An Empirical Test of the Green Paradox for Climate Legislation

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Abstract

We provide novel empirical evidence that oil markets quickly respond to changing expectations about climate legislation that limit future consumption, shifting consumption towards the present through lower prices. First, the strengthening of future climate policy, as measured by monthly variation in climate policy salience in the news, reduces contemporaneous oil prices. Second, daily oil future returns respond inversely to daily changes in the market's expectation that the Waxman-Markey bill will pass. The effects persist across maturities ranging from 1 to 24 months into the future, lowering the entire expected price path, unlike earlier periods, when shocks to the spot price had diminishing effects on longer-term maturities. Back-of-the envelope calculation imply passage of the Waxman-Markey bill would have increased oil consumption by 2.0-4.2% globally. Moreover, we find that uncertainty of the bill passing increased oil consumption by 7.7-26.69 million metric tons between May 2009 and December 2010 through lower prices, potentially discouraging renewable innovation during the period the bill was considered.

Key words: Q41, Q54, G18
JEL Codes: Green Paradox, oil consumption, climate change.

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Climate legislation often establishes goals for the future to give companies and consumers time to adapt and plan for a transition away from fossil fuels. For example, the European Union enacted the goal to be climate neutral (net zero emissions) by 2050, and China established the same goal for 2060. Fossil fuels are exhaustible resources, and their finite availability dictates their use and price path (Hotelling 1931). This scarcity leads to a price that exceeds the marginal extraction cost, resulting in resource rents that ensure less is consumed today and fossil fuels are saved for the future. The literature on the "Green Paradox" highlights that climate legislation, which limit future fossil fuel use, give resource owners an incentive to extract more in the present and medium term before the regulation binds, leading to lower prices and accelerated resource depletion today. This theoretical literature is based on Hotelling's seminal model (Hoel 2010a, Sinn 2008a, Sinn 2008b, Van der Ploeg and Withagen 2012, Van der Ploeg and Withagen 2015). By the same logic, a global carbon tax on fossil fuels with scarcity rents will not be passed on to consumers. If producers did so, then demand for fossil fuels would fall, cumulative consumption would decrease and not all fossil fuels would be used, incentivizing resource owners to lower fossil fuel prices to sell all units. In the end, much of a carbon tax would be absorbed by producer rents with limited effect on fossil fuel use (Dasgupta, Heal and Stiglitz 1980, Heal and Schlenker 2019). What is common to this literature is the concern that climate legislation might not lead to the desired reductions in cumulative fossil fuel use and may even accelerate consumption today.

Our paper adds to the emerging empirical literature on the "Green Paradox" (Lemoine 2017, Di Maria, Lange and van der Werf 2014, Merrill 2018, Grafton, Kompas, Long and To 2014). Specifically, we test the predictions of the "Green Paradox" using a news based index of climate policy salience, a prediction market with contracts contingent on climate policy passing, as well as an event study of an unexpected court ruling mandating reductions in future fossil fuel emissions. We consistently find evidence of the mechanism behind the "Green Paradox:" additional restrictions, or an increased likelihood of future restrictions on oil use, reduce both the oil spot price and oil futures prices in the years for which futures data are traded, i.e., the following two years. This occurs as supply is reallocated from the future to the present. This pattern holds true when analyzing monthly returns in conjunction with decades-long data on policy stringency, when using high-frequency daily data on oil prices coupled with daily changes in prediction market prices, as well as when estimating the oil price return after a surprising verdict.

Empirically testing the "Green Paradox" is difficult because the analysis requires information about firms' expectations of climate policy stringency; there is very little data on firm expectations regarding the stringency of future climate policy. We side step this challenge through the use of prediction market prices, a measure that should co-vary with firms' expectations, a news based index proxying for information shocks related to climate policy, and a surprising change in climate policy.

We begin by documenting that oil price shocks, i.e., changes in the daily oil price, have become stickier over the last three decades, implying that shocks are permanent rather than temporary. Under the "Green Paradox," uncertainty from climate legislation deliberations leads to persistent (sticky) price changes, as changes in expectations around future climate legislation reset the entire future oil price path and hence impact all maturities equally. Consistent with this prediction, we find the persistence of spot price shocks among maturities ranging from 1 to 24 months greatly increased during periods when climate bills were under consideration (the 2000s and 2010s). Daily changes in the oil spot price translate into roughly the same change in oil futures prices with a maturity one month into the future throughout the sample period.

However, the story differs for longer-term maturities: in the 1990s, spot price shocks phased out for oil futures with longer maturities. Specifically, only about a third of the spot price change was reflected in the oil futures with a 24-month maturity. Around 2010, the faction doubled to two thirds, i.e., daily shocks phased out slower with longer-term maturity futures. This finding only reverses in the 2020s, when COVID-related temporary supply disruptions lead to a decoupling of future and spot price movements.

In a second step, we pair monthly oil price data with monthly estimates of U.S. renewable policy and international climate negotiation salience. We measure policy salience using Noailly, Nowzohour and Van Den Heuvel (2021)'s news-based indices generated by text-mining articles from ten leading US newspapers published between 1981 and 2019. The indices reflect the monthly number of articles covering US renewable policy and international climate negotiations, respectively, relative to the total number of articles published. While the "Green Paradox" makes no direct predictions of the effect of climate policy salience on oil prices, the measure of climate policy salience used in this paper generally tracks events that strengthened future climate policy, i.e. the renewable policy index peaks after the passage of renewable policy. Hence, pairing oil prices with the news based indices can provide a suggestive yet compelling test of the paradox's prevalence over the last four decades. The "Green Paradox" predicts that the indices should be negatively correlated with oil prices. For example, increases in the international negotiations index indicate international cooperation around climate likely strengthened, elevating the expected stringency of future climate policy, causing oil producers to supply more today, and consequently reducing prices. Consistent with the paradox's predictions, we find increases in the salience of international climate negotiations significantly reduce oil prices.

On the other hand, we find increases in the salience of renewable energy policy significantly increase oil prices. Renewable energy programs have two countervailing effects: strengthening renewable energy policy could reduce the backstop price causing oil producers to increase supply today, reducing oil prices. Alternatively, strengthening of renewable policy has often occurred in place of climate policy, thereby easing the concern that there might be future restriction on fossil fuel use, resulting in higher oil prices as future supply is no longer threatened. Our finding suggests that the latter dominates, i.e., oil producers do not view current renewable policy as a threat to future oil demand and supply in the future, but instead as a distraction from climate policy, reducing the probability of stricter climate policy in the future. Another possibility, higher oil prices, associated with positive oil future returns, increase the likelihood that renewable policy is passed. We find no evidence of this reverse relationship; specifically, our findings are robust to controlling for the oil spot price.

In a third step, we present a direct test of the "Green Paradox" by pairing daily oil price data with daily estimates of the market's expectations that a US climate bill will pass. We retrieve the market's expectations using prediction market contract prices. The "Green Paradox" states that increases in the expected probability of a cap and trade bill passing should reduce contemporaneous oil prices while decreases should increase oil prices. Consistent with this prediction, we find a significant negative coefficient; prices of oil futures decline whenever the expected likelihood that the bill will pass increases. This effect is persistent across all futures contracts, even increasing for longer-term maturities, suggesting that the relationship reflects long-term adjustments in the expected oil price path rather than temporary shocks. Through our analysis we find (i) the passage of the Waxman-Markey bill would have increased oil consumption 2.0-4.2% and (ii) Waxman-Markey deliberations increased oil consumption by 7.7-26.69 million metric tons equivalent to 1-3 days of global oil consumption. We present two pieces of evidence to rule out the possibility that reverse causality could explain our finding, i.e., that lower oil prices made it more likely that a climate bill would pass, or stated differently, opposition to the bill was higher when oil prices were higher. We find that the effect is even larger and more significant when we limit the sample to days with major changes in prediction market prices – these major changes were driven by political negotiations that were scheduled in advance and should not have been influenced by day-to-day oil price movements, ruling out reverse causality. Moreover, we find no qualitative difference in the relationship when we control for the oil spot price. Finally, we find similar results when we ignore precise prediction market prices and simply use prediction market shocks to objectively identify dates when expectations around the probability a US climate bill pass drastically changed.

In a fourth step, we construct the abnormal oil price return on the day the surprise Urgenda vs. Netherlands ruling was rendered, where a Dutch court sided with an environmental group and ordered the Dutch government to have stricter limits on future fossil fuel emissions. When announced, people predicted the ruling would set a precedent for all countries subject to the European Convention. We again find significant negative coefficients, i.e., oil futures prices declined when a surprise verdict increased the expected likelihood of climate legislation limiting future oil consumption throughout Europe.

Taken together, these findings show that the oil market is indeed sensitive to climate laws and that expected restrictions on future fossil fuel use will lead to increased consumption today. The economics of exhaustible resources predicts that discoveries of an exhaustible resource influence the scarcity of a resource and its price (Ekeland, Schlenker, Tankov and Wright 2022). If total availability of an exhaustible resource goes up through a new discovery, the expected future price path resets and is lowered. The effect of climate legislation is analogous: by limiting resource use in the long-term, available resources are shifted towards the short and medium-term.

Our paper contributes the emerging empirical literature on the "Green Paradox," specifically how environmental laws can increase today's demand through lower prices. Grafton et al. (2014) show that increases in biofuel production, a substitute to fossil fuels, increase oil production. Di Maria et al. (2014) show that the passage of the acid rain program decreased the price of high-sulphur coal. Merrill (2018) finds the out-of-committee introduction of climate related bills in congress accelerate oil and gas firm wellhead investments. Lemoine (2017) observe an abnormal return in *coal* futures on the day Graham abandoned the bill on Monday, April 26, 2010.

Lemoine (2017), Merrill (2018), and Di Maria et al. (2014) test the paradox's predictions using policy or information shocks occurring at a specific moment, relying on comparisons between the period before and after a single shock. Grafton et al. (2014) uses annual variation in biofuel production as a proxy for annual variation in biofuel subsidies to test the paradox. A challenge in these papers is to determine when the market updated its beliefs about the likelihood of a policy change. The "Green Paradox" is derived from expectations of future prices, and markets might see and react to an impending regulation before it is officially implemented and ratified (Dube, Kaplan and Naidu 2011, McDermott, Meng, McDonald and Costello 2019). Our approach's reliance on monthly and daily information shocks allow us to both capture how the policy making process – announcements, upheavals, revisions, and delays – impacts oil prices and get more convincing variation in updates on the market's beliefs. Additionally, the referenced empirical "Green Paradox" literature might be susceptible to reverse causality. For political economy reasons, a bill might be more easily passed when a resource was declining in economic importance and the price was falling. Or, a subsidy might be more easily implemented when there is generally more demand for fuel. In both cases, estimates of the "Green Paradox" could instead reflect reverse causality. A key innovation of our paper is that our approach is less susceptible to reverse causality.

Our paper builds most closely on Lemoine (2017), but makes several additional contributions: First, using various time scales including high-frequency daily data over more than a year makes it less likely to confound the analysis as other events could have happened during one particular day by chance. For example, during the week of Graham's abandonment a catastrophic oil spill in the Gulf of Mexico, known as Deep Water Horizon, unfolded. This spill makes focusing on the effect of Graham's abandonment on fossil fuel prices difficult as uncoupling the effect of the spill from the bill's abandonment is empirically challenging. It is also not entirely clear when the market learned of Graham's announcement, which was first reported the Friday before. Instead, we rely on variation in prediction market prices throughout Waxman-Markey bill over deliberations that took place for more than a year to identify the effect of changes in the expected stringency of future climate policy on oil prices. Second, coal supply may be less sensitive to changes in future US climate policy than oil because air quality regulation protecting local environments already heavily restricts US coal consumption, limiting resource rents today, and consequently limiting the "Green Paradox" (Hoel 2010b).

More generally, a number of other empirical studies demonstrate the anticipation of a new environmental policy can induce behaviors counteracting the policy's intended benefits (Polasky and Doremus 1998, McDermott et al. 2019). Even more broadly, policy anticipation is a well considered topic in public economics; policy anticipation can change consumption, investment or income prior to policy implementation, affecting a policy's effectiveness (Mertens and Ravn 2011, Perotti 2012, Judd 1987, Gründler and Sauerhammer 2018). The literature on anticipation effects consistently struggles to determine when actors update beliefs and results are sensitive to these researcher choices. Unique to this literature, our paper focuses on oil prices' reaction to the policy making process, testing "Green Paradox" predictions through the use of high-frequency variation in expectations around the stringency of future regulation to identify how markets react to policy making.

1 Data

Fossil Futures Prices

Oil futures are obtained from NYMEX, specifically futures on the West Texas Intermediate (WTI) crude price. Oil futures contracts are the market's assessment of future oil prices. If traders are risk neutral and the market efficiently aggregates information, then contract prices reflect society's best guess of the future oil price (Kellogg 2014). We obtained oil futures prices for futures with liquid contracts. These range between 1 and 24 months into the future, reflecting the market's best guess of oil prices over the upcoming two years on a monthly basis (24 different contracts). Additionally, in some sensitivity checks we use coal futures, also obtained from NYMEX, specifically the Central Appalachian Contract. Lastly, we use daily WTI crude oil prices from Cushing, Oklahoma, recorded by the US Energy Information Administration as the measure of the oil spot prices. They allow us to document the evolution of the stickiness of shocks to th eoil spot price during the sample period.

Market Controls

Oil prices respond to macro-economic shocks, so throughout our analysis we generally control for daily changes in the S&P500 index, a stock market index that tracks the performance of the 500 largest publicly traded companies in the US.[1]

Prediction Market on Probability of Climate Law

Market beliefs on the probability that the US government would enact a cap-and-trade system for emissions by the end of 2010 are obtained from prediction market contract prices from Intrade. A prediction market contract is a bet on the realization of a particular event by a given date. If the event is realized by the specified date in the contract, holders receive a dollar. If the event is not realized by the specified date, holders do not receive anything. In an efficient market, the price of the betting market in cents should equal the probability of the law passing. We use prediction market prices from Intrade from May 1, 2009 to Dec 31, 2010. The end date is given by the contract, which was on the passage of a US climate bill by the end of 2010. Specifically, the prediction market was for "A cap-and-trade system for emissions trading to be established before midnight ET on 31 Dec 2010."

Internet Searches about Climate Bill

Additionally, we pull daily google trends data for the search term "waxman markey" during the period in which the prediction market operated. Google trends data provides an independent measure on whether the topic was of general interest, which we us in a sensitivity analysis by restring the data to days with high search volumes when it is more likely that belief updates occurred. This data can only be downloaded at the daily level for a maximum period of nine months. Moreover, each google trends data download is normalized based on the observations in the download. The day when the search term was the most popular has an index of 100. A day during the period when the search term was half as popular as the most popular day has an index of 50. Days with not enough search volume to determine the relative popularity of the search term have an index of zero. We construct daily google trends data between May, 2009 and June, 2010 by making three data queries. The first query covers days between May, 2009 and December, 2009, the second covers October, 2009 to June 2010, and the third covers March to November, 2010. Using the period of overlap between queries, we re-scale the indices such that the most popular day during the whole sample has an index of 100.

Measures of Policy Salience

Finally, we measure the salience of US renewable policy and international cooperation around climate using news based indices from Noailly et al. (2021). Noailly et al. (2021) develop their indices by text-mining 15 million articles published between 1981 and 2019 by the *New York Times*, *Washington Post*, *Wall Street Journal*, *Houston Chronicle*, *Dallas Morning News*, *San Francisco Chronicle*, *Boston Herald*, *Tampa Bay Times*, *San Jose Mercury News*, and *San Diego Union Tribune*. The authors identify articles pertaining to environmental policy generally using a support vector machine algorithm trained on 2,464 labeled articles. To classify environmental policy articles into sub-topics, Noailly et al. (2021) use topic modeling, an unsupervised learning algorithm. The approach recognizes recurring patterns in the set of environmental policy

[1] We downloaded the oil futures, coal futures, and S&P500 index from a Bloomberg Terminal in March 2023.

articles, creating groupings of articles that cover similar topics. The authors use this approach to construct twenty five different groupings, two of which they made publicly available, renewable energy policy and international climate negotiations. Articles classified as covering renewable energy policy include words/phrases such as renewable energy, wind, solar, energy, turbine, energy, power, electricity, renewable, wind power, farm, solar energy, turbine, etc. Articles classified as covering international climate negotiations include agreement, united, international, government, country, state, world, trade, president, European, Mexico, China, etc. Noailly et al. (2021) construct news indices for environmental policy generally, renewable policy and international climate negotiations by counting the number of articles in a given category each month and scaling the count by the total monthly volume.

Noailly et al. (2021) document that both the international climate negotiations and renewable policy index are predominantly associated with events that strengthened future US climate policy. For example, major changes in the international climate negotiations occurred during the Rio de Janeiro Earth Summit, the Kyoto Protocol signing, the Bonn Climate Change Conference, the Copenhagen Climate Change Conference, Paris Agreement, Trump's withdrawal from the Paris Agreement, and the Katowice Climate Change Conference. Generally, these events mark moments when international cooperation around climate change strengthened. The renewable policy index is elevated during the Obama era, a period of strong support for renewables, and peaks during deliberations around Bush's National Energy Policy, the decision to build the first US offshore wind farm, the announcement of the Green New Deal, Al Gore's call for a move towards ending dependence on carbon, First Solar and China's agreement to build the largest photovoltaic power plant, investigations into solar panel dumping by China, and the passage of Obama's Clean Power Plan. Moreover, Noailly et al. (2021) finds their index generally measuring environmental policy salience in the news is strongly correlated with the OECD's Environmental Policy Stringency Index for the US.[2] Throughout our paper we generally interpret increases in the international climate negotiations and renewable policy index as moments when expected future climate policy strengthened.

2 Empirical Strategy

We test theoretical predictions of the "Green Paradox" by linking daily changes in oil futures to daily changes in market expectations around the probability that a cap-and-trade bill in the US will be enacted. If financial markets expect climate change regulation to be more stringent in the future, resource owners will shift some of the supply they can no longer sell in the future towards the present, thereby lowering both the spot price as well as all futures prices with maturities between 1 and 24 months from today. Specifically, we are able to test the following two predictions: an increase in the probability that a cap-and-trade bill will be enacted (i) decreases prices and (ii) decreases prices by similar amounts for *all* futures contracts that are actively traded, i.e., for maturities ranging from 1 to 24 months into the future.

The stickiness of price shocks induced by climate change legislation is a key feature of the "Green Paradox" that sets it apart from other temporary shocks whose effect phases out over time. We therefore begin our empirical analysis by documenting correlations between the oil spot price and oil futures prices at different points in time. This analysis serves two purposes. First, it provides descriptive evidence that the persistence

[2] The OECD Environmental Policy Stringency Index measures the extent to which a country prices environmentally harmful behavior explicitly or implicitly.

of oil price shocks has changed remarkably over time, with the highest persistence during years when climate change legislation was debated. This is consistent with climate change legislation being a key factor of uncertainty that induces persistent price shocks. Second, this analysis constructs an important baseline for interpreting our causal results and motivation for robustness analyses.

As a second step, we continue our empirical analysis by documenting associations between oil price returns and monthly measures of renewable policy and international climate negotiations salience in the news. The stringency of future climate policy has been in continual flux in recent history. The "Green Paradox" predicts that information shocks informing expectations around the stringency of future climate policy should impact oil prices, i.e. information shocks indicative of more stringent future climate policy should reduce prices today. As discussed in the data section, the news based indices predominantly track events that strengthened future climate policy. Hence, the indices proxy for information shocks indicative of more stringent future climate policy, and our analysis can provide suggestive yet compelling evidence of a relationship between increases in the expected stringency of future climate policy on oil prices. More generally, this analysis tests if the "Green Paradox" has been a pervasive phenomenon throughout the last three decades.

Third, we focus on US cap and trade policy deliberations in 2009 and 2010, a particularly uncertain period in terms of future climate policy, to provide causal evidence of the "Green Paradox." Using high-frequency data, we link daily oil future returns to daily prediction market prices for a contract tied to the passage of a US cap and trade policy. As in Meng (2017), we argue price changes in the prediction market approximate market expectations of the probability that climate regulation will be passed.[3] We would expect increases in prediction market prices to be linked with negative oil future returns on average.

Finally, we test if the surprising Urgenda v. Netherlands verdict was associated with anomalous negative oil future returns in an event study design for one day. The Urgenda v. Netherlands ruling indicated future climate regulation in the Netherlands would become more stringent, and people speculated that the verdict laid the foundation for more stringent climate regulation in Europe more broadly. Thus, the announcement created an unexpected shock in market expectations around future climate regulation stringency, giving us the opportunity to test for evidence of the paradox in response to an actual policy change. We would expect the verdict announcement to be linked with negative oil future returns.

Oil Price Shock Permanence In a first step, we link daily changes in oil futures to daily changes in oil spot prices. As described in the data section, the analysis includes oil futures with maturities ranging from 1 to 24 months into the future, i.e., for each day we have 24 different future returns. The regression equation is:

$$\Delta y_{ft} = \alpha_{fm(t)} + \beta_f \ \Delta p_t + \gamma_f \ \Delta z_t + \epsilon_{ft} \tag{1}$$

We regress Δy_{ft}, the percent change in the future price[4] on day t for the oil future with a maturity of $f = 1 \ldots 24$ months into the future on the percent change in the oil spot price Δp_t on day t. The main coefficients of interest are β_f, the association between the spot price and oil future f. We allow the coefficients to vary by maturity f to show how spot price shocks impact expected prices at various points in the future.

[3] Meng (2017) pioneered the use of prediction markets for climate change legislation in a different context to derive the abatement costs of climate legislation.

[4] We use the percent change in the closing price relative to the previous closing price.

We control for changes in the overall economy by including Δz_t, the percent change in the S&P500 index on day t. The effect of the S&P500 is also allowed to vary by future (maturity) f. Finally, we include future-by-month fixed effects $\alpha_{fm(t)}$, thereby focusing the identification on changes in a particular oil future f that occur within a given month $m(t)$. Errors ϵ_{ft} are clustered by day allowing the returns of the 24 different maturities to be correlated as they might be influenced by the same market events. In a sensitivity check in the appendix we allow for different clustering options and fixed effects.

We run the analysis for different subsets of days. The degree to which climate change legislation was at the forefront of political agendas varied greatly over the last three decades. As discussed previously, we expect oil price shocks to be more permanent during periods when climate regulation is under consideration by major governing bodies, as the passage of such legislation would permanently alter future price paths. Thus, we replicate the analysis described by equation (1) for periods that begin every 5-years, starting in 1990 to see if oil price shock stickiness varied with uncertainty around future climate legislation.

Climate Policy Salience Unlike the futures data, which is available daily, the climate policy index is available monthly. We hence switch the analysis to a monthly level in an anologous fashion. We link monthly oil futures returns to monthly measures of renewable policy and international climate negotiation salience, a proxy for information shocks about future climate policy. For easier interpretation, the monthly news indices are standardized to be mean zero and to have unit standard deviation. The news indices report monthly salience measures between 1981 and 2019. The international climate negotiation index peaks during the Copenhagen Climate Change Conference at 7.5 standard deviations above the average and reaches its second highest peak during the adoption of the Paris Climate agreement at 6 standard deviations above average. The renewable policy index peaks when a group of US based companies first accused China of dumping solar panels in the US at 2.9 standard deviations above the average. The regression equation is:

$$\Delta y_{fm} = \alpha_{fq(m)} + \beta\ I_m + \theta\ R_m + \lambda\ E_m + \gamma_f\ \Delta z_m + \epsilon_{fm} \tag{2}$$

Δy_{fm} reflects the percent change in the future price at the end of month m relative to the end of month $m-1$ for the oil future with a maturity of $f = 1 \dots 24$ months into the future. We regress the percent change in the future price on standardized measures of three news-based indices: I_m, R_m, and E_m. The main coefficients of interest are β and θ, the effect of a one standard deviation in the salience of international climate negotiations (I_m) and renewable policy (R_m), respectively, on oil future returns. We include environmental policy salience generally (E_m) to control for general environmental policy salience and as a placebo.[5] As in equation (1), we control for changes in the overall economy by including Δz_m, the percent change in the S&P500 index at the end of month m relative to the end of month $m-1$. The effect is allowed to vary by future (maturity) f. Finally, we include future-by-quarter fixed effects $\alpha_{fq(m)}$, thereby focusing the identification on changes in a particular oil future f that occur within a given quarter $q(m)$.

Cap & Trade Prediction Market We link daily changes in oil futures to daily changes in prediction market prices, which estimated the probability that a US climate bill would pass. During the prediction market's lifespan, the contract price ranged from 0 to 57 cents, implying the market predicted between a 0

[5]We do not expect environmental policy salience on average to impact oil prices because on average most environmental policy news is not about climate policy (Noailly et al. 2021).

and 57% chance that the US government would enact a cap-and-trade bill by the end of 2010. The price peaked at 57 cents when the House passed the Waxman-Markey bill. The price increased by 10 cents when a cap-and-trade bill in the Senate garnered support from some Republicans, including Lindsay Graham of South Carolina (Meng 2017). While the main bill that was discussed in 2009-2010 was the Waxman-Markey bill, the prediction market contract is for the event that *any* cap-and-trade bill passes by the end of 2010. We include returns between May 1, 2009 and Dec 31, 2010, as these are the dates with prediction market prices. The regression equation for the pooled effect is:

$$\Delta y_{ft} = \alpha_{fm(t)} + \beta\ \Delta x_t + \gamma_f\ \Delta z_t + \epsilon_{ft} \tag{3}$$

As in equation (1), we use Δy_{ft}, the percent change in the future price on day t for the oil future with a maturity of $f = 1 \ldots 24$ months into the future. We now regress the percent change in the future price on the change in the prediction market probability Δx_t of a cap-and-trade bill passing[6] on day t. The main coefficient of interest is β, the effect of changes in the probability of the bill passing on oil future returns. All other controls and clustering are identical to equation (1).

We run the analysis for different subsets of days. Oil futures might be especially responsive on days when there are major changes in the probability of a bill passing and hence major changes in the price of the prediction market. We conduct the analysis for all days as well as for subsets of days when the absolute change in the probability of a climate bill passing exceeds various cutoffs ranging from 1 to 5 cents. In other words, for a given subset we include only days when $|\Delta x_t| \geq c$, with $c \in \{0, 1, 2, 3, 4, 5\}$ cents. We explore whether β increases in magnitude for "major" belief updates, i.e., as c increases, e.g., because the market is more sensitive to major updates. In an additional auxiliary analysis, we further restrict subsets using google trends for the search term "waxman markey." Including the google trends filter restricts the analysis's focus to shocks that were broadly recognized by the general population. We conduct the analysis for subsets of days when the absolute price change exceeds various cutoffs and when the google trend index on the day of the absolute change or the day after exceeded a given cutoff as well. The google trend filter is applied to the day of and day after a price shock as the prediction market may internalize new information faster than the general population.

We further relax the linearity assumption of the response and instead model it using restricted cubic splines $g(\Delta x_t)$ with knots at -5, -2, 0, 2, and 5 percent. Such an approach forces the response to be linear below the minimum knot (-5) and above the maximum knot (+5), but uses third-order polynomials in between. We expect the effect of a positive prediction market shock on oil prices to be negative and a negative shock to be positive. The equation becomes:

$$\Delta y_{ft} = \alpha_{fm(t)} + g(\Delta x_t) + \gamma_f\ \Delta z_t + \epsilon_{ft} \tag{3a}$$

We again allow for heterogeneity of the effect β by oil future maturity, i.e., β_f, while all other controls remain identical to equation (3). The modified regression equation is:

$$\Delta y_{ft} = \alpha_{fm(t)} + \beta_f\ \Delta x_t + \gamma_f\ \Delta z_t + \epsilon_{ft} \tag{3b}$$

[6] The prediction market values range from 0 to 100 cents, which in an efficient market should reflect the probability of the bill passing. We take the difference in the closing price relative to the previous closing price, thereby obtaining the change in the probability of the bill passing.

In the appendix, we test for robustness to the inclusion of the oil spot price. Lower oil prices are associated with negative future returns and could increase the likelihood that the bill will pass. Higher oil prices are associated with positive future returns and could decrease the likelihood that the bill will pass. We control for the oil spot price to asuage concerns that reverse causality drives the paper's results.

Urgenda v. Netherlands Verdict Announcement Beyond linking oil future returns to market predictions, we compare oil future returns on the day Urgenda v. Netherlands was rendered to future returns generally. Urgenda v. Netherlands was the first successful climate liability suit brought under human rights and tort law. In the ruling released on June 24, 2015, the judge acknowledged that climate change's threat was severe and stated that under Dutch law a threat of damage suffices for injunctive relief. The verdict stated that by the end of 2020, the Dutch state had to reduce greenhouse gas emission by at least twenty five percent relative to 1990 levels.

The Urgenda v. Netherlands ruling was unexpected, notable and historic. For example, the New York Times article "Ruling Says Netherlands Must Reduce Greenhouse Gas Emissions" on June 24, 2015 quoted Marjan Minnesma, the director of Urgenda, saying "Everybody in the legal scene said, 'This will never happen — this is just a P.R. stunt.' This is not a P.R. stunt." The same article quoted Michael Gerrard, director of the Sabin Center for Climate Change Law at Columbia University, saying "I think this will encourage lawyers in several other countries to see if they have opportunities in their domestic courts to pursue similar litigation." People predicted the verdict set a precedent that other countries subject to the European Convention would follow. The Dutch share of global fossil fuel consumption is minimal, and the estimated effect is hence driven by an update in the probability that other countries would follow suit. We do not have a direct estimate on the market update in the probability that other countries would follow suit, and the coefficient we find in the regression equation is not directly comparable to our prediction market analysis. It should be scaled (divided) by the change in the probability to make it comparable. However, past papers have argued that prediction markets do not reliably reflect market beliefs (Manski 2006, Fountain and Harrison 2011, Lemoine 2017). This analysis provides another source of identification using a surprise verdict.

As in the previous equations, the analysis includes oil futures with maturities ranging from 1 to 24 months away. We construct the abnormal returns on the verdict announcement date. As documented in figure A1, the permanence of oil price shocks varied significantly between 1990 and 2022. We compare returns on June 24th, 2015 to five different subsets of days to demonstrate robustness to these heterogeneous comparison groups. The regression equation for the pooled effect is:

$$\Delta y_{ft} = \alpha_{fm(t)} + \beta \ \mathbb{1}_v + \gamma_f \Delta z_t + \epsilon_{ft} \tag{4}$$

We regress Δy_{ft}, the percent change in the future price on day t for the oil future with a maturity of $f = 1 \ldots 24$ months into the future on a dummy $\mathbb{1}_v$ for June 24, 2015, the day the Urgenda v. Netherlands verdict was rendered. The main coefficient of interest is β, the effect of the verdict announcement on oil futures. Other controls and clustering are identical to the previous equations.

We subsequently allow again for heterogeneity in the effect β by oil future maturity, i.e., β_f, while all other controls remain identical to equation (4). The modified regression equation is:

$$\Delta y_{ft} = \alpha_{fm(t)} + \beta_f * \mathbb{1}_v + \gamma_f \Delta z_t + \epsilon_{ft} \tag{4a}$$

3 Empirical Results

Oil Price Shock Permanence Figure 1 highlights the persistence of oil spot price shocks on returns of future for the next 24 months. We regress daily changes in oil futures on the daily change in the spot price while accounting for daily changes in the S&P500 as outlined in equation (1). The x-axis indicates the maturity ranging from 1 to 24 months into the future, while the y-axis gives the point estimate as well as the 95% confidence band. The dark line reflects the estimates for all days between 1990 and 2022. Contracts with a maturity in one month have a coefficient of 0.95, i.e., on average 95% of the change in the daily oil spot price is reflected in the futures price with a one-month maturity. On the other extreme, only 13% of the change in the daily oil spot price is reflected in the future price with a maturity 24 months (2 years) away. Maturities in between show a roughly exponential decline, suggesting that shocks on average during the sample period were temporary and phased out over two years. The light blue (cyan) line replicates the same analysis using only days between May 2009 and December 2010, days when the cap-and-trade prediction market was active. During this period the House passed Waxman-Markey and the Senate deliberated a very similar bill. For this period, the coefficient is 0.90 for a one-month maturity and 0.58 for a 24-month maturity. In other words, when climate legislation was under consideration, shocks to the spot price were much more persistent, phasing out much slower relative to the whole sample. This is consistent with the theory of the "Green Paradox", as climate change legislation should reset the *entire* expected price path and lead to permement rather than transitory changes. Uncertainty around future legislation should yield stickier price shocks relative to other shocks.

Appendix Figure A1 further splits the sample period into five year intervals ranging from 1990-1994 to 2015-2019, as well as a 3-year end period 2020-2022. Shock persistence increases from 1990-1994 to the 2010-2014 period, when climate legislation was most actively discussed. The persistence slightly declines again in 2015-2019, before collapsing in 2020-2022, as COVID-related supply disruptions lead to short-term price fluctuations – the oil price was briefly even negative when storage levels reached capacity. Notably, shocks were most persistent during the period when cap and trade policy was heavily considered by the US Federal Government and the EU established an emission trading system. The average decay in the translation of spot price shocks to changes in futures with various maturities sets an important baseline for the next step.

Climate Policy Salience Table 1 highlights the average effect of climate policy salience in the news, generally a strong proxy for moments when future climate policy strengthened, on oil future returns. Specifically we regress monthly changes in oil futures prices on three monthly indices measuring the prevalence of articles covering environmental policy generally, international climate negotiations and renewable policy, as outlined in equation (2). Indices are standardized to be mean zero and have unit standard deviation for interpretability. We display coefficient estimates β, θ and λ. The first row displays β, the effect of a one standard deviation increase in the international climate negotiations index on future prices. The second row gives θ, which reflects the effect of a one standard deviation increase in the renewable policy index on future prices. Finally, λ displayed in the last row, reflects the effect of a one standard deviation increase in the environmental policy index on future prices. Columns differ in the included controls. The First column includes only quarter by year fixed effects. The final column includes quarter by year by maturity fixed effects and controls for monthly changes in the S&P500 index.

We find a one standard deviation increase in the international climate negotiations index is associated with a 0.918-0.975% decrease in expected oil prices over the next two years as shown in the first row of Table 1. For reference, the Paris Climate agreement is associated with an index six standard deviations above the mean. While only suggestive, this finding is consistent with "Green Paradox" predictions. Moments demonstrating international cooperation around climate change enforce expectations that climate policy will be more stringent moving forward, increasing production today and decreasing prices.

We find a one standard deviation increase in the renewable index is associated with a 2.57-2.72 increase in expected oil prices over the next two years as sown in the second row of Table 1. For reference, First Solar's signing of a memorandum with China to build the world's largest solar power plant is associated with a Renewable index of 2.75 standard deviations above the mean. Note that the coefficient has the opposite sign from climate legislation. What is the rational? There are two effects at work that move in opposite direction: Renewable policies that lead to technological progress down the road with lower backstop prices should increase oil production as the increased competition with renewable technology in the future shifts oil supply to the present. On the other hand, if the passage of renewable legislation is seen as a substitute for climate legislation, thereby lowering the probability of future supply restrictions, it should increase the price of oil today as market participants anticipate less restrictions in the future. The positive sign suggests that the latter effect dominates the former. Our finding suggests that oil producers do not view current advances in renewables as a threat to future oil demand but instead as a mechanism reducing threats to future oil demand as they may reduce the likelihood of more stringent climate policy.

One might be concerned about reverse causality where higher oil prices are associated with positive oil future returns and could increase the probability of renewable policy passing. Table A1 presents a sensitivity analysis to the results reported in Table 1 where we additionally control for the oil spot price in addition to the controls included in the main specification. We find a one standard deviation increase in the renewable index is associated with a 2.39-2.56 increase in expected oil prices over the next two years in the second row of Table A1, which is very similar to our baseline. This make a story of reverse causality unlikely.

Finally, we find the general environmental policy index is not significantly correlated with oil prices as shown in the third row of Table 1. The environmental policy index tracks the salience of environmental policy generally, picking up events affecting court cases and clean ups, air pollution, water pollution, climate policy, etc. From 1981-2000, the most prevalent topics covered by the index include water and air pollution as well as court cases and clean ups (Noailly et al. 2021). Once controlling for the salience of international negotiations and renewable policy, the index predominantly reflects the salience of non-climate environmental policy in the news proxying for moments when non-climate related environmental policy became more stringent. Thhis falsification check with the resulting the null effect is reassuring. The "Green Paradox" predicts increases in the stringency of non-climate related environmental policy should have no effect on oil prices.

Cap & Trade Prediction Market Table 2 highlights the average effect of changes in the probability of a cap and trade policy passing on expected oil prices, oil futures contracts that expired before the cap would have been implemented. Specifically, we regress daily changes in oil futures prices on daily changes in prediction market prices, a market-based measure of the probability that a climate bill passes, as outlined in equation (3). We display coefficient estimate β, the effect of changes in the prediction market on future prices, while we suppress other coefficients (future-by-month fixed effects and future-specific controls for the movement of the S&P500). Columns differ in what days are included in the regression. The first column in both panels use all days between May 2009 and December 2010, the period when the prediction market was active. A coefficient of -3.43 suggests that changing the probability of the bill passing by December 2010 from 0% (certainly not passing) to 100% (definitely passing) decreases oil futures prices by 3.43%. Recall that the prediction market contract is on a climate bill passing by the end of 2010, so market participants might still expect a bill to pass at a later point. The estimated coefficient is hence for a climate bill net of later subsequent expected climate bills. Nonetheless we find a sizable effect of 3.43 percent.

The remaining columns of Table 2 restrict the sample to days when the absolute change was at least 1, 2, 3, 4 or 5%, respectively, i.e., when the prediction market saw increasingly major updates. Accordingly, the number of days in the analysis successively decreases, but the coefficient estimate increases in magnitude from -3.43 in column (1) when we include all days to -7.08 in column (6) when we use only days that had at least a 5% change in the prediction market price. As discussed above, we would expect the oil market to be especially responsive to major events, e.g., when Republican Senator Lindsay Graham withdrew his support, and we would expect the oil market to be less responsive to smaller day-to-day changes in the probability of a bill passing. There is a use mass point at 0, i.e., days, where the prediction market price did not change, and small fluctuations might also be a result of the bid-ask spread of a market with limited liquidity. Table A2 documents the sensitivity of the results in Table 2, Panel A to various clustering options.

Panel B adds an additional restriction based on internet search volume. We require that the Google trends index for the search term "waxman markey" exceeded 1, 2, 3, 4, or 5 in absolute terms.[7] We look at the search column on the same day as well as next day, as financial markets tend to react quickly to emerging news. The cominbined restriction on both the prediction market prices and internet search volume focuses on days when the prediction market saw increasingly major updates that were reflected in search trends. Accordingly, the number of days in the analysis successively decreases, but the coefficient estimate increases in magnitude again from -3.43 in column (1) when we include all days to -6.99 in column (6), which is rather close to -7.08 in Panel A. Further restricting our sample to events that were salient both on google and in the prediction market yields similar results.

The increase in the estimated coefficient when we limit the days to major events is inconsistent with a story of reverse causality, where higher oil prices make the passage less likely. As outlined in Meng (2017), major prediction market movements were associated with politicians joining or abandoning the bill after negotiation rounds, whose previously scheduled timing was unlikely to have aligned with daily oil price changes. Moreover, public statements about why politicians joined or abandoned the bill do not mention contemporaneous oil prices. The New Yorker had a background story[8] that outlined the key events that led to the unraveling of the coalition supporting the climate bill. Oil prices as well as oil price changes are never mentioned. Rather political events that are not related to oil prices caused most fluctuations in the

[7]Recall that the trend data is relative to the most active day, which has a value of 100. A change in 2 on the index is hence equivalent to 2% of the search volume relative to the most active day.

[8]"As the World Burns: How the Senate and the White House missed their best chance to deal with climate change," October 11, 2010 issue.

probability of the bill passing. Table A3 lists news stories for the 26 days where prediction market prices changed by at least 5%, i.e., the days used in column (6) of Table 2. While we do not know what exact news the prediction market responded to, positive changes are usually associated with news stories where the bill's sponsors are speaking up in its support, while negative changes are associated with opponents voicing their dissent. These events sometimes occur on consecutive days with opposite signs. Importantly, these events are unlikely to be related to day-to-day oil price fluctuations, but rather teh result of committee meetings that were scheduled days in advance. We present an additional check for reverse causality in Table A4: we test whether controlling for the oil spot price changes our findings. Lower (higher) oil prices are associated with negative (positive) future returns and could increase (decrease) the likelihood that the bill will pass. If reverse causality drives the observed results, we would expect the main estimated effect to be lower once we control for the oil spot price. However, the association persists even when we control for the oil spot price, particularly when we limit our sample to political events that are not related to oil prices, i.e., days when the prediction market price changed by at least 4%.

Figure 2, Panel A and B present the effect of changes in the probability of a cap and trade policy passing on oil future prices, allowing the effect to vary across maturities. The different cutoffs of Table 2 are now shown in different colors. As in Table 2, Panel A applies the cuttoffs only to prediction market prices and Panel B applies the cutoff to prediction market prices and the Google trends index. In both panels, the x-axis displays the results by maturity, while the y-axis gives the point estimates as well as the 95% confidence band. Similar to the pooled analysis, the coefficients become larger in magnitude when the data is limited to days when the prediction market price changed by at least 4% (orange and red color in Figure 2 or column (5) and (6) in Table 2). Remarkably, estimated coefficients *increase* in magnitude for maturities that are further into the future, in contrast to the average relationship between oil price shocks and expected future prices, where shocks phase out over time that was shown in Figure 1. This implies that price adjustments associated with prediction market fluctuations are not phasing out but rather phasing in. This is consistent with the finding of Anderson, Kellogg and Salant (2018) that oil production from *existing* wells do not respond to oil prices in the short-term due to physical constraints, i.e., closing an existing producing well is costly (which explains why oil prices briefly turned negative during COVID shutdowns). Letting the oil flow, once a well is tapped, is usually the most economical irrespective of short-term price dynamics. Kellogg (2014) shows that drilling decisions react quickly to changes in market expectations, but it again takes a while for the oil to flow. Notably, development of infill wells respond to oil future contracts with 18 months to maturity. While the standard Hotelling model suggests that the price path will reset right away in response to a climate bill passing, physical constraints (both in closing existing wells and in opening new ones) imply that it can take a few months for adjustments to be realized, explaining why the coefficients get larger in magnitude for maturities that are further into the future. The overall effect of the climate legislation shock needs time to materialize as new oil production cannot be turned on or off overnight.

Figure 3 relaxes the linearity assumption by estimating a flexible response function using restricted cubic splines from equation(3a) using all observations, i.e., the data from column 1 of Table 2. The green histogram displays the density of the observations – there is a clear mass point at zero, i.e., days where the prediction market had no price change. The spline implementation forces the relationship to be linear below the lowest knot (-5) and above the highest knot (5), so the linear relationship is imposed for the tails. However, within $[-5, 5]$, the relationship is allowed to evolve flexibly using third-order polynomials, yet the linearity assumption still hold reasonably well. The exception is for small changes in probability $[-1, 1]$, which might not be surprising as the market has limited liquidity, there is a bid-ask spread, and prices mostly reflect discrete integer values. In this sense, changes by $+1$ or -1 might not reflect belief updates and lead to attenuation bias.

Manski (2006), Fountain and Harrison (2011), and Lemoine (2017) caution against interpreting prediction market prices as reflections of market expectations. Table A5 presents another sensitivity check where we use a step function, i.e., discretize the response function by using a dummy variable if prediction market changes are above a certain limit. This exercise attempts to glean objective information from the prediction market without relying too heavily on prediction market price levels for identification. The estimated coefficient of interest reflects the average effect of a shock on oil futures prices. To make estimates comparable to our main results in Table 2, we scale the coefficient by 100 divided by the average prediction market shock. Hence, estimates give the change in oil price in percent for a 100% change in the probability of the bill passing. Columns differ again the cutoff c used to identify shocks. Panel A only applies the cutoff to prediction market price changes to identify information shocks while Panel B applies the cutoff to price changes and the google trends index. All 10 estimated coefficients remain negative and of similar magnitude to Table 2, yet these estimates become more noisy and several are no longer statistically significant. Taken together with the linearity displayed in Figure 3 and the significant results in Table 2, it does appear that prediction market prices, at least outside the $[-1, 1]$ convey meaningful information that the market responds to.

Finally, Table A6 further aims to distinguish between demand and supply shocks. The "Green Paradox" is a supply shift, which implies that prices and storage levels should move in the same direction. If future climate legislation shifts supply to the present, both the price and storage levels should decline as the optimal allocation over time is adjusted. The reduced price increase current-period consumption, which is achieved through depleting storage storage levels as production cannot be increased in the short-term. On the other hand, demand shocks generally lead to an inverse relationship between oil prices and storage levels. An inward shift in demand reduces prices but leads to a buildup in storage levels, as production cannot be adjusted in the medium-term. While oil price data is available on a daily level, storage and production numbers are only available at the weekly level. As a first step, we therefore the regression results from Panel A in Table 2, except that we switch to a weekly level in Panel A of Table A6. The coefficients are of similar magnitude, but no longer statistically significant. Panel B of Table A6 replicates the same analysis for oil storage levels rather than price levels. The regression coefficients are again negative with one exception, although again not statistically significant. Consistent signs between the price and storage response would imply a supply rather than a demand shock. Although, we should stress again that coefficients are not statistically significant, so all we can say is that a supply shock seems more likely than a demand shock. Finally, panel C examines production changes, and finds coefficients that are smaller in magnitude and repeatedly switch sign. This is consistent with the finding that it is difficult to adjust production in the short term.

Table A7 replicates the analysis for coal futures prices. We again regress daily changes in futures prices, this time from coal contracts, on daily changes in prediction market prices, a market-based measure of the probability that a climate bill passes. The relationship is not statistically significant for the entire sample in column 1, i.e., we find that changing the probability of the bill passing by December 2010 from 0% (certainly not passing) to 100% (definitely passing) decreases coal futures prices by 1.02%. As we restrict the number of days in the analysis, to days when the absolute change in prediction market prices exceeded increasingly restrictive cutoffs, the coefficient estimate increases in magnitude from -1.02 in column (1) when we include all days to -5.50 in Panel A, column (6) when we include only days that had at least a 5% change in the prediction market price. The coefficient further increases to -8.45 in Panel B, column (6) when we include only days that had at least a 5% change in the prediction market price and a google trends index of at least 5. When we control for the oil spot price the coefficient peaks at -9.25 in column (6) of Panel B in Table A8. In other words, we obtain similar percent effects as for oil in Table 2 when we focus on the days with major updates (right columns of Tables), but not if we include days with smaller updates (left columns of Tables).

One possible reason why coal futures prices might show a lower responsiveness to prediction market prices is that coal use in the U.S. faces other possible binding future constraints due to air quality regulation. In nations such as the U.S. and Germany, coal has been phased out to improve local air quality, making changes in domestic climate policy not particularly relevant to coal extraction paths. That said, demand for coal in China and India continues to grow. Assuming sufficiently low transport and trade costs, the paradox's predictions should still apply to coal. Particularly salient prediction market shocks (i.e. significant changes in prices associated with increased google search traffic) perhaps better reflect changes in market expectations of the stringency of future *global* climate policy, hence having a more prominent affect on coal prices via the "Green Paradox."

In summary, our analysis of the cap & trade prediction market provides empirical evidence that oil and coal markets respond to changing expectations about climate legislation that limit future fossil fuel consumption. What are the policy implication of our findings? First, we can derive the effects if the law had passed on oil consumption. Using the average long-term demand elasticity of -0.6 from Hamilton (2009, Table 3), the price coefficients in Table 2 imply that the passage of the cap and trade policy considered in the US in 2009-2010 would have increased *global* oil consumption 2.0-4.2%[9], accelerating the depletion of the resource. The number is market's estimate of US regulation and its best estimate of follow-on regulation in other countries. Second, even though the legislation never passed, its discussion temporarily altered the oil price path. We derive the additional oil consumption induced by it's deliberation in the back-of-the envelope calculation. Starting with an undisturbed price path, we use the average short-term demand elasticity of -.26 from Hamilton (2009, Table 3) paired with the price coefficient associated with the one month maturity in Figure 2 to derive the resulting changes in daily prices changes comparing to a counterfactual where the bill was never discussed. As the probability of the law passing increases, the price is suppressed, leading to additional oil consumption, which in our back-of-the-envelope calculation is simply taken to be the coefficient estimate times the demand elasticity. As the probability of the law passing falls back to zero, the price path returns to the trajectory of the initial undisturbed price path. We are then summing the temporary increase in oil consumption due to the temporary price reduction for the time period for which the prediction market data is available, i.e., May 1, 2009 and Dec 31, 2010. The combined *additional* oil consumption are 7.7-26.69 million metric tons.

Urgenda v. Netherlands Verdict Announcement In a final step, we derive the oil market's response to the surprise Urgenda v. Netherlands ruling on June 24, 2015. The results for the event study examining the abnormal return on June 24, 2015 as specified in equation (4) are shown in Table 3. As always we control

[9]We obtain this number by multiplying the coefficients from Table 2 by the demand elasticity.

for overall market movements by controlling for the daily returns of the S&P500, which are allowed to vary by maturity of the future contract. Different columns use different time spans around the event day. While the estimated coefficient is always for one day (June 24, 2015), the inclusion of further days around the event itself influences the coefficient estimates γ_f in equation (4) and hence the prediction of the "normal" return on that day, which forms the basis for constructing the abnormal return.[10] Column (1) uses the smallest time period (year 2015), while column (2) adds two years before and after 2015, and column (3) adds an additional 2 years on either side. Column (4) uses all days between 1990 and the end of 2019 and hence stops before the COVID-related disruptions. Finally, column (5) also adds the COVID years. The estimated coefficient is always negative and significant ranging from -0.55 to -0.9. Note that the coefficient is not directly comparable to the point estimates in Table 2, which were scaled to reflect the impact of a change in the probability of a US cap and trade bill from certainly not passing (0% probability) by December 2010 to it passing with certainty (100% probability). As outlined above, the Netherlands account for a small fraction of global emissions, and the bigger issue of the ruling was whether courts in other countries would follow suit. To make the coefficients between the two tables comparable, the estimates of Table 3 would need to be divided by the change in probability that enough other countries adopt similar measures to add up to the same oil use restrictions as Waxman-Markey. We unfortunately have no way of knowing this probability, but instead note the inverse: if Urgenda v. Netherlands caused a 5-10% increase in market beliefs that other countries would reduce emissions to a similar extent as Waxman-Markey, then the coefficient estimates from the two tables would be consistent.[11] More importantly, both daily changes in the prediction market as well as the abnormal return on the day of the surprise Urgenda v. Netherlands ruling provide strong evidence that the financial market quickly updates its beliefs about possible future restrictions to oil use, with implications for the optimal extraction and price path. Notably, restriction in the future leads to lower prices and more consumption today, offsetting some of the savings in the future through higher extraction today.

Figure A2 allows the pooled effect of Table 3 to vary by maturity. The coefficients increase with maturity until about 4 months and then start to decrease again. The persistence is at least as high as what we observed for the 2010-2014 period in Table A1, highlighting that the market saw the news as a persistent rather than a temporary shock.

Conclusions

We provide novel evidence on the "Green Paradox" for climate change legislation using a apnel of daily data. Climate bills that limit future oil use shift oil consumption from the future towards the present, thereby lowering oil prices in the present and medium-term until the bills bind. Previous papers on the "Green Paradox" have conducted pre-post comparisons around the passage or discussion of environmental regulation to construct evidence of legislation's effect on fossil fuel prices. One of our paper's contributions is our reliance on daily oil price data and market estimates of the probability that a bill will pass. Forward-looking futures prices do not respond when laws are enacted or fail to be enacted, but rather to the release of new information on whether or not a law will pass. Oftentimes whether or not a bill will pass is clear

[10] The inclusion of further days around the event itself in equation (4) would have no impact on the estimated coefficient in the absence of controls for changes in the overall economy.

[11] Dividing the coefficients of Table 3 by 0.05-0.1 gives similar estimates to Table 2.

long before it is enacted, making bill passage not a surprise. Moreover, our reliance on daily variation and use of direct estimates of market expectations allow us to overcome reverse causality challenges common in pre-post comparisons – downward trends in prices can decrease resource owners' resistance towards a law increasing the likelihood that a bill passes. We get around this challenge by coupling market estimates of the probability that the US climate law would pass from prediction markets that are driven by political processes unrelated to daily changes in oil prices.

We provide four pieces of evidence that are consistent with the "Green Paradox" for climate change legislation. First, we document that daily shocks to the spot price for oil (changes relative to the previous day) historically quickly phase out over time, i.e., maturities further into the future show less responsiveness to changes in oil spot prices. This is consistent with temporary spot price shocks, e.g., due to temporary demand spikes (cold winters) or temporary supply disruptions. However, during the time period when a US climate bill was deliberated, the daily shocks to the spot price became much more persistent, indicating that the underlying uncertainty was more fundamental and had to be related to events that change the entirety of future oil prices for which futures are actively traded.

Second, when we link monthly changes in oil futures to changes in the salience of climate policy in the news, we find a highly significant negative relationship between the salience of international climate negotiations and oil futures consistent with a story that international cooperation around climate change enforce expectations that climate policy will be more stringent moving forward, increasing current oil consumption. Additionally, we find a significant positive relationship between the salience of renewable energy policy and oil futures consistent with a story that oil producers have not viewed advances in renewable policy as threats to future oil demand but rather as a mechanism reducing threats to future oil demand as they possibly reduce the likelihood of more stringent climate policy.

Third, when we link daily changes in oil futures to changes in the probability that the US will pass a climate bill, we find a highly significant negative relationship consistent with a story that legislation limiting future oil use increases current consumption. This relationship is even more significant and of higher magnitude when we limit the data to a few dates of key political events, ruling out reverse causality, as the timing of these political events was not driven by oil prices. By the same token, the surprise ruling of a Dutch Court that ordered the government to limit fossil fuel use was associated with a significant negative abnormal oil price return. Moreover, the verdict release date was pre-determined and not affected by daily oil price movements, again ruling out reverse causality.

Fourth, the maturity profile of the negative coefficients from both the prediction market and the Dutch court verdict show very high persistence. Effects continuously increase in magnitude for all 24 months for which oil futures are available. This is consistent with price path and consumption adjustments that are constrained by short-term supply constraints, implying that the full effect will only be felt later on. These findings are in sharp contrast to temporary spot price shocks that tend to phase out rather than in.

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Table 1: Media Coverage of Climate Policy and Prices of Oil Futures

	(1)	(2)	(3)	(4)
International Climate Negotiations	-0.918**	-0.918*	-0.958**	-0.975**
	(0.385)	(0.472)	(0.373)	(0.453)
Renewable Policy	2.667**	2.719*	2.571**	2.581*
	(1.256)	(1.533)	(1.234)	(1.501)
Environmental Policy	0.306	0.252	0.435	0.436
	(0.942)	(1.151)	(0.905)	(1.096)
Quarter x Year FEs	Yes	No	Yes	No
Maturity x Quarter x Year FEs	No	Yes	No	Yes
S&P 500 x Maturity	No	No	Yes	Yes
Observations	9216	9162	9216	9162

Notes: Table regress the change in the closing price of oil futures (24 different maturities ranging from 1 to 24 months into the future) on a monthly indices measuring the share of news articles covering international climate negotiations, renewable energy policy, and environmental policy generally. All indices are standardized to a mean of zero and unit standard deviation. Coefficients give the change in the closing oil price in percent for a one standard deviation increase in each news index. As a reference, the Paris Climate Agreement is associated with an International Climate Negotiation index 6 standard deviations above the mean. And, First Solar's signing of a memorandum with China to build the world's largest photovoltaic power plant is associated with a Renewable index of 2.75 standard deviations above the mean. Columns differ in the controls included. For example, Column (1) includes quarter by year fixed effects and Column (4) includes maturity by quarter by year fixed effects and controls for changes in the S&P500 index by maturity (Columns 1 and 2 force the effect of the S&P500 index to be the same across maturities). Errors are clustered by month.

Table 2: Probability Climate Bill Passes and Price of Oil Futures

	(1)	(2)	(3)	(4)	(5)	(6)
Min market change	0	1	2	3	4	5
Panel A: Cutoffs Only Applied to Changes in Prediction Market Prices						
Prediction Market	-3.43*	-3.68*	-3.49*	-3.89*	-6.83***	-7.08***
	(1.87)	(1.98)	(1.97)	(2.26)	(2.07)	(2.39)
Observations	10072	2880	1920	1344	912	624
Fixed Effects	480	456	384	360	264	240
Clusters	420	120	80	56	38	26
Panel B: Cutoffs Applied to Prediction Market and Google Trends						
Prediction Market	-3.43*	-4.34*	-4.35*	-5.03**	-5.23**	-6.99**
	(1.87)	(2.55)	(2.39)	(2.43)	(2.38)	(2.97)
Observations	10072	1992	1296	936	672	384
Fixed Effects	480	456	360	312	240	144
Clusters	420	83	54	39	28	16

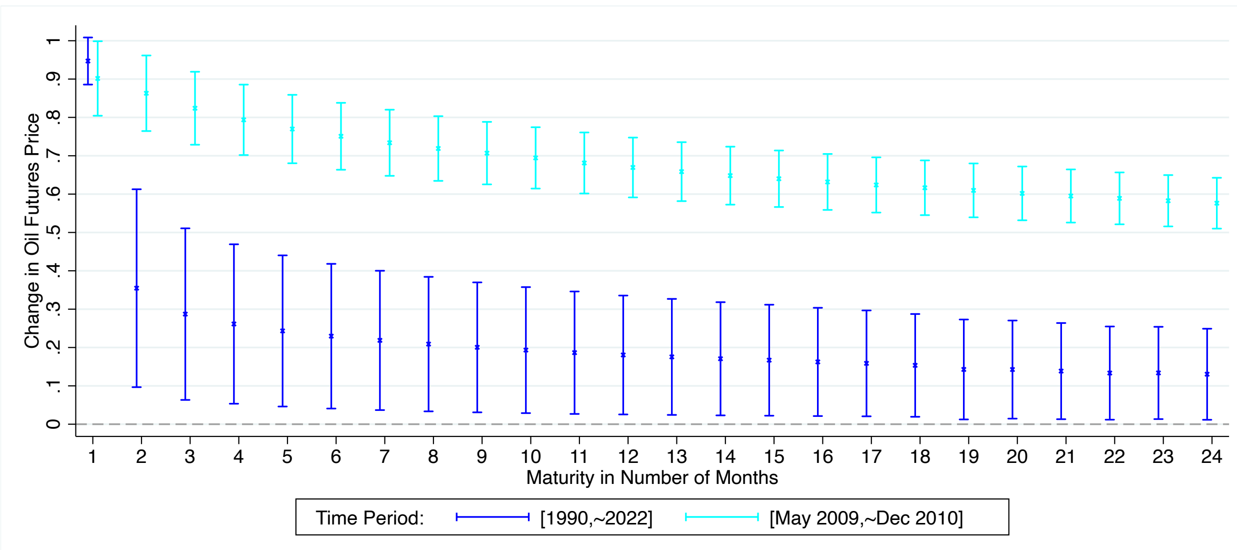
Notes: Table Panel A and B regress the daily change in oil futures (24 different maturities ranging from 1 to 24 months into the future) on the change in the prediction market probability that a US cap-and-trade bill will pass. Coefficients give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Columns differ by what days are used in the analysis, with the top row listing the cutoff value for the absolute change in the prediction market price (and google trend index) required for a day to be included. For example, Panel A Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). Panel B Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5% relative to the day with the highest search volume, counting both the day itself or the day after. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Table 3: Urgenda vs Netherlands Court Ruling and Prices of Oil Futures

	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_v$	-0.573**	-0.618**	-0.653**	-0.929***	-0.895***
	(0.276)	(0.260)	(0.258)	(0.281)	(0.277)
Observations	6275	31449	56515	181665	200539
Fixed Effects	300	1500	2700	8819	9719
Clusters	251	1258	2261	7538	8294
Years	[15,15]	[13,17]	[11,19]	[90,19]	[90,22]

Notes: Table regresses the change in oil futures (24 different maturities ranging from 1 to 24 months into the future) on a dummy $\mathbb{1}_v$ for June 24, 2015, the day the Urgenda vs Netherlands verdict was rendered. Coefficients give the change in oil price in percent. Columns differ by what days are included in the analysis with the bottom row listing the range of years used to derive the controls. Column (1) focuses only on days in the year the ruling occurred, while column (5) includes all days between 1990-2022. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

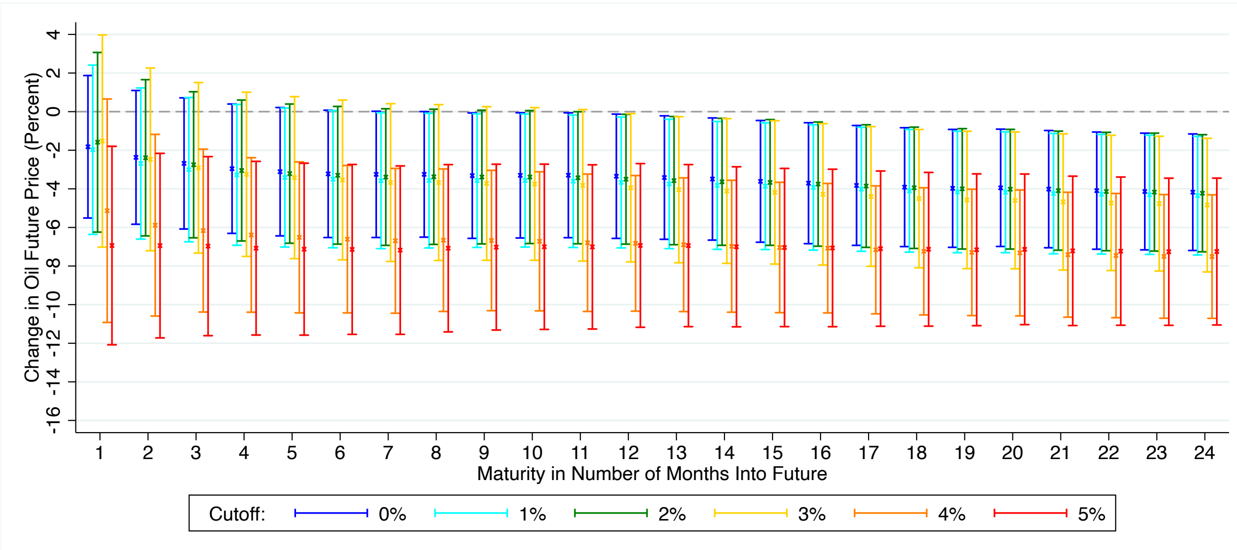
Figure 1: Oil Spot Price and Prices of Oil Futures for Various Maturities



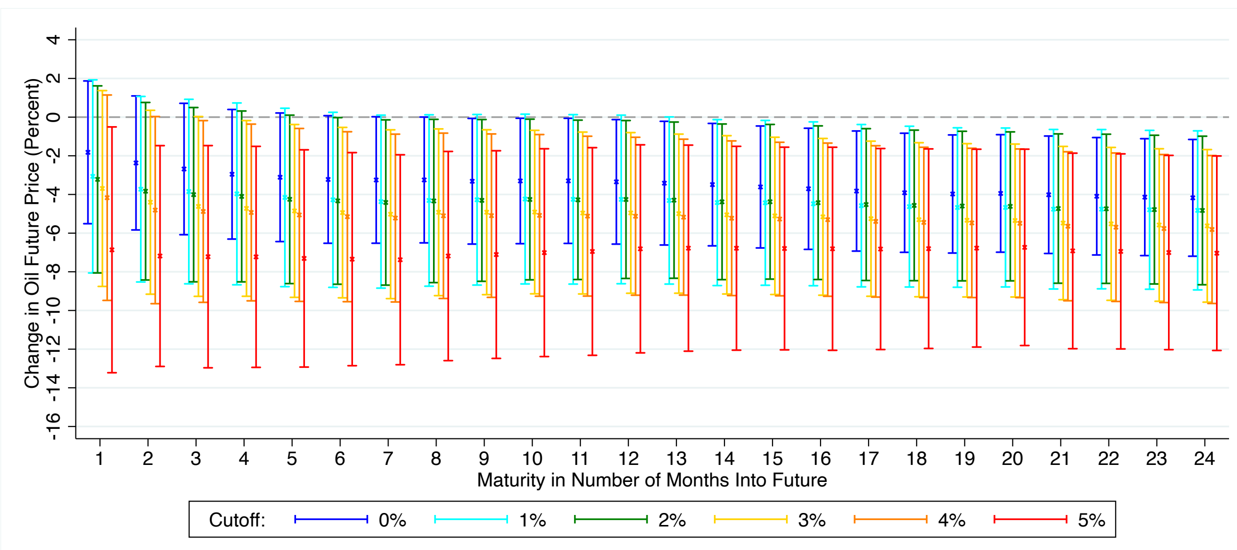
Notes: Figure plots the effect when we regress the change in daily oil futures prices on corresponding change in the oil spot price. The coefficients and 90% confidence intervals are allowed to vary by maturity ranging from 1 to 24 months. Point estimates (marked as x) give the change in oil futures price for a given change in the spot price. The two colors represent various temporal subsets of the data. Regressions controls for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Figure 2: The Effect of Changes in the Probability of the Climate Bill Passing on Oil Futures by Maturity

(a) Cutoffs Only Applied to Changes in Prediction Market Prices

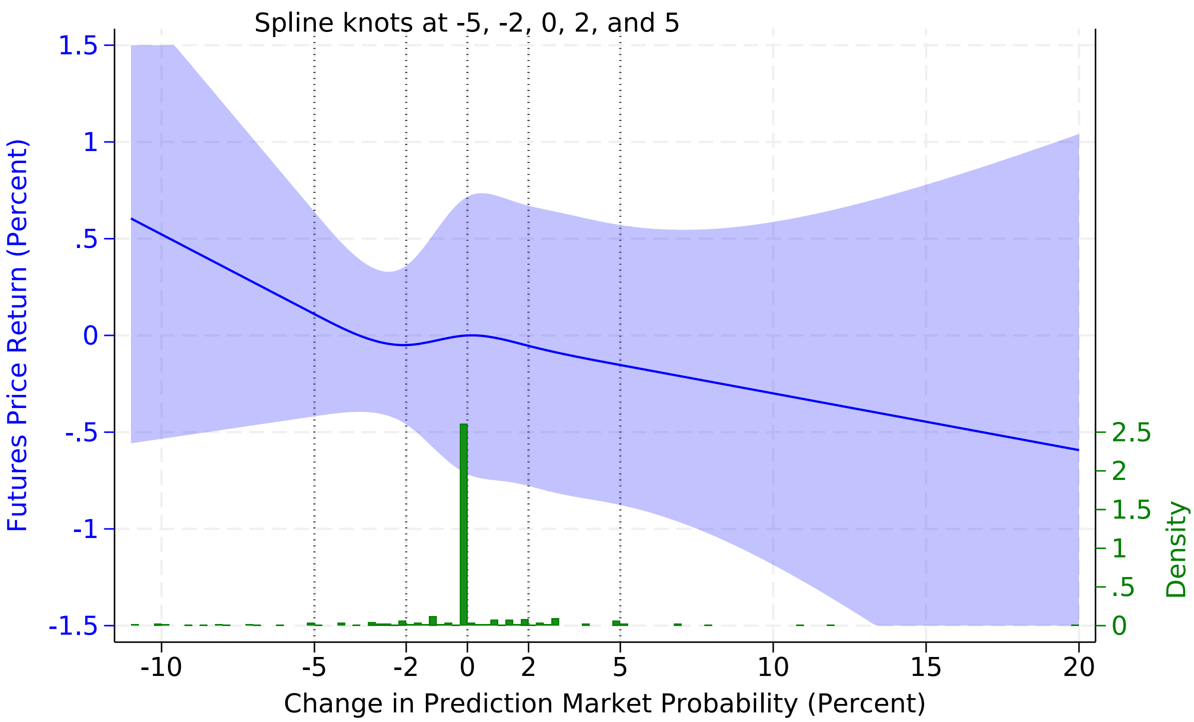


(b) Cutoffs Applied to Changes in Prediction Market Prices and in Google Trends Indices



Notes: Figure Panel A and B plots the effect of a change in prediction market probability for the passage of a US cap-and-trade bill on oil futures prices. Coefficients in Panel A and B as well as 90% confidence intervals are analogous to the coefficients in Table 2, except that the effect is allowed to vary by maturity. Point estimates (marked as x) give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty it won't pass to that it will pass). Colors differ by what days are included in the analysis. The six colors represent the different cutoffs of the six columns in Table 2. For example, in Panel A the blue lines include all days, while the red lines include only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). In Panel B, the blue lines again include all days, while the red lines include only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day or day after the prediction market change. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Figure 3: Testing Nonlinear Relationship between Prediction Market and Futures Returns



Notes: Figure plots the effect of a change in prediction market probability for the passage of a US cap-and-trade bill on oil futures prices by pooling across all maturities but allowing for a non-linear relationship. Specifically, we use restricted cubic splines with 5 knots (indicated by dashed lines). The point estimates (blue line) as well as the 95% confidence band are shown on the left y-axis. The density in observed changes in the probability of prediction markets is shown in green on the right axis - there is a probability mass at zero as the price does not change for the majority of days.

A Appendix

List of Tables

List of Figures

Table A1: Sensitivity Check: Climate Policy Salience and Oil Futures Controlling For Spot Price

	(1)	(2)	(3)	(4)
International Climate Negotiations	-0.804**	-0.803	-0.852**	-0.869*
	(0.399)	(0.489)	(0.386)	(0.470)
Renewable Policy	2.506**	2.556*	2.393*	2.395
	(1.262)	(1.540)	(1.245)	(1.518)
Environmental Policy	0.084	0.028	0.233	0.236
	(0.966)	(1.180)	(0.927)	(1.123)
Quarter x Year FEs	Yes	No	Yes	No
Maturity x Quarter x Year FEs	No	Yes	No	Yes
S&P 500 x Maturity	No	No	Yes	Yes
Oil Spot Price x Maturity	Yes	Yes	Yes	Yes
Observations	9216	9162	9216	9162

Notes: Table presents a sensitivity analysis of the main results in Table 2, where we control for the oil spot price. Table regress the change in the closing price of oil futures (24 different maturities ranging from 1 to 24 months into the future) on a monthly indices measuring the share of news articles covering international climate negotiations, renewable energy policy, and environmental policy generally. All indices are standardized to a mean of zero and unit standard deviation. Coefficients give the change in the closing oil price in percent for a one standard deviation increase in each news index. As a reference, the Paris Climate Agreement is associated with an International Climate Negotiation index 6 standard deviations above the mean. And, First Solar's signing of a memorandum with China to build the world's largest photovoltaic power plant is associated with a Renewable index of 2.75 standard deviations above the mean. Columns differ in the controls included. For example, Column (1) includes quarter by year fixed effects and Column (4) includes maturity by quarter by year fixed effects and controls for changes in the S&P500 index by maturity. Errors are clustered by month.

Table A2: Sensitivity Check: Prediction Market and Oil Futures - Clustering

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Cluster by Day					
Prediction Market	-3.43*	-3.68*	-3.49*	-3.89*	-6.83***	-7.08***
	(1.87)	(1.98)	(1.97)	(2.26)	(2.07)	(2.39)
Clusters	420	120	80	56	38	26
	Panel B: Cluster by Future-Maturity and Month					
Prediction Market	-3.43**	-3.68***	-3.49**	-3.89*	-6.83***	-7.08***
	(1.50)	(1.26)	(1.55)	(1.91)	(1.44)	(2.07)
Clusters	44	43	40	39	35	34
	Panel C: Cluster by Future-Maturity-Month					
Prediction Market	-3.43***	-3.68***	-3.49***	-3.89***	-6.83***	-7.08***
	(0.31)	(0.27)	(0.32)	(0.40)	(0.31)	(0.42)
Clusters	480	456	384	360	264	240
	Panel D: Robust Standard Errors					
Prediction Market	-3.43***	-3.68***	-3.49***	-3.89***	-6.83***	-7.08***
	(0.39)	(0.41)	(0.41)	(0.47)	(0.43)	(0.49)
Observations	10072	2880	1920	1344	912	624
Fixed Effects	480	456	384	360	264	240
Min market change	0	1	2	3	4	5

Notes: Table replicates Table 2 in panel A, and presents sensitivity analysis for various clustering structures in panels B-D. Each entry regresses the change in oil futures (24 different maturities ranging from 1 to 24 months into the future) on the change in the prediction market probability that a US cap-and-trade bill will pass. Coefficients give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Columns differ by what days are used in the analysis, with the bottom row listing the cutoff value for the absolute change in the prediction market price required for a day to be included. For example, column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5cents (equivalent to a 5% change in the probability of passing). Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects.

Table A3: News Coverage on Days when Prediction Market Price Changed by at Least 5 Cents

Date	Change	Lexis-Nexis Search for News Coverage
05/11/09	-10.0	"While Democrats met behind closed doors, Republicans held a public energy summit to consider alternative solutions to what they dub a 'cap and tax' program." (SNL Energy Dataset, S&P Global Marketplace)
05/12/09	+20.0	"The U.S. House of Representatives will pass a sweeping climate change bill by the end of next week, House Energy Committee Chairman Henry Waxman said." (Reuters)
05/13/09	-10.0	"The Economic Impact of Waxman-Markey." (States News Service on Heritage Foundation Report)
06/01/09	+5.2	"The 30-page report, commissioned by the U.S. Department of Energy, focuses on draft bills introduced individually by Senate Energy and Natural Resources Committee Chairman Jeff Bingaman, D-N.M., and House Subcommittee on Energy and Environment Chairman Edward Markey, D-Mass., and a joint bill by Markey and House Energy and Commerce Committee Chairman Henry Waxman, D-Calif. Bingaman's bill did not fare as well as the others in terms of raising renewable capacity and reducing emissions, according to the report." (SNL Energy Dataset, S&P Global Marketplace)
06/08/09	+5.0	"A new analysis of the bill by the Congressional Budget Office (CBO) shows the legislation is a fiscally-responsible clean energy plan." (States News Service on press release by Markey)
07/01/09	+5.0	"Duke CEO: New state-federal relationship needed to meet Waxman-Markey targets." (SNL Power Daily Northeast, S&P Global Marketplace)
07/09/09	-6.9	"The Waxman-Markey bill passed by the U.S. House of Representatives last month would set strict new carbon dioxide emissions levels for new coal plants, requiring them to come close to current natural gas plants in CO2 emissions." (SNL Power Daily Northeast, S&P Global Marketplace)
08/17/09	-9.8	"EPA denies senators' request to redo Waxman-Markey analysis." (SNL Electric Utility Report, S&P Global Marketplace)
08/27/09	-9.8	"The National Association of Manufacturers today launched a multi-state, multi-million-dollar comprehensive advertising campaign opposing the American Clean Energy and Security Act (H.R. 2454), also known as the Waxman-Markey climate change bill." (States News Service)
11/04/09	-11.0	"Consulting firm Point Carbon notes that recent legislative proposals in the US Congress hold oil companies accountable for both refinery and tailpipe emissions, making them more vulnerable to carbon controls than the coal-dominated electric utility sector. And the Energy Policy Research Foundation (EPRINC) calculates that climate change legislation currently being debated in Congress could put as much as 8 million barrels per day of US refining capacity at risk of closure – an astounding 45% of total operable domestic capacity." (Oil Daily)
11/19/09	-5.0	"The American Recovery and Reinvestment Act recommitted or country to science and technology. And the Waxman-Markey clean energy legislation that the House passed this past June will extend this commitment by investing $200 billion through 2025 to unleash the clean energy revolution waiting to happen across America." (US Fed News)
12/21/09	-7.0	"Sens. Maria Cantwell, D-Wash., and Susan Collins, R-Maine, unveiled a climate change bill in the Senate on Dec. 11 that would auction carbon permits to producers and importers of coal, natural gas and oil, which is an approach that differs dramatically from the Waxman-Markey cap-and-trade bill that the House of Representatives passed in June." (SNL Electric Utility Report, S&P Global Marketplace)
12/28/09	-10.8	"The findings, contained in a new analysis from the environmental think tank Resources for the Future, bolster the rationale for a cap-and-dividend plan introduced earlier this month by Sens. Maria Cantwell (D-WA) and Susan Collins (R-ME), which calls for auctioning all allowances and returning 75 percent of the revenue raised to the public in the form of monthly rebates. The Cantwell-Collins bill is a competitor to the leading Senate cap-and-trade proposal authored by Sens. John Kerry (D-MA) and Barbara Boxer (D-CA), which mirrors the House bill." (Carbon Control News)
03/15/10	+12.0	"A new report prepared for the environmental group Natural Resources Defense Council (NRDC) finds that requiring carbon capture and storage (CCS) technology to be installed on new power generation and industrial facilities would not cause severe damage to the U.S. economy, but could provide economic benefits by boosting domestic oil production 3 million to 3.6 million barrels a day by 2030 if the CO2 were injected underground for enhanced oil recovery." (Carbon Control News)
03/17/10	-8.0	"Bingaman: Comprehensive energy legislation not likely in Senate in 2010." (SNL FERC Power Report, S&P Global Marketplace)
03/23/10	+7.0	"In a March 22 letter addressed to Sen. Maria Cantwell, D-Wash., the International Emissions Trading Association said the Carbon Limits and Energy for America's Renewal Act, or CLEAR Act, is fundamentally flawed as written, and the group expressed its concern the legislation will not achieve its stated emissions reduction objectives in the most cost-effective manner possible. On Dec. 11, 2009, Cantwell and Sen. Susan Collins, R-Maine, unveiled a climate change bill in the Senate that would auction carbon permits to producers and importers of coal, natural gas and oil, an approach that differs dramatically from the Waxman-Markey cap-and-trade bill, which the House of Representatives passed in June of 2009." (SNL Power Daily, S&P Global Marketplace)
03/24/10	-9.0	"The American Petroleum Institute released the following statement today from its President and CEO Jack Gerard commenting on some media reports characterizing API's position on the Kerry-Graham-Lieberman climate discussions: [...] Moving away from the House Waxman-Markey approach was imperative. The House bill would have eliminated millions more jobs than it created and unfairly burdened families, farmers, truckers and other regular users of gasoline, diesel and other petroleum products." (States News Service)
03/26/10	+5.1	"Cap and Trade Loses Its Standing as Energy Policy of Choice." (New York Times)
04/05/10	-10.0	"The House of Representatives-passed Waxman-Markey climate bill allows holders of RGGI allowances to exchange them for federal emission permits based on the average auction price paid for the allowances in a given year. However, the passage of similar climate legislation in the Senate has faced an uphill battle since the end of last year." (SNL Power Daily, S&P Global Marketplace)
04/14/10	+7.0	"Chairman Markey: Climate Bill Has Multiple Benefits." (Congressional Documents and Publications)
04/19/10	+5.1	"Congress weighs far-reaching global warming bill. [...] If Congress balks, the Obama administration has signaled a willingness to use decades-old clean air laws to impose tough new regulations for motor vehicles and many industrial plants to limit their release of climate-changing pollution." (Associated Press International)
04/26/10	-6.0	"South Carolina Republican Sen. Lindsey Grahamn is getting an enormous amount of flack for subtracting his initial from the Kerry-Graham-Lieberman energy bill that was due to be revealed this morning. Graham's decision delays debate and could possibly be fatal for the bill's prospects." (Atlantic Online)
05/14/10	-8.0	"Sens. John Kerry, D-Mass., and Joe Lieberman, I-Conn., released the details of their long-awaited Senate energy and climate change legislation." (SNL Renewable Energy Weekly, S&P Global Marketplace)
05/19/10	+8.0	"Markey Statement on New National Academy of Science Reports." (States News Service)
07/13/10	-7.8	"Maryland Republican Party Spokesman Ryan Mahoney issued the following statement today: [...] Cap And Trade Could Cause The Loss Of Up To 41,500 Jobs In Maryland." (States News Service)
07/23/10	-8.5	"Democrats Call Off Climate Bill Effort." (New York Times)

Notes: Table provides the results from a Lexis-Nexis search on the terms "Waxman Mareky" on the 26 days where prediction markets changed by at least 5%, i.e., the days used in column (6) of Table 2. The first column gives the date, the second the change in the prediction market probability the legislation will pass, and the third the news story.

Table A4: Sensitivity Check: Prediction Market and Oil Futures Controlling For Spot Price

	(1)	(2)	(3)	(4)	(5)	(6)
Min market change	0	1	2	3	4	5
Panel A: Cutoffs Only Applied to Changes in Prediction Market Prices						
Prediction Market	-2.69	-3.23	-3.16	-3.33	-6.16***	-6.66***
	(1.90)	(1.99)	(2.05)	(2.38)	(2.13)	(2.39)
Observations	10072	2880	1920	1344	912	624
Fixed Effects	480	456	384	360	264	240
Clusters	420	120	80	56	38	26
Panel B: Cutoffs Applied to Prediction Market and Google Trends						
Prediction Market	-2.69	-4.09	-4.00	-4.64*	-4.66*	-6.89**
	(1.90)	(2.55)	(2.42)	(2.51)	(2.58)	(2.94)
Observations	10072	1992	1296	936	672	384
Fixed Effects	480	456	360	312	240	144
Clusters	420	83	54	39	28	16

Notes: Table presents a sensitivity analysis of the main results in Table 2, where we control for the oil spot price. Panel A and B regress the change in oil futures (24 different maturities ranging from 1 to 24 months into the future) on the change in the prediction market probability that a US cap-and-trade bill will pass. The difference is the regression controls for the WTI oil spot price. Coefficients give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Columns differ by what days are used in the analysis, with the top row listing the cutoff value for the absolute change in the prediction market price (and google trend index) required for a day to be included. For example, Panel A Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). Panel B Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day of the shock or the day after. Regressions control for the oil spot price, changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Table A5: Sensitivity Check: Prediction Market and Oil Futures - Step Function

	(1)	(2)	(3)	(4)	(5)
Min market change	1	2	3	4	5
Panel A: Cutoffs Only Applied to Changes in Prediction Market Prices					
$\text{I}_{\text{Prediction Market Shock}}$	-2.52	-2.12	-3.46	-4.89**	-3.81
	(2.55)	(2.32)	(2.20)	(2.26)	(2.39)
Average Prediction Market Shock (%)	4	5	6	7	8
Event Count	2904	2016	1416	1032	720
Observations	10072	10072	10072	10072	10072
Fixed Effects	480	480	480	480	480
Clusters	420	420	420	420	420
Panel B: Cutoffs Applied to Prediction Market and Google Trends					
$\text{I}_{\text{Prediction Market Shock}}$	-8.46***	-4.86*	-4.35	-5.38*	-3.12
	(3.20)	(2.84)	(2.78)	(2.80)	(2.91)
Average Prediction Market Shock (%)	4	5	6	7	8
Event Count	1752	1272	984	720	504
Observations	10072	10072	10072	10072	10072
Fixed Effects	480	480	480	480	480
Clusters	420	420	420	420	420

Notes: Table Panel A and B regress the change in oil futures (24 different maturities ranging from 1 to 24 months into the future) on a prediction market shock. Our main results displayed in Table 2 rely on variation in prediction market prices to identify the effect of a US cap-and-trade bill on oil prices. Some prediction market skeptics argue that prediction market price levels are unreliable. In this exercise we ignore variation in prediction market levels within categories but only examine a response between categories. Specifically, we regress the change in oil futures on a piece-wise function $S(\Delta x_t, c)$ such that:

$$S(\Delta x_t, c) = \begin{cases} 1 & \text{if } \Delta\ x_t \geq c \\ 0 & \text{if } |\Delta\ x_t| < c \\ -1 & \text{if } \Delta\ x_t \leq -c \end{cases}$$

We expect the effect of a positive prediction market shock on oil prices to be negative and a negative shock to be positive. Thus, we allow the effect of a prediction market shock to vary in direction by shock sign. The coefficient associated with $S(\cdot)$ reflects the average effect of prediction market information shocks on oil future returns. Coefficients are scaled by $\frac{100}{\overline{P}}$, where $\overline{P}$ equals the average prediction market change designated as a shock by $S(\cdot)$. Hence, coefficients give the change in the oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Columns differ in what days are designated as shocks, with the top row listing the cutoff value for the absolute change in the prediction market price (and google trend index) required for a day to be designated as a shock. The event count row documents the number of days designated as shocks based on the cutoff value. For example, Panel A Column (5) designates 720 days as shocks; on these days the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing) as days when positive or negative shocks occurred. Panel B Column (5) designates 504 days as shocks; on these days the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day of or day after the shock. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Table A6: Sensitivity Check: Prediction Market and Oil Storage and Production

	(1)	(2)	(3)	(4)	(5)	(6)
Min market change	0	1	2	3	4	5
Panel A: Weekly Effect on Oil Prices						
Prediction Market	-3.60	-7.43	-8.68	-7.22	-7.03	-2.14
	(8.41)	(8.82)	(8.50)	(7.98)	(7.90)	(8.45)
Observations	2040	984	816	672	576	336
Fixed Effects	168	144	144	144	144	120
Clusters	85	41	34	28	24	14
Panel B: Weekly Effect on Oil Storage						
Prediction Market	-3.04	-2.46	-2.31	-2.05	-2.35	0.34
	(2.56)	(2.29)	(2.33)	(2.33)	(2.45)	(2.43)
Observations	85	41	34	28	24	14
Fixed Effects	7	6	6	6	6	5
Clusters	85	41	34	28	24	14
Panel C: Weekly Effect on Oil Production						
Prediction Market	-0.44	0.99	0.50	-0.13	-0.40	-0.60
	(2.10)	(2.05)	(2.14)	(2.09)	(2.07)	(1.59)
Observations	85	41	34	28	24	14
Fixed Effects	7	6	6	6	6	5
Clusters	85	41	34	28	24	14

Notes: Table Panel A presents a sensitivity analysis of the main results in Table 2, where the effect of changes in the probability of the climate bill passing is estimated using weekly rather than daily variation in prediction market prices. Panel B (C) regresses the change in oil storage (production) on the change in prediction market prices at the weekly level. Panel A regresses the change in oil futures (24 different maturities ranging from 1 to 24 months into the future) on the change in the prediction market probability that a US cap-and-trade bill will pass at the daily and weekly level. Panel A coefficients give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Panel B (C) coefficients give the change in oil stored (produced) in percent for a 100% change in the probability of the bill passing. Columns differ by what weeks are used in the analysis, with the top row listing the cutoff value for the absolute change in the prediction market price required for a week to be included. For example, Panel A Column (1) includes all weeks, while column (6) includes only the weeks when the prediction market price changed by at least 5 cents. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-quarter fixed effects. Errors are clustered by week.

Table A7: Sensitivity Check: Prediction Market and Coal Futures

	(1)	(2)	(3)	(4)	(5)	(6)
Min market change	0	1	2	3	4	5
Panel A: Cutoffs Only Applied to Changes in Prediction Market Prices						
Prediction Market	-1.02	-1.39	-2.60	-3.00	-3.75*	-5.50*
	(1.63)	(1.66)	(1.81)	(1.89)	(1.99)	(2.91)
Observations	10080	2880	1920	1344	912	624
Fixed Effects	480	456	384	360	264	240
Clusters	420	120	80	56	38	26
Panel B: Cutoffs Applied to Prediction Market and Google Trends						
Prediction Market	-1.02	-4.12*	-4.55*	-4.96*	-5.22*	-8.45**
	(1.63)	(2.29)	(2.66)	(2.65)	(2.94)	(3.24)
Observations	10080	1992	1296	936	672	384
Fixed Effects	480	456	360	312	240	144
Clusters	420	83	54	39	28	16

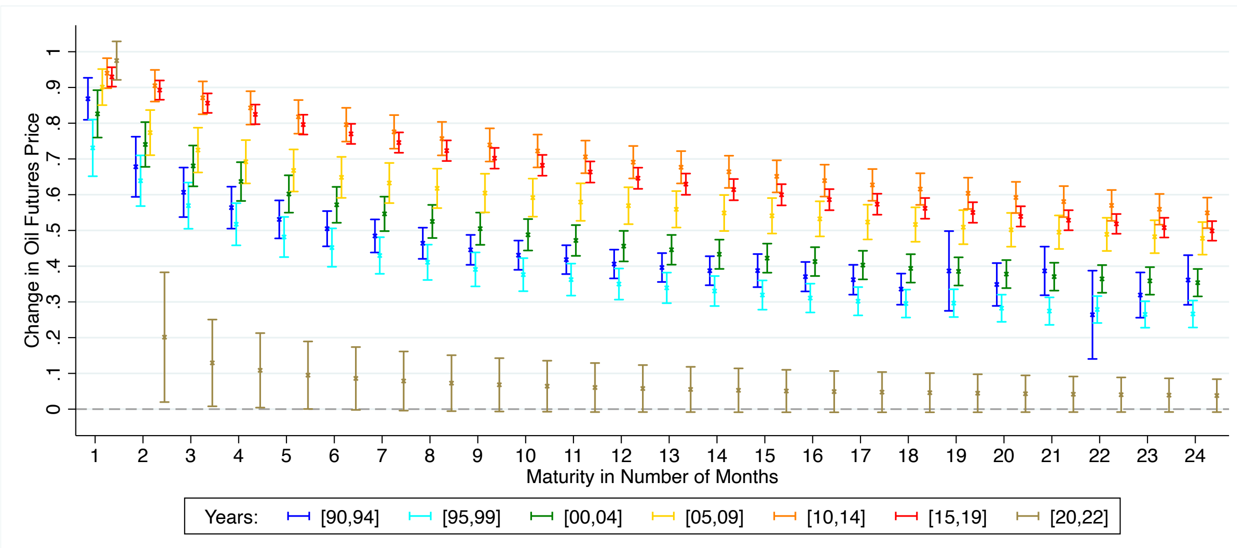
Notes: Table Panel A and B regress the change in coal futures (24 different maturities ranging from 1 to 24 months into the future) on the change in the prediction market probability that a US cap-and-trade bill will pass. Coefficients give the change in coal price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Columns differ by what days are used in the analysis, with the top row listing the cutoff value for the absolute change in the prediction market price (and google trend index) required for a day to be included. For example, Panel A Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). Panel B Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day of the shock or the day after. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Table A8: Sensitivity Check: Prediction Market and Coal Futures Controlling For Spot Price

	(1)	(2)	(3)	(4)	(5)	(6)
Min market change	0	1	2	3	4	5
Panel A: Cutoffs Only Applied to Changes in Prediction Market Prices						
Prediction Market	-0.93	-1.46	-2.97	-3.84*	-4.85**	-6.12*
	(1.65)	(1.78)	(1.94)	(2.10)	(2.31)	(3.04)
Observations	10080	2880	1920	1344	912	624
Fixed Effects	480	456	384	360	264	240
Clusters	420	120	80	56	38	26
Panel B: Cutoffs Applied to Prediction Market and Google Trends						
Prediction Market	-0.93	-4.19*	-4.95*	-5.46**	-6.06**	-9.25***
	(1.65)	(2.33)	(2.76)	(2.51)	(2.61)	(2.28)
Observations	10080	1992	1296	936	672	384
Fixed Effects	480	456	360	312	240	144
Clusters	420	83	54	39	28	16

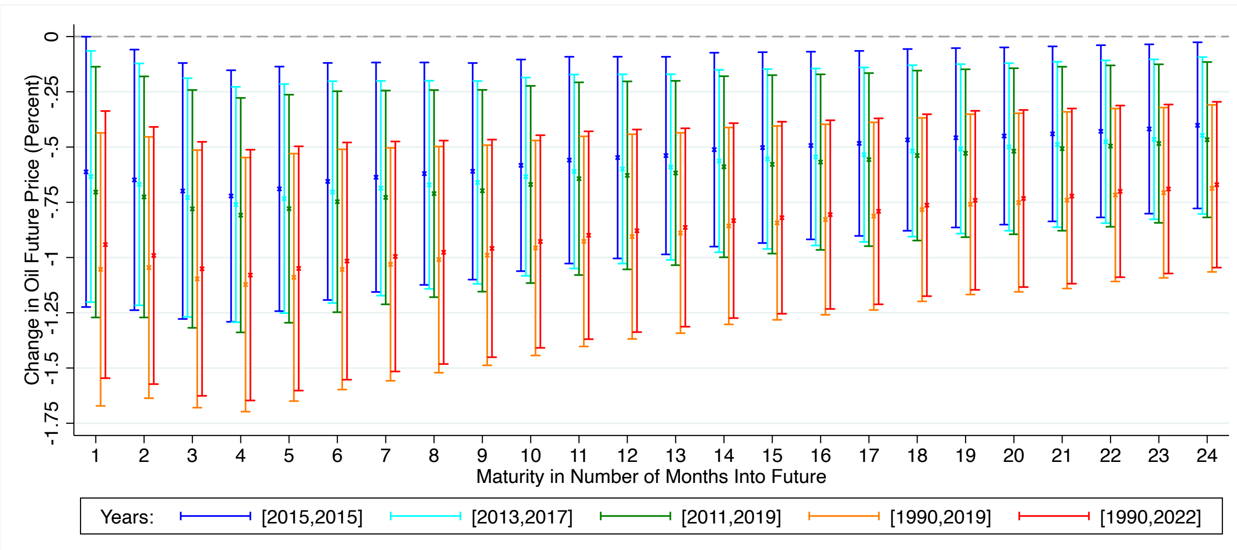
Notes: Table presents a sensitivity analysis of the main results in Table A7, where we control for the oil spot price. Panel A and B regress the change in coal futures (24 different maturities ranging from 1 to 24 months into the future) on the change in the prediction market probability that a US cap-and-trade bill will pass. The difference is the regression controls for the WTI oil spot price. Coefficients give the change in coal price in percent for a 100% change in the probability of the bill passing (i.e., from certainty in won't pass to that it will pass). Columns differ by what days are used in the analysis, with the top row listing the cutoff value for the absolute change in the prediction market price (and google trend index) required for a day to be included. For example, Panel A Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). Panel B Column (1) includes all days, while column (6) includes only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day of the shock or the day after. Regressions control for the oil spot price, changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Figure A1: Oil Spot Price Shocks and Oil Futures Return by Maturity - Temporal Evolution



Notes: Figure replicates Figure 1 but breaks the overall period into sub-periods. It again plots the effect when we regress the change in daily oil futures prices on corresponding change in the oil spot price. The coefficients and 90% confidence intervals are allowed to vary by maturity ranging from 1 to 24 months. Point estimates (marked as x) give the change in oil futures price for a given change in the spot price. The seven colors represent various temporal subsets of the data. Regressions controls for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

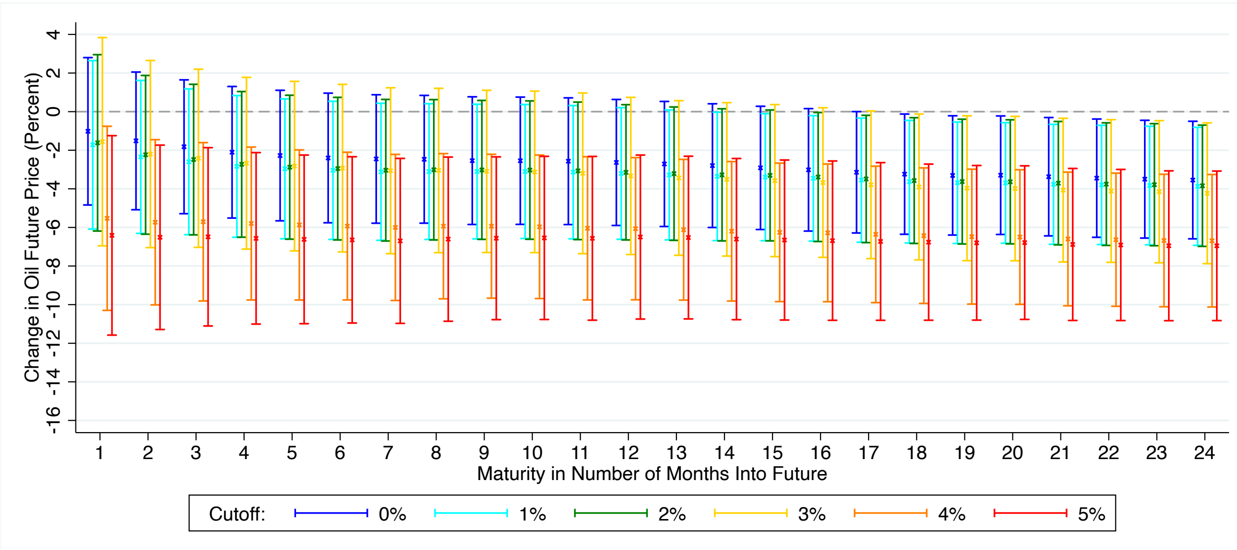
Figure A2: Oil Future Returns On Day of Urgenda vs Netherlands Ruling by Maturity



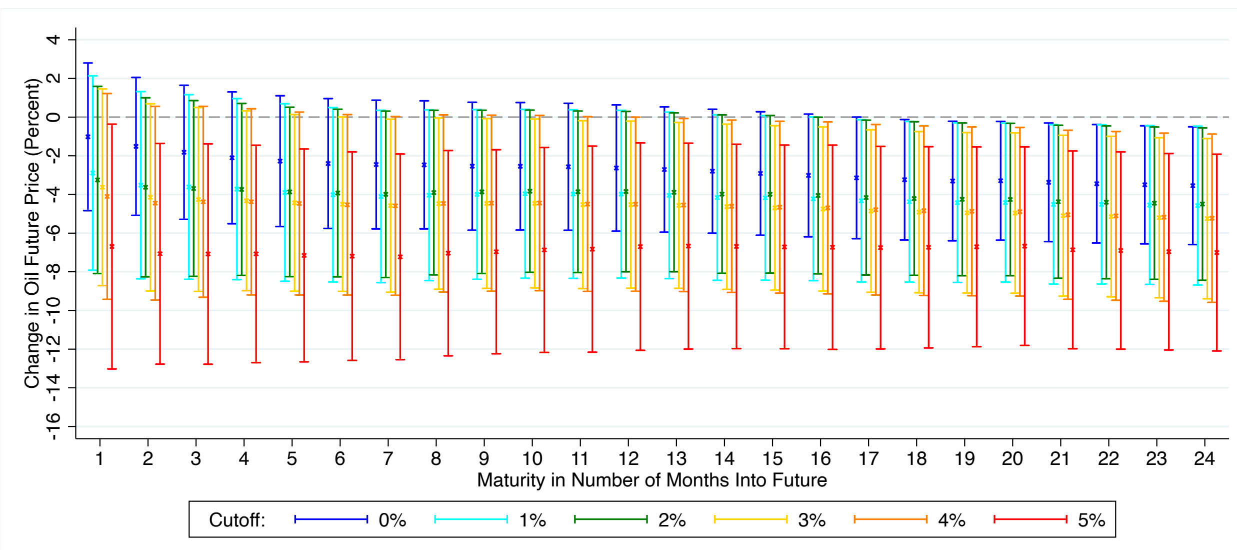
Notes: Figure plots the effect of the Urgenda vs Netherlands ruling on oil futures prices. The coefficients and 90% confidence intervals are allowed to vary by maturity ranging from 1 to 24 months. Point estimates (marked as x) give the change in oil futures price on the day the verdict was rendered. Colors differ by what days are included in the analysis with the five colors representing the range of years used in the five columns of Table 3. For example, the blue lines focus only on days in the year the ruling occurred, while the red lines include all days between 1990-2022. Regressions control for changes in the S&P500 index by maturity as well as maturity-by-month fixed effects. Errors are clustered by day.

Figure A3: Sensitivity Check: Prediction Market and Oil Futures by Maturity Controlling for Spot Price

(a) Cutoffs Only Applied to Changes in Prediction Market Prices



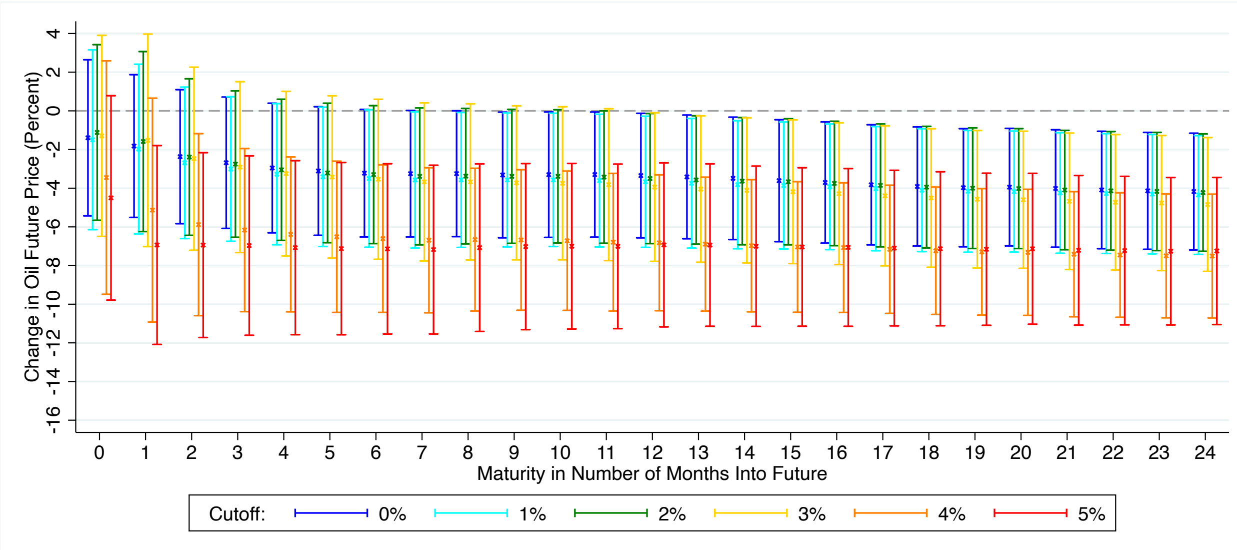
(b) Cutoffs Applied to Changes in Prediction Market Prices and in Google Trends Indices



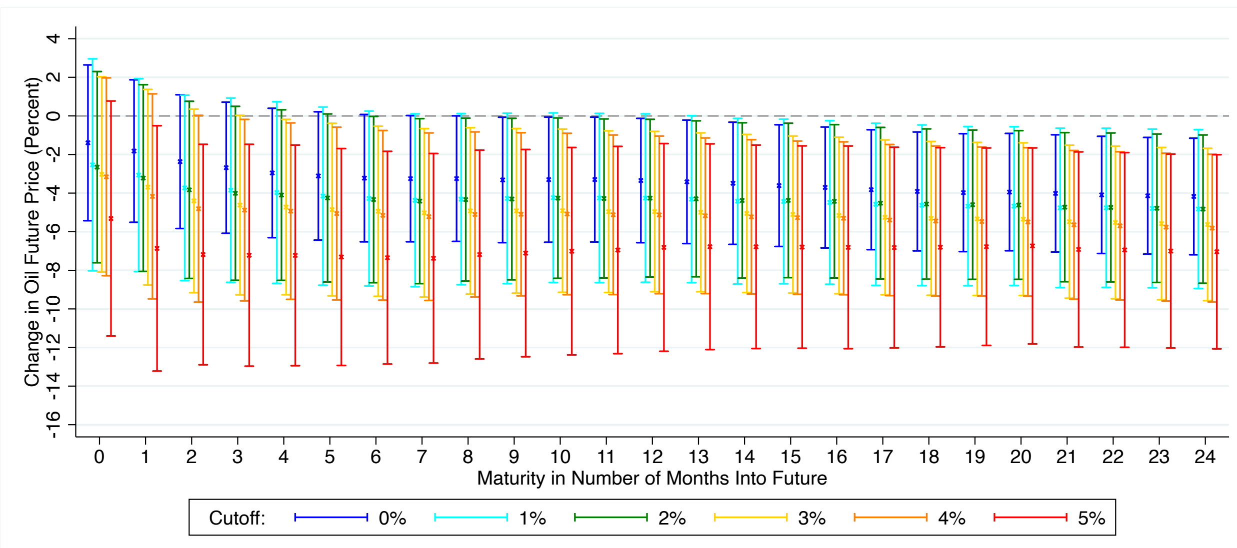
Notes: Figure presents a sensitivity analysis to the main results in Figure 2, where we control for the oil spot price. Panel A and B plots the effect of a change in prediction market probability for the passage of a US cap-and-trade bill on oil futures prices. Point estimates (marked as x) give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty it won't pass to that it will pass). Colors differ by what days are included in the analysis. The six colors represent the different cutoffs of the six columns in Table 2. For example, in Panel A the blue lines include all days, while the red lines include only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). In Panel B, like Panel A, the blue lines include all days, while the red lines include only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day or day after the prediction market shock. Regressions control for changes in the S&P500 index by maturity, oil spot price, as well as maturity-by-month fixed effects. Errors are clustered by day.

Figure A4: Sensitivity Check: Prediction Market and Oil Futures and Spot Price as Outcome Variable

(a) Cutoffs Only Applied to Changes in Prediction Market Prices



(b) Cutoffs Applied to Changes in Prediction Market Prices and in Google Trends Indices



Notes: Figure presents an auxiliary analysis to the main results in Figure 2, where we also include the oil spot price (shown as maturity of zero month). Panel A and B plots the effect of a change in prediction market probability for the passage of a US cap-and-trade bill on oil futures prices. Point estimates (marked as x) give the change in oil price in percent for a 100% change in the probability of the bill passing (i.e., from certainty it won't pass to that it will pass). Colors differ by what days are included in the analysis. The six colors represent the different cutoffs of the six columns in Table 2. For example, in Panel A the blue lines include all days, while the red lines include only the days when the prediction market price changed by at least 5 cents (equivalent to a 5% change in the probability of passing). In Panel B, like Panel A, the blue lines include all days, while the red lines include only the days when the prediction market price changed by at least 5 cents and the google trend index was at least 5 on the day or day after the prediction market shock. Regressions control for changes in the S&P500 index by maturity, oil spot price, as well as maturity-by-month fixed effects. Errors are clustered by day.