2009). Technological revolutions and stock prices. *American Economic Review 99*(4), 1451–83.

Pastor, L. and P. Veronesi (2012). Uncertainty about government policy and stock prices. *The Journal of Finance 67*(4), 1219–1264.

Pindyck, R. S. and N. Wang (2013). The Economic and Policy Consequences of Catastrophes. *American Economic Journal: Economic Policy 5*(4), 306–339.

Ramey, V. A. (2011). Identifying government spending shocks: It's all in the timing. *The Quarterly Journal of Economics 126*(1), 1–50.

Ready, R. (2015). Oil Consumption, Economic Growth, and Oil Futures: A Fundamental Alternative to Financialization. *Working Paper*.

Ricke, K. L. and K. Caldeira (2014). Maximum warming occurs about one decade after a carbon dioxide emission. *Environmental Research Letters 9*(12), 124002.

Romer, C. D. and D. H. Romer (2010). The macroeconomic effects of tax changes: estimates based on a new measure of fiscal shocks. *American Economic Review 100*(3), 763–801.

Santa-Clara, P. and R. Valkanov (2003). The presidential puzzle: Political cycles and the stock market. *The Journal of Finance 58*(5), 1841–1872.

Sialm, C. (2006). Stochastic taxation and asset pricing in dynamic general equilibrium. *Journal of Economic Dynamics and Control 30*(3), 511–540.

Sinn, H.-W. (2007). Public policies against global warming. Technical report, National Bureau of Economic Research.

Stern, N. (2007). *The Stern Review: The economics of climate change*. Cambridge University Press.

Zickfeld, K. and T. Herrington (2015). The time lag between a carbon dioxide emission and maximum warming increases with the size of the emission. *Environmental Research Letters 10*(3), 031001.