Not All Energy Transitions Are Alike: Disentangling the Effects of Demand- and Supply-Side Climate Policies on Future Oil Prices*

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Abstract

We use structural scenario analysis to show that the climate policy mix—supply-side versus demand-side policies—leads to different oil price paths in a net-zero emissions scenario. If emission reductions were only driven by demand-side climate policies, oil prices would decline to 25 USD per barrel by 2030, benefiting consuming countries. Vice versa, if there were only supply-side climate policies to curb oil production, prices would increase to 130 USD per barrel, benefiting countries that keep on producing. As policies are formulated at the country level and hard to predict, the transition raises uncertainty about the price outlook.

Keywords: Conditional forecasts, structural vector autoregressive model, structural scenario analysis, energy transition, oil prices, climate change.

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1 Introduction

The economic literature typically assumes that fossil fuel prices are negatively affected by climate policies (see e.g., Nordhaus and Boyer, 2000, Hassler and Krusell, 2012, van der Ploeg and Rezai, 2020). For example, the International Energy Agency (2022) estimates that prices will decline as fossil fuel consumption falls by 60 percent until 2050 in a net-zero emissions scenario. The implicit assumption is that the energy transition is driven by a series of negative fossil fuel-specific demand shocks. Subsidies for electric cars, for instance, cause negative oil specific demand shocks, as oil is substituted with electricity.

This paper shows that a declining global fossil fuel consumption path could also arise from curbing fossil fuel production (i.e., from negative policy-induced oil supply shocks), leading to rising prices over the long term. This is in line with theoretical models by Hoel (1994) and Harstad (2012), where fossil fuel prices can increase due to supply-side climate policies. For example, climate regulation may directly restrict oil output, while public preferences may shift in favor of sustainable investment—thereby, raising the cost of capital for fossil fuels companies and, eventually, lowering oil supply (Delis et al., 2019, Ehlers et al., 2022, Seltzer et al., 2022).[1] Higher policy uncertainty could lead to a decline in fossil fuel investment (Bogmans et al., 2023). Importantly, as policies are mostly formulated at the country level, the mix between demand-side and supply-side climate policies is hard to

[1] Examples for supply-side climate policies are the US government's restrictions on offshore oil leases in Alaska in 2023 and the European Investment Bank's stop in lending to oil and gas firms in 2022. Examples for demand-side climate policies are the EU ban of new combustion engine cars in 2035 and US incentives for the purchase of electric vehicles with a tax credit of up to $7,500 in the Inflation Reduction Act.

predict at the global level, leading to unexpected shifts in the supply and demand curves. This way the energy transition raises uncertainty about the price outlook.

We apply structural scenario analysis following Antolín-Díaz et al. (2021) to illustrate how the policy mix affects price scenarios. We model the impact of the energy transition on oil prices as a sequence of shocks to either oil-specific demand or oil-specific supply growth.[2] The derived shock series match the global oil consumption scenarios from 2023 to 2030 (and in an extension to 2050) from the International Energy Agency (2022). In other words, our structural approach finds series of shocks that incentivize the oil consumption and output paths in line with the scenarios. We then derive the implied scenario price paths. Modelling the energy transition in this way has the advantage that we can distinguish among structural oil-specific demand and supply shocks, which have substantially different implications for prices.

If we make the stark but illustrative assumption that there were only demand-side climate policies, oil prices could decline to $25 (inflation-adjusted) in 2030. In this illustrative scenario, there would be negative consequences for oil producers as both prices and volumes would decline. Rents would diminish and oil production would come under pressure in high-cost regions. This would change the geographical distribution of oil production and lead to a more concentrated market.

On the flip side, if we make the extreme assumption that reductions in oil production were driven only by supply-side climate policies, this would put strong upward pressures

[2] We also identify a global aggregate demand shock that refers to innovations to global real economic activity that cannot be explained based on the oil-specific demand and supply shocks.

on prices, taking them to roughly \$130 per barrel in 2030. This would benefit net oil producer countries at the expense of net consumer countries. As oil production would be profitable for all producers, the main determinants for the distribution of production and rents would be country restrictions, environmental regulations, and access to capital.

Consequently, the two illustrative price scenarios show that it is wrong to assume that fossil fuel prices will necessarily decline because of the energy transition. Instead, supply-side climate policies could exert upward price pressures (being akin to supply growth shocks with permanent effects on oil production levels), while demand-side climate policies would do the opposite. The reality is likely a mix of the two. We therefore also show an energy transition scenario that is equally driven by supply- and demand-side climate policies. The oil price would fluctuate around 2022 levels and end at \$85 per barrel in 2030. As a benchmark, we also show scenario price paths in a business-as-usual stated policy scenario that is based on announced climate policies in 2021, which are expected to lead to a slightly increasing oil production until 2030. In this case prices would hover around \$70.

To illustrate the potentials and downsides of using structural scenario analysis in a context of longer period scenarios, we show how it can be used for a horizon until 2050. Prices could decline to \$15 per barrel in 2050 in the demand-side climate policies scenario or increase to \$300 per barrel in a supply-side climate policies scenario.

Our results are robust to the use of a four-variable VAR with inventories that accounts explicitly for changes in expectations of future demand due to announced policies such as carbon taxes. Expanding on Kilian and Murphy (2014), we fully identify the model relying on two types of oil-specific demand shocks: a contemporaneous one and an expectational oil-specific demand one. The former leads to a contemporaneous fall in oil-specific demand that increases inventories. The latter leads to a fall in demand that lowers inventories. We assume that both shocks jointly drive the fall in crude oil demand resulting from the energy transition. We examine the sensitivity of our results to changes in the sample horizon, elasticity bounds, lag length, and a variety of different economic activity measures.

We showcase some of the limitations of the methodology and provide robustness checks. First, the scenarios span a relative long horizon of several years under contrasting climate policy scenarios which imply different estimated elasticities. This is due to the structural scenario methodology, following Antolín-Díaz et al. (2021), that estimates the structural parameters extending the sample to include the scenario data (see Waggoner and Zha, 1999 for more details). The implied different elasticities are warranted to some extent: For instance, a purely demand-side climate policy scenario increases the price elasticity of supply. That's because the supply curve is not so likely to shift, based on historical data, to meet such a declining oil production path. It also seems reasonable to expect higher supply elasticities during the energy transition, as it is easier to reduce production than increase it.[3] Second, we model the energy transition as an historically unprecedented shift in the distribution of shocks in the illustrative scenarios (see critique in Lucas, 1976; Leeper and Zha, 2003). Agents could change their decision rule, partly anticipating the oil demand or supply declines due to climate policies, and front-load the price effect. Finally,

[3]In the absence of additional investment, global oil production should decline by about 7 percent per year. The resulting production path would be consistent with the net-zero scenario, without having to shut-in producing oil fields.

innovation, the technology mix, and policy-making lead to large uncertainty surrounding the consumption scenarios.

To our knowledge we are the first to show the different impact of the climate policy mix on future oil price scenarios from an empirical perspective. Hoel (1994) and Harstad (2012) model theoretically that fossil fuel prices rise due to supply-side climate policies.

Our findings imply that integrated assessment models of climate change may need to take into account policies on both the supply and demand sides. They are mostly focused on the demand side, assuming declining fossil fuel prices as a result of the energy transition (e.g., Nordhaus and Boyer, 2000, Hassler and Krusell, 2012, Golosov et al., 2014).

Our paper also contributes to the literature of conditional forecasting and counterfactual analysis with vector autoregressive models (VARs) (see Waggoner and Zha, 1999, Antolín-Díaz et al., 2021 and Wolf and McKay, 2023) as well as oil price forecasts (e.g., Alquist et al., 2013, Baumeister and Kilian, 2014b) and scenarios (e.g., Baumeister and Kilian, 2014a, Kilian and Lewis, 2011, and Kilian and Zhou, 2020). Similar to Boer et al. (2023), we show how to use structural time series models to produce scenarios for the clean energy transition. We illustrate that structural scenario analysis can become an important tool when thinking about scenarios for longer time horizons. In contrast to the previous literature, our focus is on long-term price forecasts that are conditional both on economic observables and specific series of structural shocks.

Our scenarios suggest that if the mix of countries' climate policies is unpredictable and uncoordinated, the price effects of the energy transition are ultimately hard to determine, and this raises uncertainty about the price outlook. Countries would need to prepare for this higher price uncertainty and adjust their macroeconomic and fiscal policies. A coordinated mix of policies among net-consumer and net producer countries of fossil fuels could help to reduce policy uncertainty.

2 Scenarios and Data

2.1 Energy Transition Scenario

The International Energy Agency (2022) provides oil production paths for the Net-Zero Emissions (NZE) Scenario. The scenario is based on the premise that global temperature increases can be limited to 1.5°C in 2050. It is the most ambitious with the highest chance of limiting global warming to 1.5°C. The total production of oil would decline by about 23 percent until 2030 and by roughly 80 percent until 2050 when compared to 2022 production levels (see Figure B.1 in the appendix).

We benchmark the net-zero emissions scenario against results for the stated policy scenario by the International Energy Agency (2022). In this business as usual scenario, based on current and announced national policies, global oil production would increase by about six percent between 2022 and 2030 and then roughly stay flat until 2050.

2.2 Data

We use monthly data for global industrial production, global oil production and the real oil price. For sensitivity analysis, we also use global inventories data and different types of measures for global economic activity.

For our baseline we use the updated monthly global industrial production series from Baumeister and Hamilton (2019). Our sample runs from January 1973 to December 2022. We also use the updated global real economic activity index from Kilian (2009) and the global economic conditions index from Baumeister et al. (2022) in sensitivity checks.

We employ global crude oil output data, including condensates, from the US Energy Information Administration (introduced in log-differences). We use monthly US WTI price data deflated with the U.S. all urban consumers price index. Both are from FRED.[4]

3 Econometric Model

We set up a standard oil-market VAR model (e.g., Kilian, 2009; Antolín-Díaz and Rubio-Ramírez, 2018; Baumeister and Hamilton, 2019) with three endogenous variables $\mathbf{y}_t = (\mathbf{REA}_t, \mathbf{\Delta Q}_t, \mathbf{P}_t)'$. We use a measure of global real economic activity $\mathbf{REA}_t$ (the log-difference in global industrial production in the baseline), the log-difference in global oil production $\mathbf{\Delta Q}_t$, and the log of the real price of crude oil (WTI) $\mathbf{P}_t$. Notice that this specification allows non stationarity in the oil production *level* which is crucial to capture

[4]Results for real price of Brent are in line with the WTI results and available upon request.

the declining path such as the one in the IEA net-zero scenarios. We estimate

$$\mathbf{y}_t = \mathbf{A}_1\mathbf{y}_{t-1} + ... + \mathbf{A}_p\mathbf{y}_{t-p} + \mathbf{\Pi}\,\mathbf{D}_t + \mathbf{u}_t \ , \tag{1}$$

with a lag length of $p = 24$ months, where $\mathbf{A}_i$ are the reduced-form VAR coefficients and $\mathbf{u}_t$ the reduced-form forecast errors. The matrix of deterministic terms $\mathbf{D}_t$ consists of a constant. The reduced-form VAR in (1) can be expressed in a structural form given by

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}_1\mathbf{y}_{t-1} + ... + \mathbf{B}_p\mathbf{y}_{t-p} + \mathbf{\Gamma}\,\mathbf{D}_t + \boldsymbol{\varepsilon}_t. \tag{2}$$

In equation (2), $\boldsymbol{\varepsilon}_t$ are independent structural shocks with an economic interpretation. These are related to the reduced-form errors via the linear transformation $\mathbf{u}_t = \mathbf{B}_0^{-1}\boldsymbol{\varepsilon}_t$. Thus, $\mathbf{B}_0^{-1}$ contains the impact effects of the structural shocks on the three endogenous variables in $\mathbf{y}_t$. By assuming a unit variance for the uncorrelated structural shocks, i.e., $\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \mathbf{I}_n$ (an identity matrix), the reduced-form covariance matrix $\mathbf{\Sigma}_u$ is related to the structural impact multiplier matrix as $\mathbf{\Sigma}_u = \mathbb{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{B}_0^{-1}\mathbb{E}(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t')\mathbf{B}_0^{-1\prime} = \mathbf{B}_0^{-1}\mathbf{B}_0^{-1\prime}$.

3.1 Identification

Without further information it is not possible to identify $\mathbf{B}_0^{-1}$ and thereby the structural form in (2). The literature has come up with different restrictions placed directly on $\mathbf{B}_0^{-1}$ to solve this identification problem. We apply conventional sign restrictions (e.g., Faust, 1998, Canova and Nicolo, 2002, and Uhlig, 2005) on the elements in $\mathbf{B}_0^{-1}$, i.e., we assume that the structural shocks have either a positive or negative effect on the endogenous variables on impact. We base these impact restrictions on economic intuition as specified in Table 1. We assume that climate policies are one source that can lead to unexpected shifts in the demand and supply curves among many others. This is in line with the standard assumption in the literature that different events or sources of, e.g., supply shocks, have similar effects on prices once they shift the supply curve.

	Global economic activity	Global oil production	Real oil price
Aggregate demand shock	-	-	-
Oil supply shock	-	-	+
Oil-specific demand shock	+	-	-

Table 1: Sign restrictions on impact effects

We interpret the first shock as an aggregate demand shock that is related to the global business cycle and thereby affects the demand for oil. A negative shock decreases global economic activity, global oil production and its real price.[5]

We label the second shock as an oil supply shock, capturing changes in production (possibly permanent or very persistent) that are unexpected based on the VAR information set. These unexpected changes can be caused by a broad variety of factors including supply-led climate policies and shifts in capital costs due to sustainable investment criteria.

[5]In this paragraph and in the following, we describe the assumptions about the sign restrictions normalized such that the underlying shock lowers oil production. We assume that the shocks are symmetric, and hence, the reverse effects hold.

A negative shock that reduces global oil production is assumed to drive down global economic activity and to increase the real oil price on impact. Impulse responses show the oil supply shock having a permanent effect on oil production (see Appendix B1 and B2)

We interpret the third shock as an oil-specific demand shock that characterizes demand-led policies for the energy transition in our structural scenario analysis. This shock represents an unexpected shift in the demand curve due to a variety of factors that can affect the demand for oil including climate policies such as subsidies for electric vehicles. Note that this shock may also capture precautionary demand shocks, namely shifts in the demand for above-ground inventory due to forward-looking behavior. This is important, because the energy transition may also affect oil markets through this anticipation channel. We assume that a negative oil-specific demand shock decreases production and the oil price. It increases global economic output on impact as a result of the oil price decrease (see also Kilian, 2009; Baumeister and Peersman, 2013a).

To exclude potential model draws with implausibly high supply elasticities on impact, we assume an upper bound of 0.2 on the oil output response relative to the price response given an oil-specific demand shock and an aggregate demand shock in our baseline.[6] This

[6] It is common among some applied researchers to define this impulse response-based ratio of equilibrium impacts as a supply elasticity (see, e.g., Kilian and Murphy (2014), Ludvigson et al., 2017, Antolín-Díaz and Rubio-Ramírez, 2018, Basher et al., 2018, or Herrera and Rangaraju, 2020). Baumeister and Hamilton (2023) note that this concept does not entail the usual ceteris paribus assumption of an elasticity because an oil-specific demand shock does not only trigger a response in price but also a response in other variables. A supply elasticity that takes into account the ceteris paribus requirement is obtained directly from the impact elasticity in the structural $\mathbf{B}_0$ matrix (see Baumeister and Hamilton, 2023). The relevant normalized element of this matrix indicates the simultaneous response of oil output to a change in the oil price holding all other variables constant. Based on our specified upper bound of 0.2, the implied upper bound on the impact supply elasticity obtained from the $\mathbf{B}_0$ matrix is 0.198 across draws in our empirical exercise, while the resulting median supply elasticity estimate is 0.14 in the demand-side climate policy scenario. For the related measure based on the oil output response relative to the price response given an oil-specific demand shock, we obtain a median estimate of 0.18.

bound includes the estimates from Caldara et al. (2019) and Baumeister and Hamilton (2019)—which are around 0.1 and 0.15, respectively—but allows for potentially somewhat higher elasticities during the course of the energy transition. The idea is that it could be easier to reduce production facing low oil prices. For example, US and OPEC+'s oil production dropped by about 30 percent and 20 percent, respectively, withing two months during the pandemic in 2020. We check for the sensitivity of our results for a lower upper bound of 0.1, as several studies have specified bounds in a range of 0.026 to 0.1 (Kilian and Murphy, 2014; Antolín-Díaz and Rubio-Ramírez, 2018; Zhou, 2020; Herrera and Rangaraju, 2020) as well as for a specification with a higher bound of 0.3, which is the highest estimate of short run supply elasticities measured in the literature by Coyle et al. (2012) (see Fally and Sayre, 2018) and Rao (2018).

We impose one narrative sign restriction following Antolín-Díaz and Rubio-Ramírez (2018). This restriction on the set of admissible historical shock series helps to sharpen identification. We assume that the aggregate demand shock was the least important contributor to the observed unexpected movements in the real price of oil in August 1990 when the Persian Gulf War broke out. Antolín-Díaz and Rubio-Ramírez (2018) find that this single restriction, an accepted interpretation of historical events, yields equivalent results to using a set of different restrictions used in their baseline specification.

3.2 Structural Scenario Analysis

We conduct structural scenario analysis for the real oil price following the framework of Antolín-Díaz et al. (2021). Our object of interest is a conditional forecast $\mathbf{y}_{T+1,T+h}$ over the next 8 years, i.e., $h = 96$ months, for the endogenous variables, where T denotes December 2022. The conditional forecast restricts some of the variables in $\mathbf{y}_{T+1,T+h}$ and a subset of the future shocks $\varepsilon_{T+1,T+h}$. It links the path of future variables directly to certain shocks. We lay out the underlying intuition tailored to the oil consumption scenarios from the International Energy Agency (2022), while the appendix A provides technical details.

We take the oil consumption scenario as given, pre-specifying the oil quantities in the conditional forecasts $\mathbf{y}_{T+1,T+h}$. We set global oil consumption equal to global production in the scenarios from the International Energy Agency (2022), assuming no short-term changes in inventories. The future paths of global economic activity and the oil price are left unspecified. Concerning the paths of future shocks, we first constrain the aggregate demand shock and the oil supply shock to their unconditional distributions and leave the oil-specific demand shock unrestricted. The algorithm finds a series of oil-specific demand shocks that incentivizes the oil production path needed for the energy transition and we can derive the implied price path.

Second, we constrain the aggregated demand shock and the oil-specific demand shock to their unconditional distribution. The oil supply shock is left unspecified to sketch out the supply-side climate policy scenario.

Compared to traditional conditional forecasts, this methodology has the advantage that it can attribute the future path of endogenous variables to the path of a specific structural shock. The energy transition as a scenario can result from a series of policy-induced oil-specific demand shocks or from oil supply shocks.

In our case the classical reduced-form conditional forecasting question is "What is the likely path of the oil price, given that oil production has to decline due to the energy transition?" The answer is confounded by a lack of causal structure. Oil prices could be low due to negative demand shocks, incentives less supply. However, it could also be the opposite: negative supply shocks could drive supply downward, thus driving prices up. Due to the structural scenario framework, we can handle this reverse causality.

3.3 Estimation and Inference

Estimation and inference are based on standard Bayesian techniques laid out in Waggoner and Zha (1999), Rubio-Ramirez et al. (2010), and Antolín-Díaz et al. (2021). We draw from a joint posterior distribution of the structural parameters and the conditional forecast

$$p(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+ | \mathbf{y}^T, \mathbf{IR}(\mathbf{B_0}, \mathbf{B}_+), \mathbf{R}(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+)) \;, \tag{3}$$

where $\mathbf{y}^T$ is the historical sample, $\mathbf{B'}_+ = [\mathbf{B'}_1 \ldots \mathbf{B'}_p \, \mathbf{\Gamma}]$ collects the structural VAR lag coefficients including the exogenous parts, $\mathbf{IR}(\mathbf{B_0}, \mathbf{B}_+)$ are the identification restrictions and $\mathbf{R}(\widetilde{\mathbf{y}}_{T+1,T+h}, \mathbf{B}_0, \mathbf{B}_+)$ the structural scenario restrictions. The structural scenario restrictions depend on the structural VAR parameters via equation (11) in the appendix.

To draw from this distribution, we use the algorithm by Antolín-Díaz et al. (2021).

It uses a Gibbs sampler procedure that iterates between draws from the conditional distributions of the structural parameters and the conditional forecast.[7] Hence, we pick a random draw of structural parameters out of 25,000 potential draws that relies both on the actual data and on a structural scenario. We use the structural parameters from this randomly picked draw to draw the scenario paths of the price series and the economic activity index for the structural scenario that fits the specified oil production path. The next 25,000 draws for structural parameters rely on the original data and the data from the just drawn structural scenario.

We use a Minnesota-type prior with standard shrinkage parameters (Giannone et al., 2015) with a sum-of-coefficients prior (Doan et al., 1984) and a dummy-initial-observation prior (Sims, 1993) to estimate equation (1) and the conditional forecasts.[8]

Identification via sign restrictions does not yield point estimates but instead sets of possible parameter values for the different elements in $\mathbf{B}_0^{-1}$. For each model we obtain a set of 1,000 admissible draws, where each draw consists of a conditional forecast, future shocks, and an associated $\mathbf{B}_0^{-1}$ matrix that satisfies the identifying restrictions. These draws are also used for inference, i.e., they yield an indication of the uncertainty around the pointwise median estimates. Following Antolín-Díaz and Rubio-Ramírez (2018) and

[7] Each draw of structural parameters must consider the restrictions implied by the structural scenario, i.e., the forecasted path of the variables and the restrictions on the non-driving shocks.

[8] The variance for the priors on the reduced-form VAR coefficients is given by $var\Big((A_i)_{j,j}\Big) = \frac{\lambda^2 \psi_j}{i^\alpha}$, where i denotes the lag and j the variable. The tightness parameter λ is set to 0.2, the decay parameter is $\alpha = 2$, and the scale parameters ψ_j are set to the OLS residual variance of an auto-regressive model for each variable j. The variance for priors on the exogenous variables are set to 1,000. This should shrink the reduced-form VAR towards a more parsimonious naïve benchmark and helps to maximize the out-of-sample forecast accuracy, in which we are particularly interested.

Antolín-Díaz et al. (2021), we report pointwise median and percentiles of impulse responses for set-identified structural VAR models, as it is common in the literature.

The literature has made substantial progress on Bayesian inference, which is important to take into account when interpreting our results. First, Baumeister and Hamilton (2015, 2020) and Watson (2019) remark that readers are used to associating error bands with sampling uncertainty, but in large-sample sign-restricted SVARs these error bands only result from the prior for the rotation matrix Q, not sampling uncertainty. Inoue and Kilian (2020) point out that the share of uncertainty resulting from the prior on Q tends to be small in most applications, in particular, when assuming several sign restrictions.

For our baseline model with three variables the Haar prior placed on the rotation matrix Q is uninformative about the structural impulse responses (a special case as Baumeister and Hamilton, 2015 show). However, the concern of an informative prior materializes when we extend the model to the four-variables case in the sensitivity section. We recognize that in this case our inference summarizes both prior uncertainty and sampling uncertainty to some extent. We therefore report the full set of impulse responses to provide the reader with a better sense of the uncertainty around the estimates.

Second, we note that the posterior median response function does not represent one of the structural models. Thus, we also report the Bayes estimator under a quadratic loss function following Inoue and Kilian (2022). The loss function ranks the admissible models according to each model's joint quadratic distance between its impulse responses and the impulse responses of all the other admissible models. The Bayes estimator is the model with the smallest joint quadratic distance, meaning that it is closest to the set of all admissible models. The results are rather insensitive to the choice of the loss function.

Estimating the structural VAR on data from both the historical sample and the scenario horizon warrants some discussion because it implies that the scenario data has a non-negligible impact on the estimated structural parameters. However Antolín-Díaz et al. (2021) stress that it would not be correct to estimate the structural VAR merely on the historical sample. Our historical sample runs from January 1973 to December 2022 and the scenario from January 2023 to June 2030 which yields a sample share of 13% for the scenario. Hence, the estimated structural parameters will depend on the chosen scenario. Concretely, a scenario driven by shocks due to demand-side climate policies implies higher price elasticities of supply as the oil supply curve is less likely to shift—loosely speaking, in such a world, producers must have been more likely to adjust to low prices (see Table C.2 in the appendix). Analogously, in a scenario where climate policies work through the oil supply side, demand elasticities become larger in absolute terms as consumers would be more likely to adapt to such a high price environment, eventually.[9]

[9]The dependency of parameter estimates to the scenario is an advantage for constructing scenarios that have no precedent in historical data sample and may imply substantial movements in prices from their historical average. Historical data, instead, should be analyzed over the historical sample only.

4 Empirical Results

4.1 Price Scenarios

We use the case of crude oil markets to illustrative quantitatively how supply-side and demand-side climate policies would affect oil prices in the Net-Zero Emissions Scenario by the International Energy Agency (2022).

We first consider a structural scenario with oil-specific demand shocks only. In this illustrative scenario, the shocks are assumed to originate from unexpected demand-side climate policies. Oil prices could decline to $25 per barrel in 2030 (figure 1, blue line).[10]

[10]The price scenarios are subject to high uncertainty, reflected in the large, implied bounds. Large confidence bands (we therefore represent 40% highest posterior density credible sets in line with Antolín-Díaz et al. (2021)) may originate from the uncertainty about the reduced-form VAR coefficients, measurement errors in the historical data, uncertainty about the oil consumption scenario paths, uncertainty about other future shocks influencing the price along the scenario horizon, and the uncertainty around the structural impact effects of the different shocks. We also present more conventional 68% credible sets in the online appendix in figure B.11. Moreover, figures B.2 and B.3 show the underlying impulse responses which display an insensitivity to additionally placing dynamic sign restrictions on the oil price and output responses.

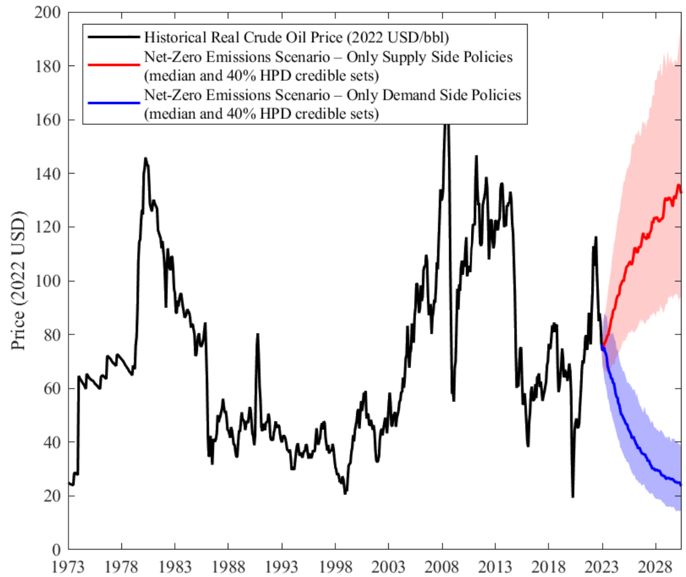


Figure 1: Oil prices in the supply and demand-side climate policy scenario (Net Zero Emissions by 2050).

In the opposite scenario, where reductions in oil output only result from supply-side climate policies, prices would experience substantial upward pressures. They could climb to roughly $135 per barrel until 2030. Consequently, the illustrative price scenarios show that it is wrong to assume that fossil fuel prices will necessarily decline because of the energy transition. Instead, supply-side climate policies could exert upward price pressures, while demand-side climate policies would do the opposite.

The reality is likely a mix of demand- and a supply-side climate policies during the energy transition, as individual countries determine their policy mixes on their own and these may also be shifting over time. Figure 2 shows a price scenario, where supply- and demand-side climate policies cause both oil-specific supply and demand shocks, which are assumed to both drive the reductions in oil production equally until 2030. Prices increase slightly until 2030 but stay in the historical range of about $80 per barrel in inflation adjusted terms in this illustrative scenario.

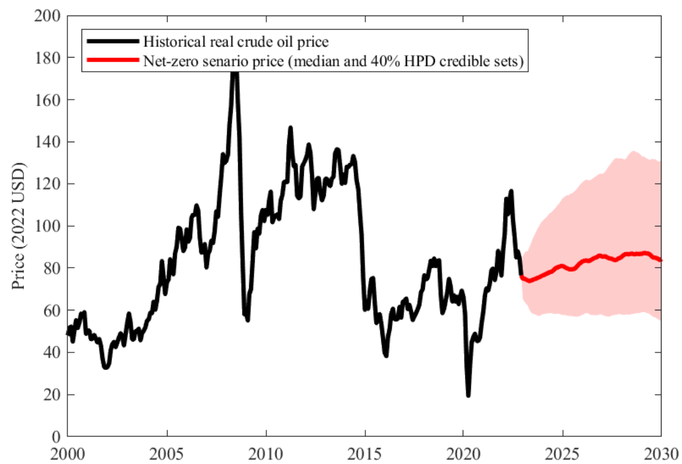


Figure 2: Oil prices in the net-zero emissions scenario with equally important supply and demand side policies

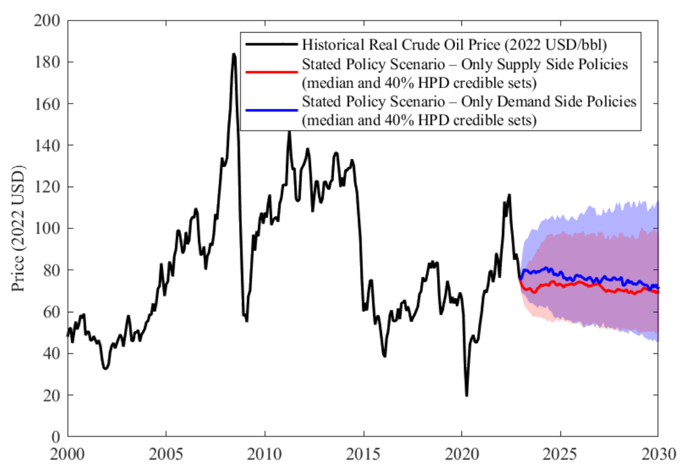


Figure 3: Oil prices in the supply and demand-side climate policy scenarios (Stated Policy Scenario).

As a benchmark, we also show scenario price paths for the stated policy scenario by the International Energy Agency (2022). Prices would hover around \$70 as figure 3 shows. This is true for both the demand-side and the supply-side climate policy scenarios. There is not much of a difference because the production path from the stated policy scenario is by and large in line with the historical trend. That's why no large oil-specific demand shocks are needed to incentivize downwards adjustments in supply. The same is the case on the supply side.

4.2 Plausibility

Antolín-Díaz et al. (2021) provide a statistic to judge how plausible a structural scenario is. The concept is closely related to the statistic for modest interventions by Leeper and Zha (2003). It compares the characteristics of the different shocks over the scenario horizon to their historical counterparts. Based on entropic forecast tilting (see Robertson et al., 2005 and Giacomini and Ragusa, 2014) the Kullback-Leibler (KL) statistic

$$D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF}) = \frac{1}{2}\big(tr(\mathbf{\Sigma}_{\varepsilon} + \mu_{\varepsilon}'\mu_{\varepsilon} - nh - ln(det\mathbf{\Sigma}_{\varepsilon})\big) \tag{4}$$

represents a divergence of the distribution of shocks compatible with the structural scenario $\mathcal{N}_{SS}$ from the distribution of the unconditional forecast $\mathcal{N}_{UF}$. The statistic depends on μ_{ε}, the mean, and $\mathbf{\Sigma}_{\varepsilon}$, the covariance of the restricted future shocks with tr denoting the trace operator and det the determinant. Hence, it does not only take into account the median shock series but also its variance.

Antolín-Díaz et al. (2021) calibrate the statistic to a scale between 0.5 and 1 such that it displays the divergence between two binomial distributions, one with probability q and one with probability 1/2.[11] In other words, the calibrated KL statistic gives an indication of how far away the scenario is from the unconditional path represented by the comparison of the flip of a fair and a biased coin.

We use the KL statistic to judge how unusual the scenarios are and whether one should expect a structural break in the model equations. Table 2 reports the plausibility statistics for the different net-zero emissions scenarios. The scenario shock series lead to relatively high KL statistics, however, not signalling completely implausible policy scenarios with respect to historical precedent.[12] The scenario of an energy transition completely driven by demand-side climate policies is less plausible compared to historical precedent. The higher KL statistic for the demand-side climate policy scenario also indicates that oil-specific demand shocks have played a smaller role in explaining oil output fluctuations compared to oil supply shocks in the historical sample. In other words, oil-specific demand shocks have to be relatively larger than oil supply shocks (in absolute terms) to induce the scenarios (see Figure B.29 in the appendix).

[11] The statistic is calibrated to the parameter q that solves the equation $D_{KL}(\mathcal{B}(nh, 0.5)||\mathcal{B}(nh, q)) = D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$ where $\mathcal{B}(m, p)$ denotes the Binomial distribution for m independent experiments with success probability p. The solution to the equation is $q = \frac{1}{2}\big(1+\sqrt{1-e^{-\frac{2z}{nh}}}\big)$, where $z = D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$.

[12] Antolín-Díaz et al. (2021) note that for a system with only one active policy shock, a one-time 2 s.d. shock leads to $q = 0.6$, a sequence of 1 s.d. shocks over 12 periods or a single 3.5 s.d. shock to $q = 0.67$ and a single 10 s.d. shock to $q = 0.9$.

	Calibrated KL Statistic	
	Net-Zero Emissions Scenario	Stated Policy Scenario
Supply-side climate policy scenario	0.67	0.65
Demand-side climate policy scenario	0.83	0.82

Table 2: Scenario Plausibility Statistics

Figure B.28 in the appendix displays the mean shock series over the scenario horizon for the two policy scenarios. The scenarios are characterized by a repeated series of either negative supply or demand shocks that are not larger than -0.5 standard deviations while the other two shock series fluctuate around 0.[13]

5 Oil Market Shares

The different price scenarios have major implications for the distribution of production reductions across countries (see sections 4).

Under the demand-side climate policy scenario, oil prices are predicted to decline substantially. In this low-price and low-consumption scenario, scarcity rents would decline and oil production in high cost regions would come under pressure. This would have implications for the distribution and concentration of oil assets globally. Currently, the top 3 oil producers account for almost 40 percent of global oil production, with US and Russia accounting for about 16 and 12 percent in 2023, respectively.[14] Oil production costs, how-

[13] We also report the scenario shock series for the stated policy scenario for comparison (see Figure B.29 in the appendix). The shocks are centered around 0 while the demand-side scenario shows a much larger variance of the oil-specific demand shock leading to the relatively high KL statistic of 0.82. For reference, a stated policy scenario allowing for both oil-specific demand and supply shocks in their historically observed proportion yields a KL statistic of 0.59.

[14] Compared to some metals, such as copper or cobalt, oil production is less concentrated.

ever, vary significantly depending on geology and location with onshore conventional oil being one of the cheapest. If oil prices declined, some oil fields would become unprofitable, including some US shale oil regions, while low-cost regions would become more exploited.

To determine the share of global oil production by country under the various scenarios, we use breakeven oil prices at the field level from Rystad. The breakeven price is defined as the constant real Brent oil price that, for a given a discount rate, makes the net present value of an oil field's revenue flows and costs even.[15] Breakeven prices are estimated for existing and producing oil wells as well as for known oil resources that have yet to be developed, but not for yet-to-be-discovered resources. The data-set includes 59,260 individual oil fields out of which 49,139 have a positive breakeven prices. As of 2023, 13,285 fields are producing. The average well production stands at 10,000 barrels per day. However, the distribution is heavily right-skewed.

Our results in figure 4 indicate that when oil prices reach $25 per barrel in 2030, under the demand-side climate policy scenario, the oil market will become much more concentrated with about 66 percent of global oil output from the Persian Gulf, a 30 p.p. increase from 2023 (while OPEC+ would reach over 80 percent market share). By 2050, market concentration would rise even more, with the Persian Gulf's countries reaching a 95 percent market share (see Appendix).[16] Some of the countries experiencing the highest

[15]The breakeven price indicates at which flat real Brent oil prices the continued operation of assets is commercial, as seen from 2023, i.e., the oil price required for a positive net present value of continued operation, based on the total remaining resources for each asset. Both commercial and non-commercial assets are included in the calculation. Tax effects of previous investments and abandonment costs are not included, but taxes and government fees are subtracted.

[16]Using 2050 data is less recommended as breakeven prices would come mostly from oil wells that have not been discovered yet. In a steep oil consumption scenario, like 2050 net-zero, discoveries of new fields are not needed; hence, only discoveries of new deposits that are at the very low range of the extraction-cost

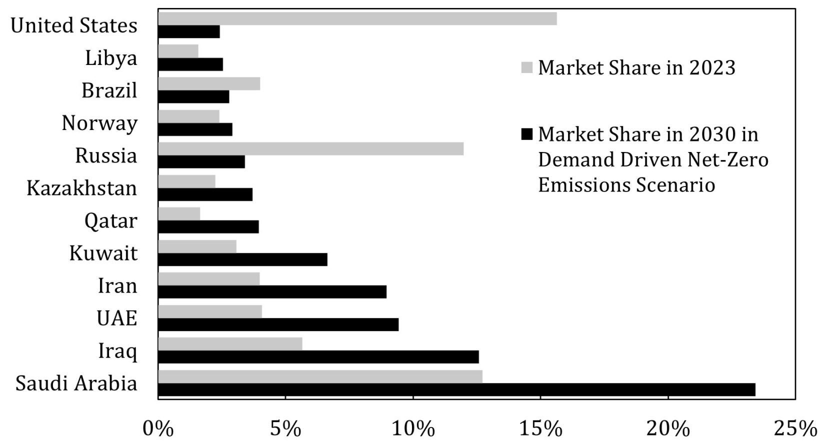


Figure 4: Market shares 2023 vs 2030 in the demand driven net-zero scenario.

declines in production would be the United States, Russia and Canada.

Reductions in emissions that are hypothetically driven only by supply-side climate policies would exert strong upward pressure on oil prices (see section 4.1), benefiting producing countries at the expense of consuming countries. Since oil production would be profitable for all producers, however, the main determinants for the distribution of production and rents would be country restrictions, environmental regulations, and access to capital. In a supply-led scenario revenues would increase to previous historical highs but would be concentrated among the few remaining producers, who would benefit strongly.

distribution would alter our estimated market shares.

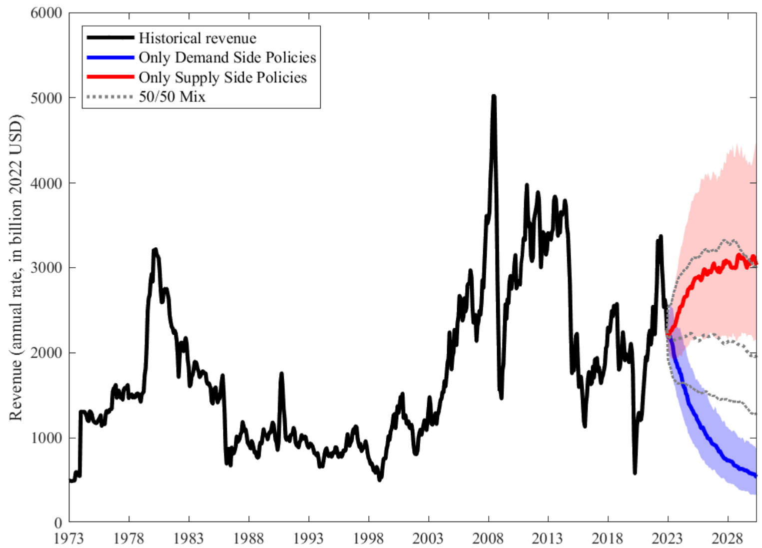


Figure 5: Oil revenues in the different net-zero emissions scenarios. Median estimates and 40% HPD credible sets. Oil revenues are calculated as quantity times price.

A scenario equally driven by supply and demand side climate policies would see revenues gradually taper off while production volumes decrease such that fewer producers see larger revenues individually (see figure 5).

Globally, the different scenarios have also major implications for the value of the oil market. In a demand-side climate policy scenario, oil revenues would fall to historical lows where only the lowest cost producers stay profitable. In the opposite case, the price increases would more than offset the decline in volumes leading to an increase in global oil revenues (see figure 5), especially for some low-cost oil producing countries which would see only a modest decline in oil production given the higher market share.

6 Price Scenarios Until 2050?

The Net-Zero Emissions Scenario and the Stated Policy Scenario from the International Energy Agency (2022) both run until 2050. What are the challenges in applying the structural scenario analysis over such a long time horizon? What results does this yield?

Structural scenario analysis over long time horizons presents significant challenges. First, there is high uncertainty associated with the more distant future. Second, the decline in global oil quantities gains speed after 2030 in the net-zero scenario consumption.Third, the structural scenario methodology leads to diverging underlying elasticities across scenarios when the scenario horizon increases. As noted in section 3.3, the draws from the posterior of structural parameters and conditional forecast depend both on the historical sample and on realizations of the conditional forecast. The more data points we add to the scenario horizon and thus increase the relative weight of the scenario compared to the historical sample, the more influence on the structural parameters these data points obtain. Waggoner and Zha (1999) label this a 'shift in distribution' phenomenon and it becomes more severe the longer the scenario horizon is. In our case this would mean a stronger divergence of oil supply and demand elasticities between the oil supply-side and oil demand-side climate policies scenarios.[17]

Figure 6 panel (a) shows the illustrative oil price scenarios for the two policy cases in

[17] Altering the algorithm such that it does not take the scenario horizon into account when estimating the structural parameters, we obtain an upper price of \$120 in 2030 in the supply-side climate policy scenario and \$33 in the demand-side climate policy scenario. Somewhat less strong price changes compared to \$135 and \$25 in our baseline.

the net-zero emissions scenario until 2050. To produce these figures we specified a bound of 0.3 on the impact supply elasticity, i.e., the production response relative to the price response after an oil-specific demand shock.[18] For this long horizon we again rely on the model using global industrial production as the global real economic activity index model produces implausible impulse responses even implying a slightly increasing price trend under the demand side driven policies scenario.

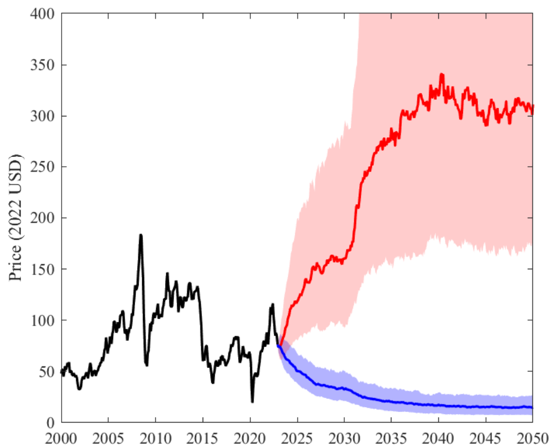
In the demand-side climate policy scenario, prices fall to around $30 per barrel by 2030, reaching a level of around around $15 by 2040 and stay around that level until 2050. The scenario price path during the initial period until 2030 is broadly in line with our baseline scenario. A KL statistic of 0.72 indicates that this scenario is somewhat more plausible than the demand-side climate policy scenario until 2030 only which results from the larger upper bound on the supply elasticity.

In the supply-side climate policy scenario, prices rise to around $300 in the mid 2030s and stay around those levels until 2050.[19] Prices increase somewhat less drastically in our baseline supply scenario estimated up to 2030 only. The KL statistic of 0.68 indicates that the scenario until 2050 is only marginally less plausible than the one until 2030.

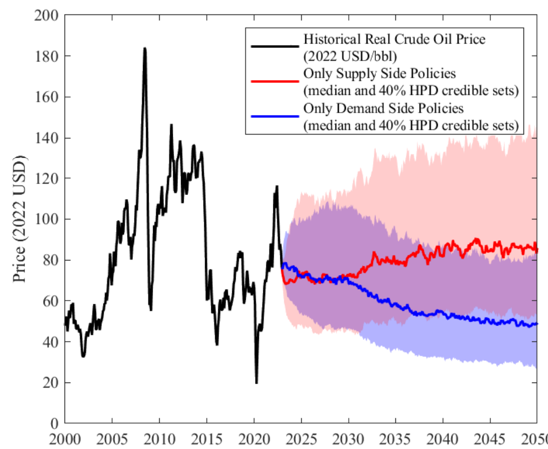
In the stated policy scenarios, prices range between $50 per barrel at the end of 2050 for the demand-side climate policy scenario and $80 per barrel by 2050 in the supply-side climate policy scenario (see panel (b) of figure 6). While prices are close across the two

[18] A bound of 0.2 would not yield any draws for the demand-side driven scenario. The bound of 0.3 implies a realized upper bound of 0.29 for the ceteris paribus supply elasticity directly obtained from the B_0 matrix.

[19] Confidence bands are much broader for the supply side scenario as the model is estimated using log levels of prices and they are reconverted here for illustrative purposes.



(a) Net-zero emissions scenario



(b) Stated policy scenario

Figure 6: Oil Supply and demand-side climate policy scenarios until 2050.

scenarios until 2030, there is an increasing gap from 2030 to 2050. This is driven by the underlying oil production scenario, in which global output stops growing around 2030 and then stays roughly constant until 2050, implying a deviation from the historical trend.

7 Robustness

We check the sensitivity of our results using a model with four variables that includes global oil inventories, using different economic activity indicators, alternative elasticity bounds, a shorter lag lengths of 12 months, as well as shorter historical samples (see also table C.1 in the appendix).

7.1 Inventories and Expectational Oil Specific Demand Shocks

One of the shortcomings of the three variable model is that the identified oil-specific demand shock does not differentiate between contemporaneous and expectational oil-specific demand components. Concerning the energy transition, it is plausible to assume that agents anticipate the potential future policy-induce decreases of oil demand, at least partially. Kilian and Murphy (2014) and Känzig (2021) show that shifts in expectations play a crucial role for explaining variations in oil prices. We extend the three variables model by global inventories, which allows us to differentiate between contemporaneous and expectational oil-specific demand components.[20]

We identify two types of oil-specific demand shocks, a contemporaneous one and an expectational one, using sign restrictions as shown in table 3 and following the approach in Boer et al. (2023). Both shocks when negative are assumed to decrease oil production and prices, while increasing economic activity as a result of a negative price shock in the first month. We presume that the two shocks differ in their impact on inventories, however. A negative contemporaneous oil-specific demand shock increases inventories on impact. Agents built-up inventories in response to a shift in the demand curve as less oil is used. The expectational negative demand shock is assumed to lead to a draw-down in inventories, because agents anticipate lower future oil demand. This shifts the demand for

[20]Moreover, including inventories improves identification of the oil-demand elasticty as the three-variable model ignores that produced oil is either stored or consumed (see Kilian, 2022).

above-ground inventory due to forward-looking behavior.[21]

	Global economic activity	Global oil production	Real oil price	Global oil inventories
Aggregate demand shock	-	-	-	
Oil supply shock	-	-	+	
Contemporaneous oil-specific demand shock	+	-	-	+
Expectational oil-specific demand shock	+	-	-	-

Table 3: Sign restrictions on impact effects

We allow both types of oil-specific demand shocks to jointly drive the scenario output path, assuming that some of the lower oil demand due to the energy transition is anticipated. The aggregate demand and oil-specific supply shocks are restricted to their unconditional means.

Results based on this model for the demand-side climate policies scenario are robust with respect to our baseline. Using both oil-specific demand shocks to drive the energy transition oil consumption path yields a decrease in oil prices to around $25 like in our baseline model (see figure B.12 in the appendix). Relying on the identification from Kilian and Murphy (2014) with three identified shocks, where the oil-specific demand shock increases inventories, i.e., using only the expectational oil-specific demand shock, prices

[21]The estimation of the expectational oil-specific demand shock may also capture discoveries and news about future supply developments. While relevant for a historical decomposition, it does not invalidate the construction of the structural scenarios.

decrease to around \$30 (see figure B.15 in the appendix).

7.2 Alternative Economic Activity Indicators

For short-term oil price forecasts of 1 to 24 months, Baumeister et al. (2022) find that VARs including global industrial production outperform models relying on other economic activity indicators. Hence, we use global industrial production in our baseline model. Relying on alternative economic activity indicators yields slightly different scenario price paths. Replacing global industrial production with the global real economic activity index from Kilian (2009), i.e., a measure derived from global bulk dry cargo shipping rates (see Kilian and Zhou (2018) for a discussion of the relative merits of this index over global industrial production), gives a median price of around \$50 in 2030 under the demand-side climate policy scenario and a price of around \$120 in the supply-side climate policy scenario (see figure B.16 in the appendix). In the scenario with an equally driven policy mix the median price in 2030 is around \$90.

We also investigate a model including the global economic conditions index from Baumeister et al. (2022), which the authors find to outperform other indicators when jointly forecasting oil consumption and prices. This index is the first principal component of a set of 16 indicators that are linked to energy demand. Relying on this measure yields median 2030 real prices of \$14 in the demand side climate policy scenario, \$120 in the supply side climate policy scenario (see figure B.19) and \$73 in the scenario with an equal mix of supply and demand side climate policies.

7.3 Alternative Elasticity Bounds

In our baseline analysis, we assume an upper bound of 0.2 on the oil output response relative to the price response given an oil-specific and aggregate demand shock. This bound is slightly above most estimates in the literature, which has largely settled on a first-month supply elasticity of around 0.1 (see Caldara et al., 2019), because we want to account for uncertainty around these estimates.

We check results for a lower upper bound of 0.1 as several studies have specified bounds in a range of 0.026 to 0.1 (Kilian and Murphy, 2014; Antolín-Díaz and Rubio-Ramírez, 2018; Zhou, 2020; Herrera and Rangaraju, 2020). For the demand-side climate policy scenario, results are sensitive to the bound as most draws imply an impact supply elasticity close to the bound, the more so, the lower we set the bound. Median real prices in the demand-side climate policy scenario reach $14 by 2030 (see appendix figure B.23). Replacing global industrial production by the real economic activity index from Kilian (2009) results in a median price of $29 (see appendix figure B.24). The sensitivity of results to different assumptions about the supply elasticity bound and the variable used to capture global economic activity are recognized in the oil price literature, as highlighted by Herrera and Rangaraju (2020) for example. These sensitivities also show up in our structural scenario analysis. To obtain a result similar to our baseline demand-side climate policy scenario price of $25 in 2030 (applying the industrial production index and a bound of 0.2), the model needs both the real economic activity index and a lower bound on the impact supply elasticity.

To allow for possibly higher than historical supply responses as a result of expectations of the energy transition, we also specify an upper bound of 0.3.[22] This is the highest estimate of short run supply elasticities measured in the literature by Coyle et al. (2012) (see Fally and Sayre, 2018) and Rao (2018).

Given a higher supply elasticity, output is curbed more strongly when reacting to negative demand shocks. Under the higher upper bound we obtain a median real price of $33 in 2030 in the demand side climate policy scenario (see figure B.21 in the appendix) and $56 when we use the real economic activity index from Kilian (2009) (see appendix figure B.22).

7.4 Alternative Samples

Several studies have raised the issue of potential structural breaks in the global oil market since the 1970s (e.g., Blanchard and Galí, 2007; Dvir and Rogoff, 2009; Blanchard and Riggi, 2013; Baumeister and Peersman, 2013b; Bruns and Lütkepohl, 2023). Bruns and Lütkepohl (2023) find a structural break in the transmission of shocks to oil price expectations at the time of the 1990/91 gulf war. Blanchard and Galí (2007) and Blanchard and Riggi (2013) focus on different effects of shocks to oil prices pre and post 1984. Baumeister and Peersman (2013b) analyze a sample split in 1986.

To check the sensitivity of our scenario results to potential structural breaks and without the need to make an assumption on the volatility and VAR parameter regimes over

[22]This bound implies a realized upper bound of 0.28 of the impact supply elasticity obtained directly from the B_0 matrix. Moreover, Table C.2 in the appendix gives an overview of the realized elasticities across different model specifications.

the scenario horizon, we analyze different samples, starting in either January 1984, January 1986 or October 1990. We obtain minimum prices of \$28, \$34, and \$32 per barrel in 2030 in the demand side climate policy scenario and maximum prices of \$212, \$244, and \$232 per barrel in the supply side climate policy scenario for the three different starting periods, respectively (figure B.26 in the appendix shows the net-zero price scenarios based on the October 1990 sample start). The maximum prices in the supply-side climate policy scenario are higher compared to the baseline results, as we obtain lower price elasticities of demand for the models with a later starting point of the sample (Baumeister and Peersman, 2013a,b discuss this steepening of the oil demand curve). Figure B.9 in the appendix shows the impulse responses for the model with the October 1990 sample start.

8 Conclusion

We illustrate that the impact of the energy transition on fossil fuel markets is different depending on the mix of the climate policy shocks at the example of the oil market. We typically think about the energy transition as a series of negative demand shocks to fossil fuels, lowering prices. However, some policies such as the curb of investment flows into oil and gas (through stricter ESG criteria) can also negatively affect the supply side of fossil fuel markets, leading to higher prices.

We show in illustrative scenarios that if there were only demand-side climate policies, oil prices could decline to the \$20s in 2030. This would have negative effects on oil exporters. Rents would diminish and oil output would come under pressure in high-cost regions. In contrast, in a scenario driven by only supply-side climate policies would put strong upward pressures on prices, taking them to roughly $130 per barrel. This would benefit producing countries. As oil production would be profitable for all producers, the main determinants for the distribution of out and rents would be countries' restrictions, environmental regulations, and firms' access to capital.

If the mix of countries' policies is unpredictable and uncoordinated, the price effects of the energy transition are ultimately hard to determine, which raises uncertainty. Countries will need to prepare for this higher price uncertainty and adjust their macroeconomic and fiscal policies accordingly. A coordinated climate policy mix among consumer and producer countries of fossil fuels would help to reduce this source of energy price uncertainty. Doing so would help countries to make necessary policy adjustments during the energy transition.

References

Alquist, R., Kilian, L., and Vigfusson, R. J. (2013). Forecasting the price of oil. In *Handbook of Economic Forecasting*, volume 2, pages 427–507.

Antolín-Díaz, J., Petrella, I., and Rubio-Ramírez, J. F. (2021). Structural scenario analysis with SVARs. *Journal of Monetary Economics*, 117(C):798–815.

Antolín-Díaz, J. and Rubio-Ramírez, J. F. (2018). Narrative sign restrictions for SVARs. *American Economic Review*, 108(10):2802–2829.

Basher, S. A., Haug, A. A., and Sadorsky, P. (2018). The impact of oil-market shocks on stock returns in major oil-exporting countries. *Journal of International Money and Finance*, 86:264–280.

Baumeister, C. and Hamilton, J. D. (2015). Sign restrictions, structural vector autoregressions, and useful prior information. *Econometrica*, 83(5):1963–1999.

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

Baumeister, C. and Hamilton, J. D. (2020). Drawing conclusions from structural vector autoregressions identified on the basis of sign restrictions. *Journal of International Money and Finance*, 109(C).

Baumeister, C. and Hamilton, J. D. (2023). Advances in using vector autoregressions to estimate structural magnitudes. *Econometric Theory*, forthcoming.

Baumeister, C. and Kilian, L. (2014a). Real-Time Analysis of Oil Price Risks Using Forecast Scenarios. *IMF Economic Review*, 62(1):119–145.

Baumeister, C. and Kilian, L. (2014b). What central bankers need to know about forecasting oil prices. *International Economic Review*, 55(3):869–889.

Baumeister, C., Korobilis, D., and Lee, T. K. (2022). Energy markets and global economic conditions. *The Review of Economics and Statistics*, 104(4):828–844.

Baumeister, C. and Peersman, G. (2013a). The role of time-varying price elasticities in accounting for volatility changes in the crude oil market. *Journal of Applied Econometrics*, 28(7):1087–1109.

Baumeister, C. and Peersman, G. (2013b). Time-varying effects of oil supply shocks on the U.S. economy. *American Economic Journal: Macroeconomics*, 5(4):1–28.

Blanchard, O. J. and Galí, J. (2007). The Macroeconomic Effects of Oil Price Shocks: Why Are the 2000s so Different from the 1970s? In *International Dimensions of Monetary Policy*, NBER Chapters, pages 373–421. National Bureau of Economic Research, Inc.

Blanchard, O. J. and Riggi, M. (2013). Why are the 2000s so different from the 1970s? a structural interpretation of changes in the macroeconomic effects of oil prices. *Journal of the European Economic Association*, 11(5):1032–1052.

Boer, L., Pescatori, A., and Stuermer, M. (2023). Energy transition metals: Bottleneck for net-zero emissions? *Journal of the European Economic Association*, forthcoming.

Bogmans, C., Prifti, E., and Pescatori, A. (2023). The Impact of Climate Policy on Oil and Gas Investment: Evidence from Firm-Level Data. IMF Working Paper 23-140, International Monetary Fund.

Bruns, M. and Lütkepohl, H. (2023). Have the effects of shocks to oil price expectations changed?: Evidence from heteroskedastic proxy vector autoregressions. Discussion Papers of DIW Berlin 2036, DIW Berlin, German Institute for Economic Research.

Caldara, D., Cavallo, M., and Iacoviello, M. (2019). Oil price elasticities and oil price fluctuations. *Journal of Monetary Economics*, 103:1–20.

Canova, F. and Nicolo, G. D. (2002). Monetary disturbances matter for business fluctuations in the g-7. *Journal of Monetary Economics*, 49(6):1131–1159.

Coyle, D., DeBacker, J., and Prisinzano, R. (2012). Estimating the supply and demand of gasoline using tax data. *Energy Economics*, 34(1):195–200.

Delis, M. D., de Greiff, K., Iosifidi, M., and Ongena, S. R. G. (2019). Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans. Swiss Finance Institute Research Paper No. 18-10.

Doan, T., Litterman, R., and Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews*, 3(1):1–100.

Dvir, E. and Rogoff, K. S. (2009). Three epochs of oil. Technical Report 14927, National Bureau of Economic Research.

Ehlers, T., Packer, F., and de Greiff, K. (2022). The pricing of carbon risk in syndicated loans: Which risks are priced and why? *Journal of Banking & Finance*, 136(C).

Fally, T. and Sayre, J. (2018). Commodity trade matters. NBER Working Papers 24965, National Bureau of Economic Research, Inc.

Faust, J. (1998). The robustness of identified VAR conclusions about money. In *Carnegie-Rochester Conference Series on Public Policy*, volume 49, pages 207–244.

Giacomini, R. and Ragusa, G. (2014). Theory-coherent forecasting. *Journal of Econometrics*, 182(1):145–155.

Giannone, D., Lenza, M., and Primiceri, G. (2015). Prior selection for vector autoregressions. *The Review of Economics and Statistics*, 97(2):436–451.

Golosov, M., Hassler, J., Krusell, P., and Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88.

Harstad, B. (2012). Buy coal! A case for supply-side environmental policy. *Journal of Political Economy*, 120(1):77–115.

Hassler, J. and Krusell, P. (2012). Economics and climate change: Integrated assessment in a multi-region world. *Journal of the European Economic Association*, 10(5):974–1000.

Herrera, A. M. and Rangaraju, S. K. (2020). The effect of oil supply shocks on US economic activity: What have we learned? *Journal of Applied Econometrics*, 35(2):141–159.

Hoel, M. (1994). Efficient climate policy in the presence of free riders. *Journal of Environmental Economics and Management*, 27(3):259–274.

Inoue, A. and Kilian, L. (2020). The role of the prior in estimating VAR models with sign restrictions. Manuscript, Federal Reserve Bank of Dallas.

Inoue, A. and Kilian, L. (2022). Joint Bayesian inference about impulse responses in VAR models. *Journal of Econometrics*, 231(2):457–476.

International Energy Agency (2022). World energy outlook 2022. International Energy Agency. Paris, France.

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *The American Economic Review*, 99(3):1053–1069.

Kilian, L. (2022). Understanding the estimation of oil demand and oil supply elasticities. *Energy Economics*, 107:105844.

Kilian, L. and Lewis, L. T. (2011). Does the Fed respond to oil price shocks? *The Economic Journal*, 121(555):1047–1072.

Kilian, L. and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3):454–478.

Kilian, L. and Zhou, X. (2018). Modeling fluctuations in the global demand for commodities. *Journal of International Money and Finance*, 88:54–78.

Kilian, L. and Zhou, X. (2020). Does drawing down the us strategic petroleum reserve help stabilize oil prices? *Journal of Applied Econometrics*, 35(6):673–691.

Känzig, D. R. (2021). The macroeconomic effects of oil supply news: Evidence from opec announcements. *American Economic Review*, 111(4):1092–1125.

Leeper, E. M. and Zha, T. (2003). Modest policy interventions. *Journal of Monetary Economics*, 50(8):1673–1700.

Lucas, R. E. (1976). Econometric policy evaluation: A critique, in the carnegie-rochester conference series, the phillips curve.

Ludvigson, S. C., Ma, S., and Ng, S. (2017). Shock restricted structural vector-autoregressions. *NBER Working Paper*, (w23225).

Nordhaus, W. D. and Boyer, J. (2000). *Warming the world: economic models of global warming*. Cambridge, MA, MIT Press.

Rao, N. L. (2018). Taxes and us oil production: Evidence from California and the windfall profit tax. *American Economic Journal: Economic Policy*, 10(4):268–301.

Robertson, J. C., Tallman, E. W., and Whiteman, C. H. (2005). Forecasting using relative entropy. *Journal of Money, Credit and Banking*, 37(3):383–401.

Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies*, 77(2):665–696.

Seltzer, L. H., Starks, L., and Zhu, Q. (2022). Climate Regulatory Risk and Corporate Bonds. NBER Working Papers 29994, National Bureau of Economic Research, Inc.

Sims, C. A. (1993). A nine-variable probabilistic macroeconomic forecasting model, in business cycles, indicators and forecasting. *NBER Studies in Business Cycles, In J.H. Stock and M.W. Watson (eds.) University of Chicago*, pages 179–212.

Uhlig, H. (2005). What are the effects of monetary policy on output? Results from an agnostic identification procedure. *Journal of Monetary Economics*, 52(2):381–419.

van der Ploeg, F. and Rezai, A. (2020). The risk of policy tipping and stranded carbon assets. *Journal of Environmental Economics and Management*, 100:102258.

Waggoner, D. and Zha, T. (1999). Conditional forecasts in dynamic multivariate models. *The Review of Economics and Statistics*, 81(4):639–651.

Watson, M. (2019). Comment on "The empirical (ir) relevance of the zero lower bound constraint". *NBER Macroeconomics Annual*, 34.

Wolf, C. K. and McKay, A. (2023). What can time-series regressions tell us about policy counterfactuals? *Econometria*, forthcoming.

Zhou, X. (2020). Refining the workhorse oil market model. *Journal of Applied Econometrics*, 35(1):130–140. https://doi.org/10.1002/jae.2743.

Appendices

A Structural Scenario Analysis

In the following we provide some background on structural scenario analysis as formalized in Antolín-Díaz et al. (2021). The goal is to forecast our variables of interest $\mathbf{y}_t$ for h periods ahead given certain restrictions on future observables and future shocks. In the case of no restrictions, the endogenous variables' unconditional forecast for periods $T+1$ to $T+h$ is given by

$$\mathbf{y}_{T+1,T+h} = \mathbf{b}_{T+1,T+h} + \mathbf{M}'\boldsymbol{\varepsilon}_{T+1,T+h} \ , \tag{5}$$

where $\mathbf{y}_{T+1,T+h} = (\mathbf{y}_{T+1}...\mathbf{y}_{T+h})$ and $\mathbf{b}_{T+1,T+h}$ represent the deterministic part of the forecast, which depends on past observables, the reduced-form VAR parameters $\mathbf{A}_i$ for $i = 1, .., p$ and the deterministic part $\mathbf{D}_t$. The matrix $\mathbf{M}$ represents the effects of the structural shocks on future values of the endogenous variables as a function of the structural parameters in $\mathbf{B_i}$ and the reduced-form parameters in $\mathbf{A}_i$ (see Antolín-Díaz et al., 2021 or Waggoner and Zha, 1999 for further details). The unconditional forecast is independent of the structural parameters. It is distributed according to $\mathbf{y}_{T+1,T+h} \sim \mathcal{N}(\mathbf{b}_{T+1,T+h}, \mathbf{M}'\mathbf{M})$, where $\mathbf{M}'\mathbf{M}$ depends only on the reduced-form parameters.

To answer the question of how oil prices fare in a net-zero emissions scenario, we perform a restricted forecast of the endogenous variables $\widetilde{\mathbf{y}}_{T+1,T+h}$, for which we place restrictions both on parts of the future observable variables and future shocks. Hence, the future observables are restricted as

$$\overline{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} = \overline{\mathbf{C}}\mathbf{b}_{T+1,T+h} + \overline{\mathbf{C}}\mathbf{M}'\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\overline{\mathbf{f}}_{T+1,T+h}, \overline{\boldsymbol{\Omega}}_f) \tag{6}$$

where $\overline{\mathbf{C}}$ is a (k_0 x nh) pre-specified selection matrix, including k_0 restrictions. $\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h}$ denotes the restricted future shock series that is distributed as $\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}\big(\mu_\varepsilon, \boldsymbol{\Sigma}_\varepsilon\big)$. The ($k_0$ x 1) vector $\overline{\mathbf{f}}_{T+1,T+h}$ denotes the mean of the constrained endogenous variables and the (k_0 x k_0) matrix $\overline{\boldsymbol{\Omega}}_f$ denotes the covariance restrictions, i.e., the uncertainty around the restrictions on the observables.

In our baseline case, we restrict the path for oil output according to the scenarios and we set $\overline{\boldsymbol{\Omega}}_f = \overline{\mathbf{C}}\mathbf{M}'\mathbf{M}\overline{\mathbf{C}}'$ following Antolín-Díaz et al. (2021). This allows for uncertainty around the scenario consumption path. The literature before Antolín-Díaz et al. (2021) usually assumed no uncertainty around scenarios and set this variance to 0.

Secondly, we restrict k_s elements of the future shocks via the (k_s x nh) selection matrix $\boldsymbol{\Xi}$ expressed as $\boldsymbol{\Xi}\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\mathbf{g}_{T+1,T+h}, \boldsymbol{\Omega}_g)$. The ($k_s$ x 1) vector $\mathbf{g}_{T+1,T+h}$ denotes the mean and $\boldsymbol{\Omega}_g$ the covariance restrictions on the shocks in the conditional forecast.[23]

[23]When implementing the algorithm in Matlab, we also impose an upper absolute bound of 5 standard deviations on all future shocks. We show the point-wise mean of the scenario shocks in the online-appendix.

Under invertibility of the VAR, the restricted shocks can be related to restrictions on the observables starting from equation (5) for the restricted future observables $\widetilde{\mathbf{y}}_{T+1,T+h}$ via

$$\mathbf{M}'^{-1}\widetilde{\mathbf{y}}_{T+1,T+h} = \mathbf{M}'^{-1}\mathbf{b}_{T+1,T+h} + \widetilde{\varepsilon}_{T+1,T+h}, \tag{7}$$

$$\Xi\mathbf{M}'^{-1}\widetilde{\mathbf{y}}_{T+1,T+h} = \Xi\mathbf{M}'^{-1}\mathbf{b}_{T+1,T+h} + \Xi\widetilde{\varepsilon}_{T+1,T+h}\ , \tag{8}$$

yielding

$$\underline{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} = \underline{\mathbf{C}}\mathbf{b}_{T+1,T+h} + \Xi\widetilde{\varepsilon}_{T+1,T+h} \sim \mathcal{N}(\underline{\mathbf{f}}_{T+1,T+h}, \underline{\mathbf{\Omega}}_f)\ , \tag{9}$$

where $\underline{\mathbf{C}} = \Xi(\mathbf{M}')^{-1}$ and $\underline{\mathbf{\Omega}}_f = \mathbf{\Omega}_g$. We would like to explain a pre-specified path in oil output (one component of $\widetilde{\mathbf{y}}_{T+1,T+h}$) via the oil-specific demand shock or the oil supply shock. The other shocks should occur according to their unconditional distribution. In other words, we would like to restrict these non-driving shocks, while leaving the respective shock unspecified. Thus, we impose $\Xi\widetilde{\varepsilon}_{T+1,T+h} \sim \mathcal{N}(\mathbf{0}_{k_s}, \mathbf{I}_{k_s})$ such that equation (9) becomes

$$\underline{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} \sim \mathcal{N}(\underline{\mathbf{C}}\mathbf{b}_{T+1,T+h}, \mathbf{I}_{k_s}). \tag{10}$$

The restrictions in equations (6) and (10) can then be stacked according to

$$\widehat{\mathbf{C}}\widetilde{\mathbf{y}}_{T+1,T+h} \sim \mathcal{N}\left(\underbrace{\begin{bmatrix}\overline{\mathbf{f}}_{T+1,T+h}\\ \underline{\mathbf{C}}\mathbf{b}_{T+1,T+h}\end{bmatrix}}_{\widehat{\mathbf{f}}_{T+1,T+h}}, \underbrace{\begin{bmatrix}\overline{\mathbf{\Omega}}_f & \mathbf{0}_{k_0 \text{x} k_s}\\ \mathbf{0}_{k_s \text{x} k_0} & \mathbf{I}_{k_s}\end{bmatrix}}_{\widehat{\mathbf{\Omega}}_f}\right)\ , \tag{11}$$

where $\widehat{\mathbf{C}}' = [\overline{\mathbf{C}}', \underline{\mathbf{C}}']$ such that the upper part relates to the conditions on observables and the lower part to the conditions on the shocks.

Antolín-Díaz et al. (2021) show how to solve for the restricted forecast of the observables $\widetilde{\mathbf{y}}_{T+1,T+h}$ such that the restrictions in equation (11) hold. In our baseline application we place $k_0 = 90$ restrictions on the observables, i.e., future oil output is constrained to the scenario output in each of the forecasted $h = 90$ months from January 2023 to June 2030. Moreover, we place $k_s = 2 \cdot 90 = 180$ restrictions on the non-driving shocks. Thus, the total number of restrictions $k = k_0 + k_s$ is equal to nh, the length of $\widetilde{\mathbf{y}}_{T+1,T+h}$. For the case $k = nh$, there exists a unique solution of the restricted forecast (see Antolín-Díaz et al., 2021). For the scenario that is equally driven by demand and supply side policies we assume sequences of 3 demand and 3 supply shocks in a row and present a resulting 6-month moving average of the scenario price for technical reasons.

B Additional Figures

B.1 IEA Scenarios

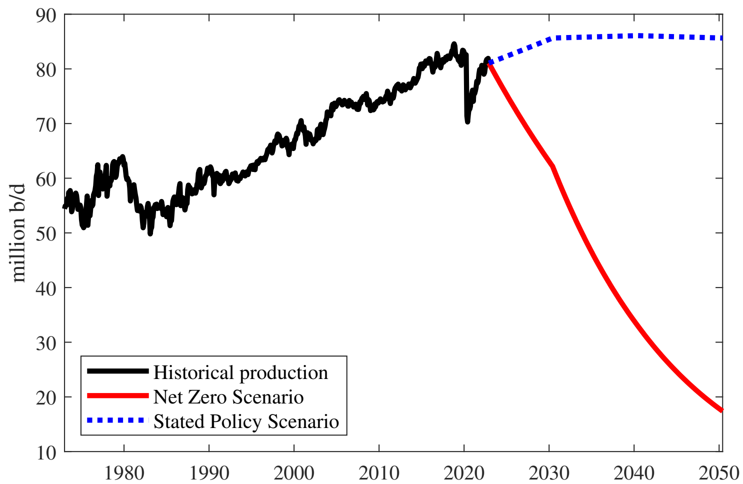


Figure B.1: Global Oil Output Scenarios Until 2050 (Source: International Energy Agency, 2022)

B.2 Impulse Responses

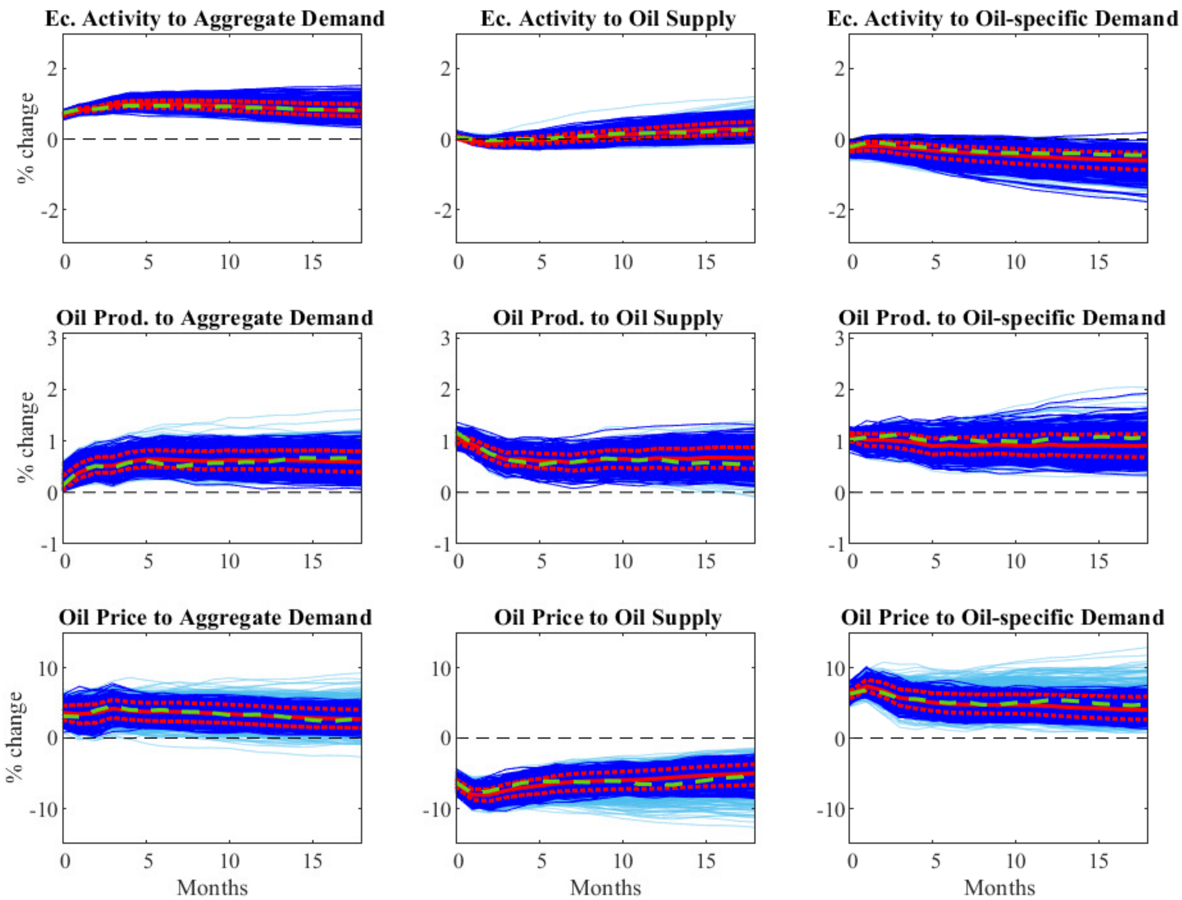


Figure B.2: Impulse Responses for the Demand-Side Climate Policy Scenario

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

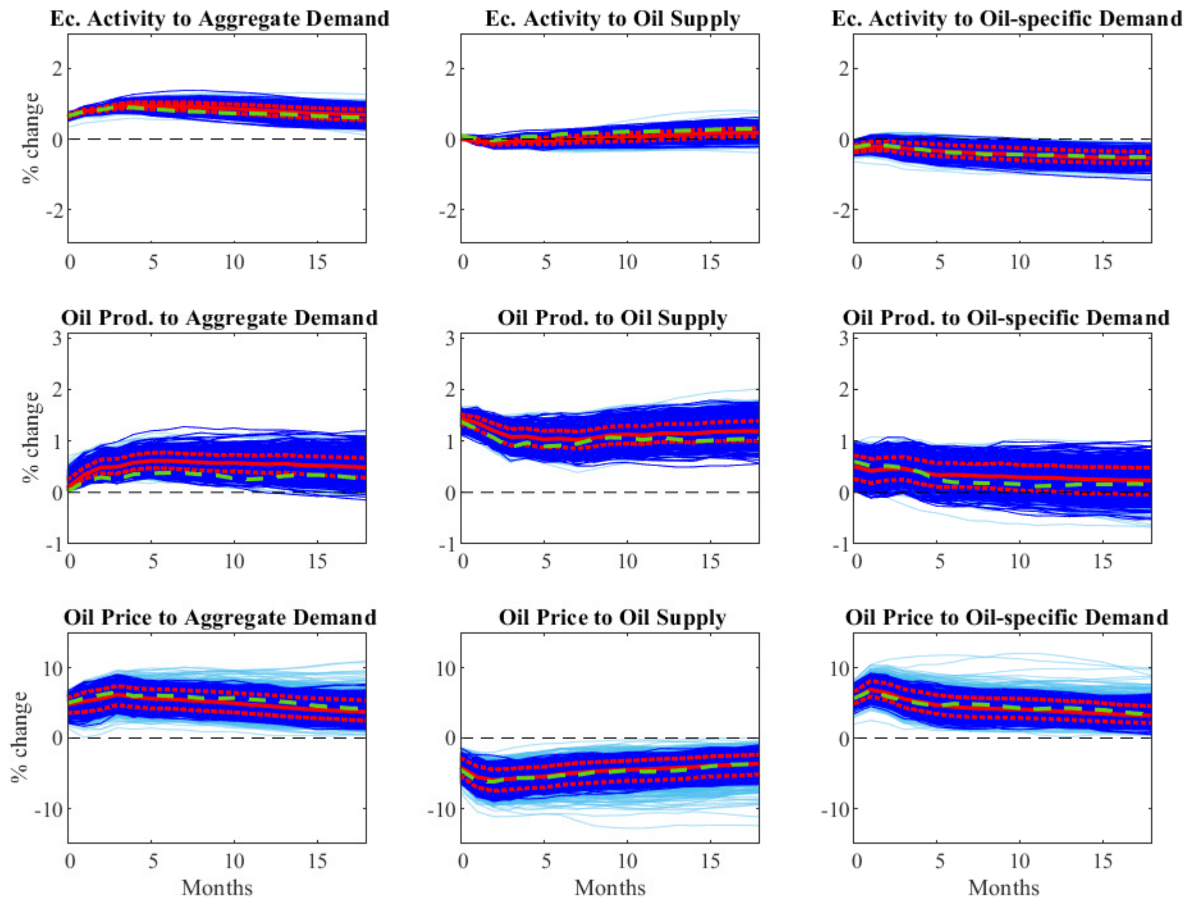


Figure B.3: Impulse Responses for the Supply-Side Climate Policy Scenario

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

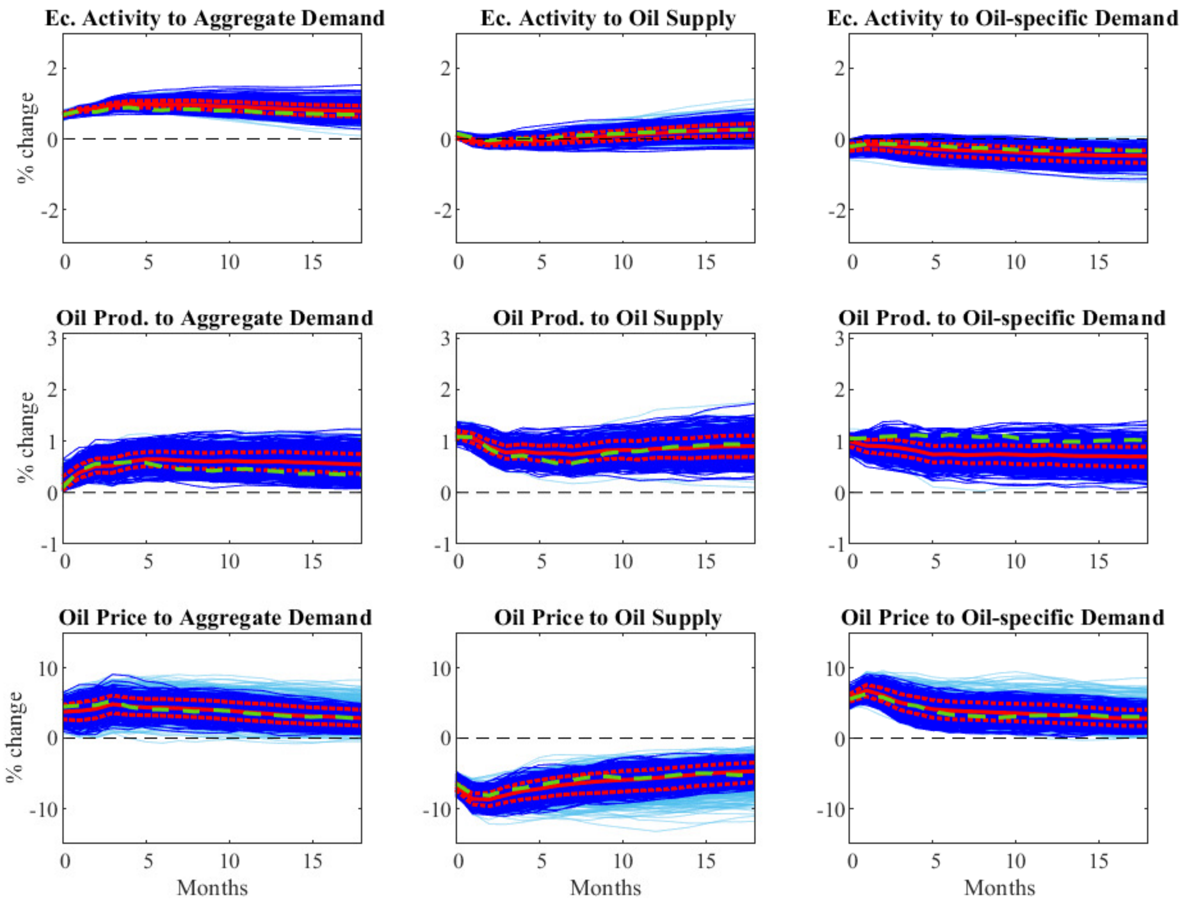


Figure B.4: Impulse Responses for the Equally Supply- and Demand-Side Climate Policies Scenario

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

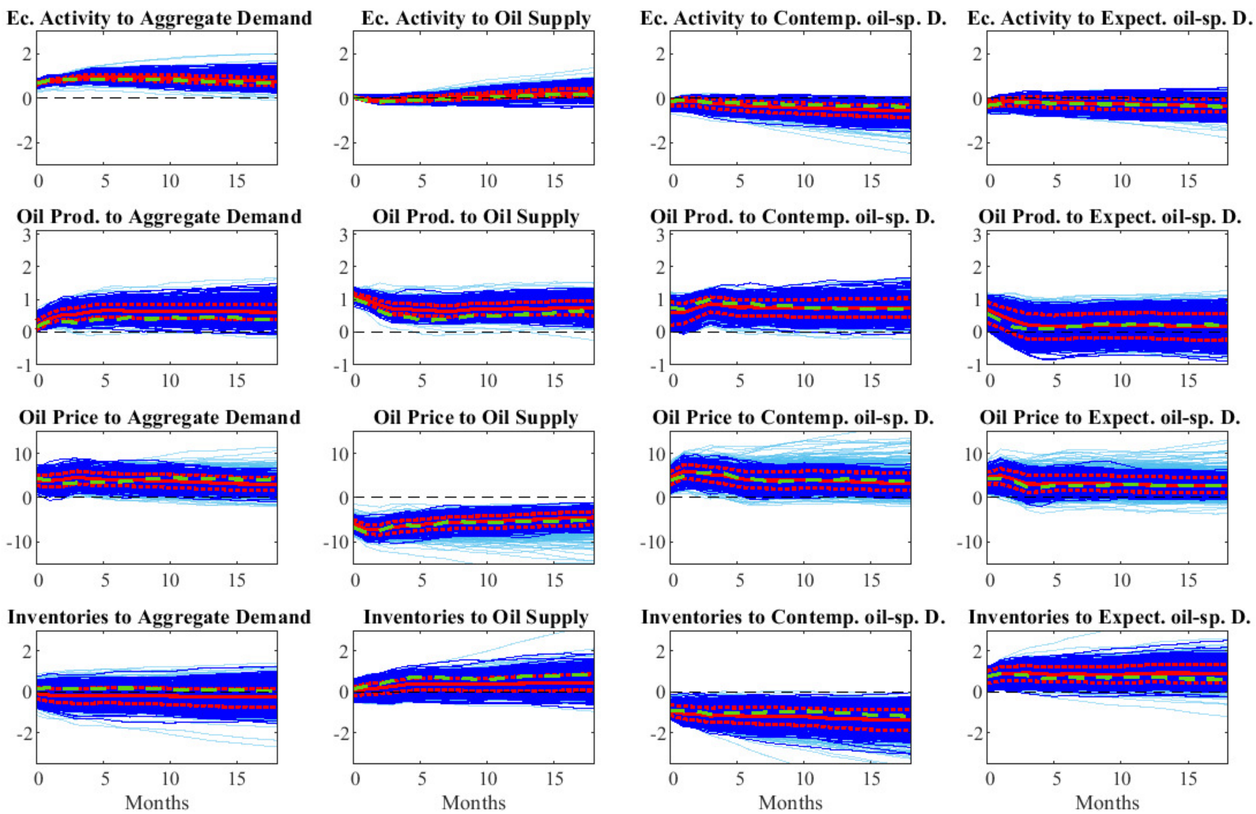


Figure B.5: Impulse Responses for the Demand-Side Climate Policy Scenario in the 4-Variables Model with Expectational and Contemporaneous Oil-Specific Demand Shocks.

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

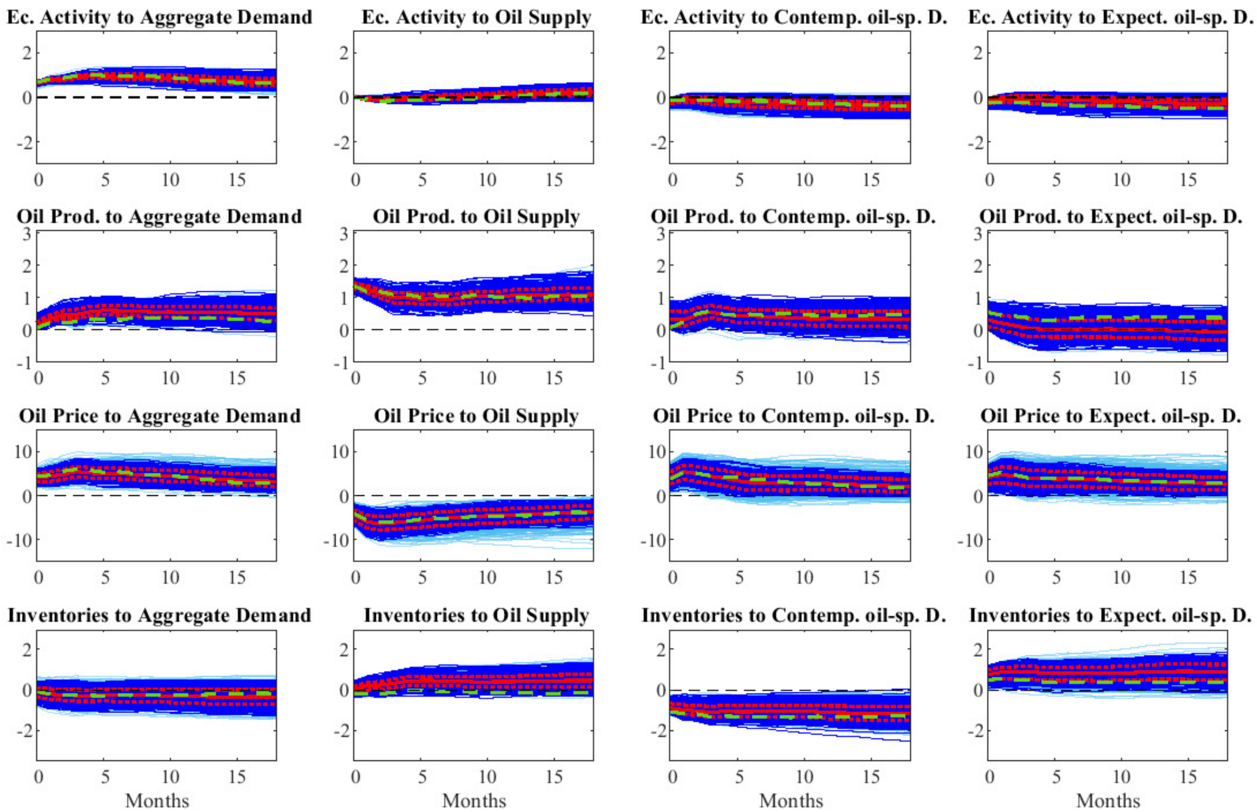


Figure B.6: Impulse Responses for the Supply-Side Climate Policy Scenario in the 4-Variables Model with Expectational and Contemporaneous Oil-Specific Demand Shocks.

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

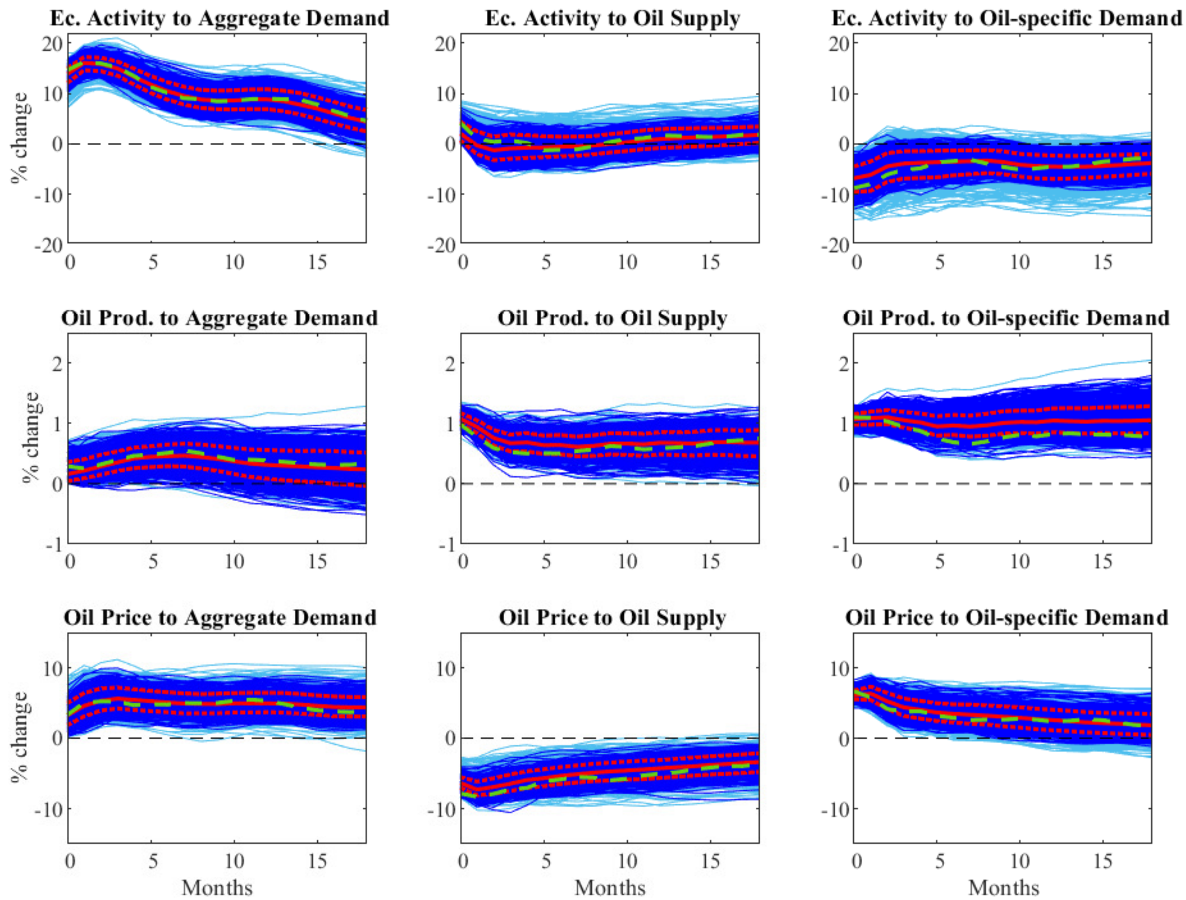


Figure B.7: Impulse Responses for the Demand-Side Climate Policy Scenario Including the Global Real Economic Activity Index from Kilian (2009).

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

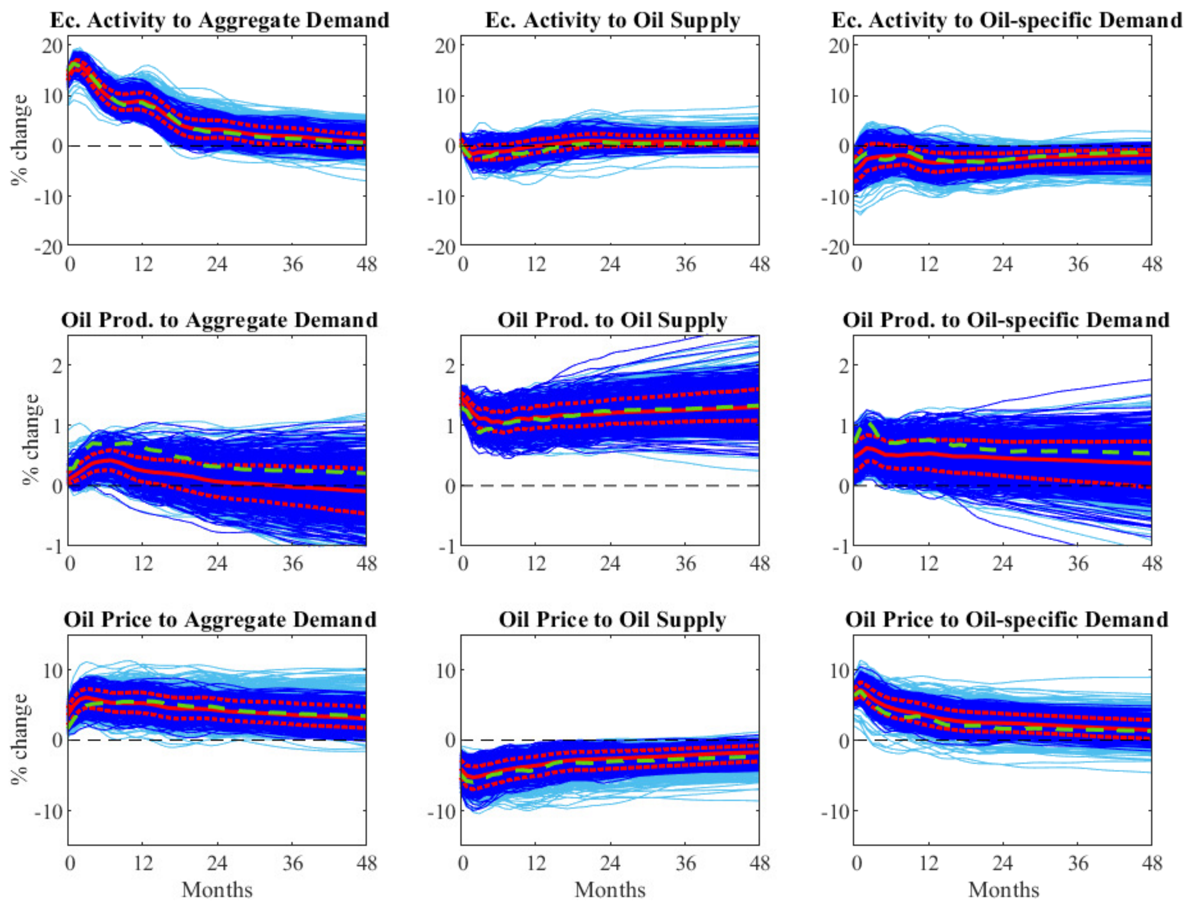


Figure B.8: Impulse Responses for the Supply-Side Climate Policy Scenario Including the Global Real Economic Activity Index from Kilian (2009).

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

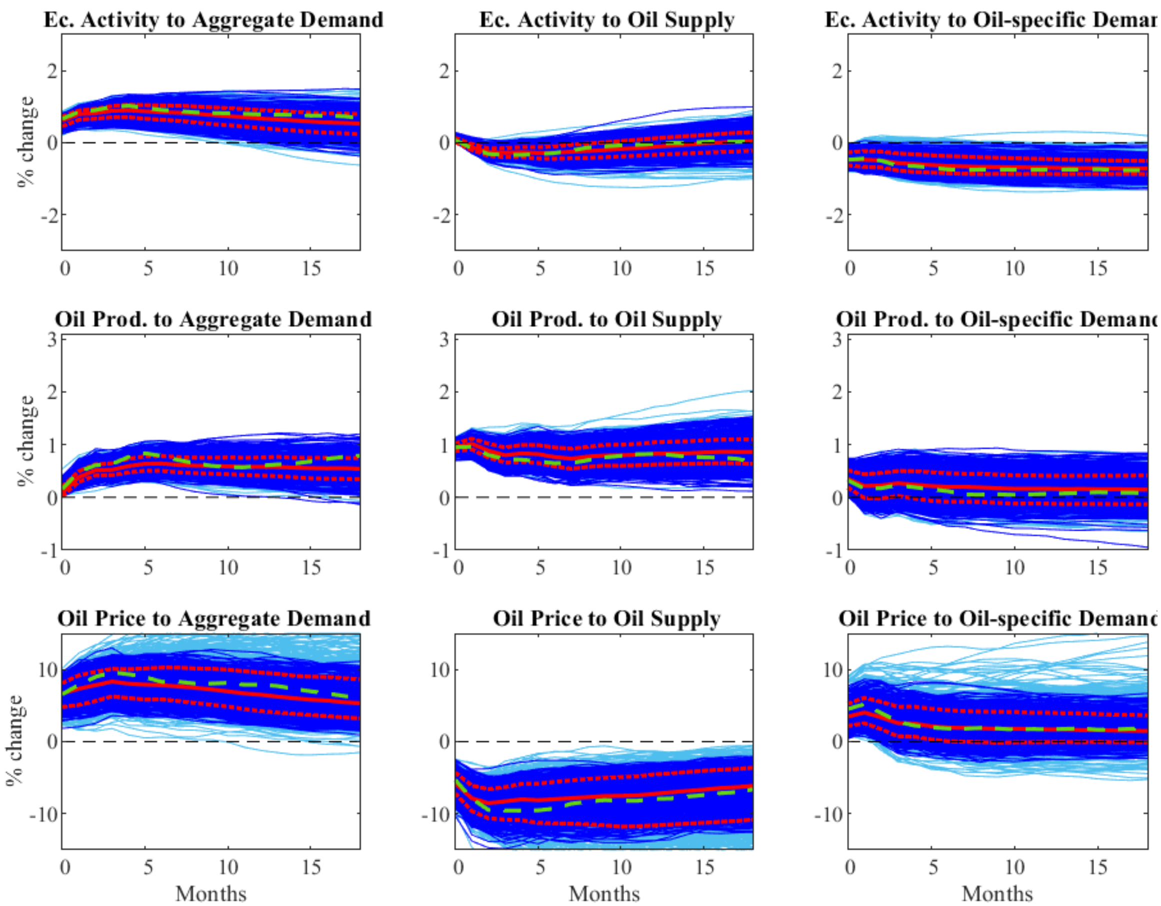


Figure B.9: Impulse Responses for the Supply-Side Climate Policy Scenario in the Model starting the Sample in 1990m10.

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

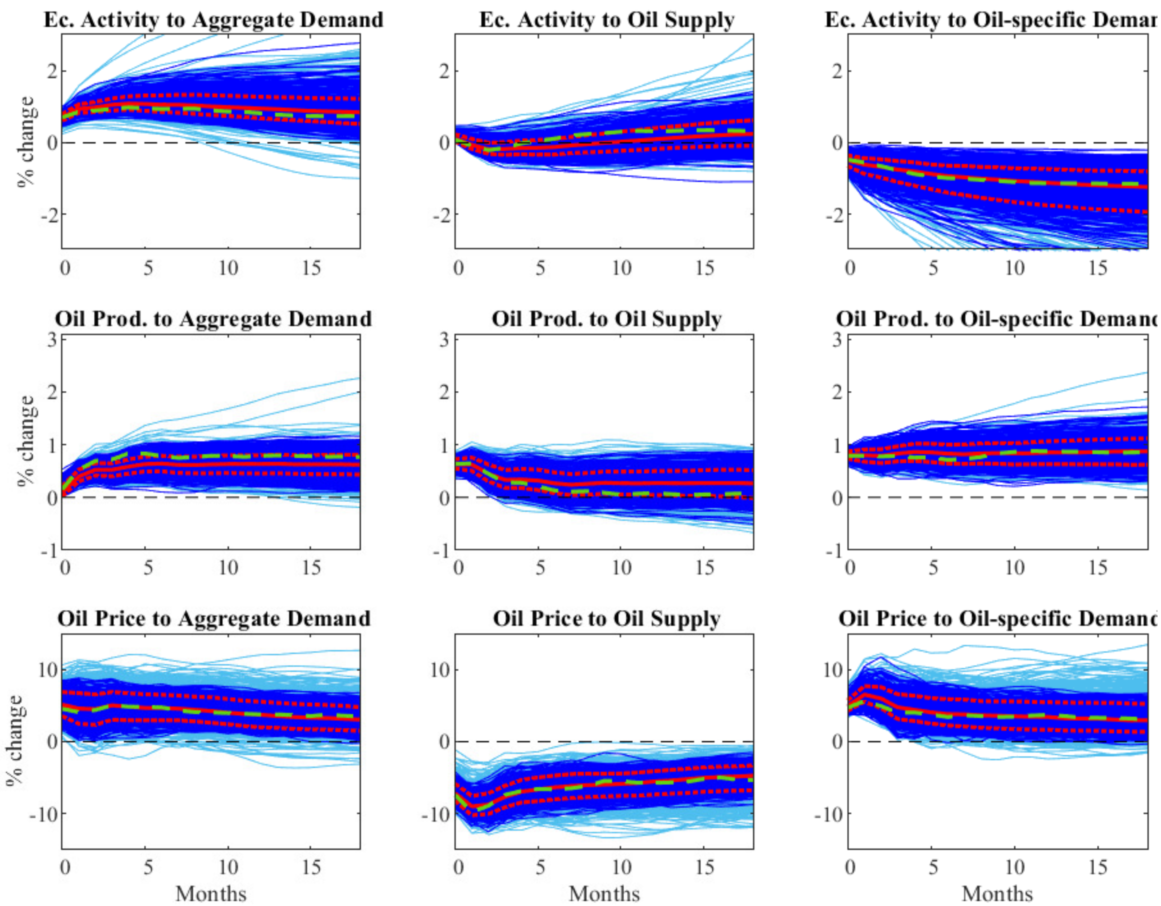


Figure B.10: Impulse Responses for the Demand-Side Climate Policy Scenario in the Model starting the Sample in 1990m10.

Notes: The responses are based on 1,000 draws showing the pointwise median (red solid line) with 68% pointwise credible sets (red dotted lines) and the Bayes estimator under quadratic loss (green dashed line) among the full set of impulse response where the 68% joint credible set under quadratic loss is presented in dark blue and the rest in light blue.

B.3 Scenario Price Paths

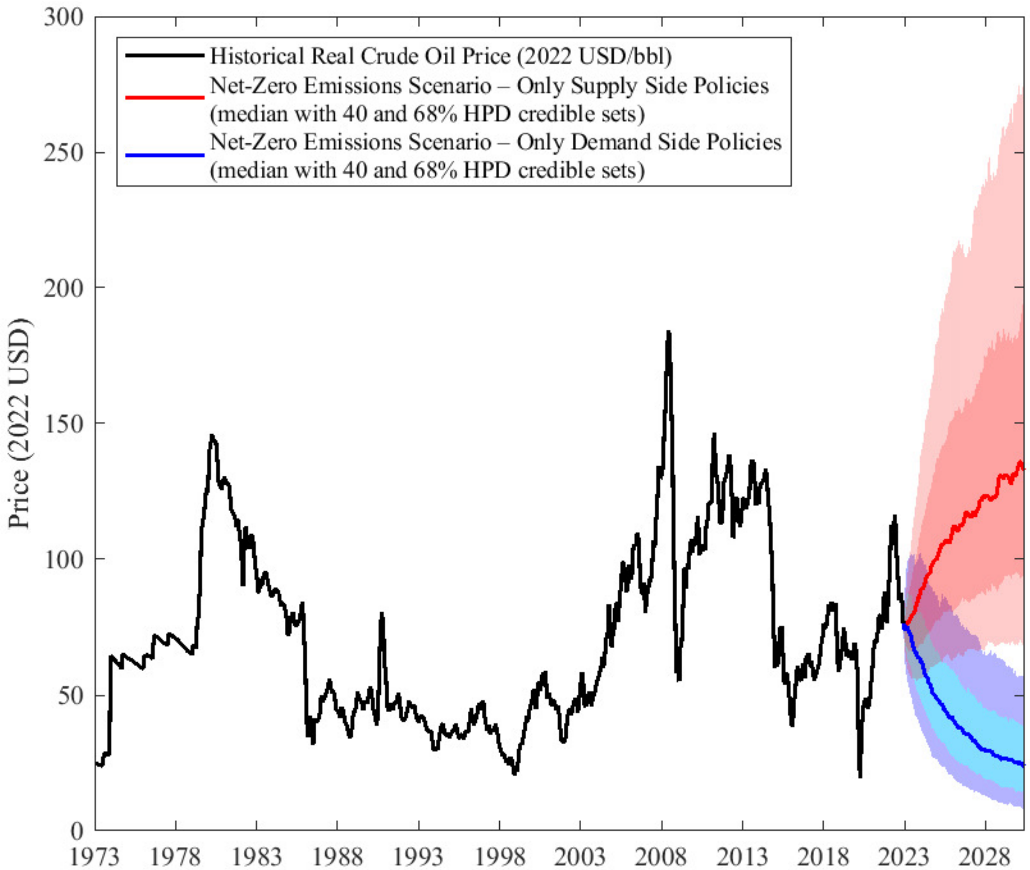


Figure B.11: Oil price scenarios in the baseline model including 40 and 68% highest posterior density credible sets.

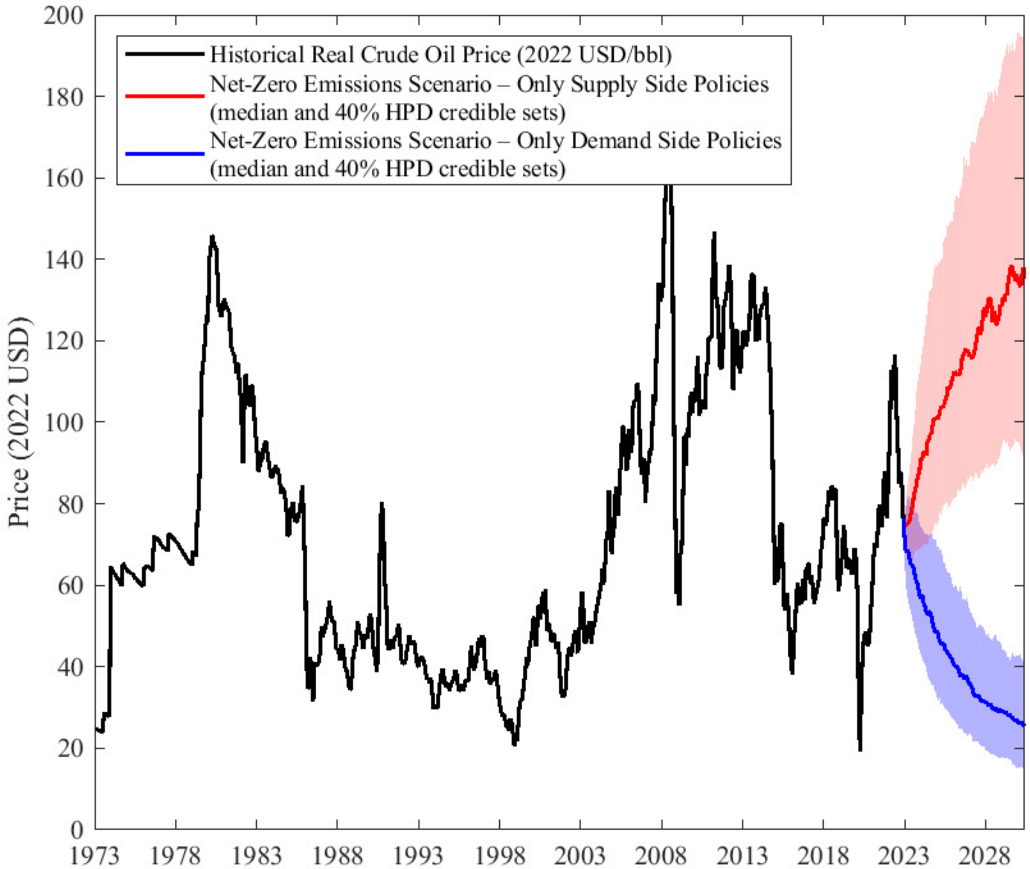


Figure B.12: Oil price scenarios in the model including inventories and differentiating between contemporaneous and expectational oil-specific demand shocks.

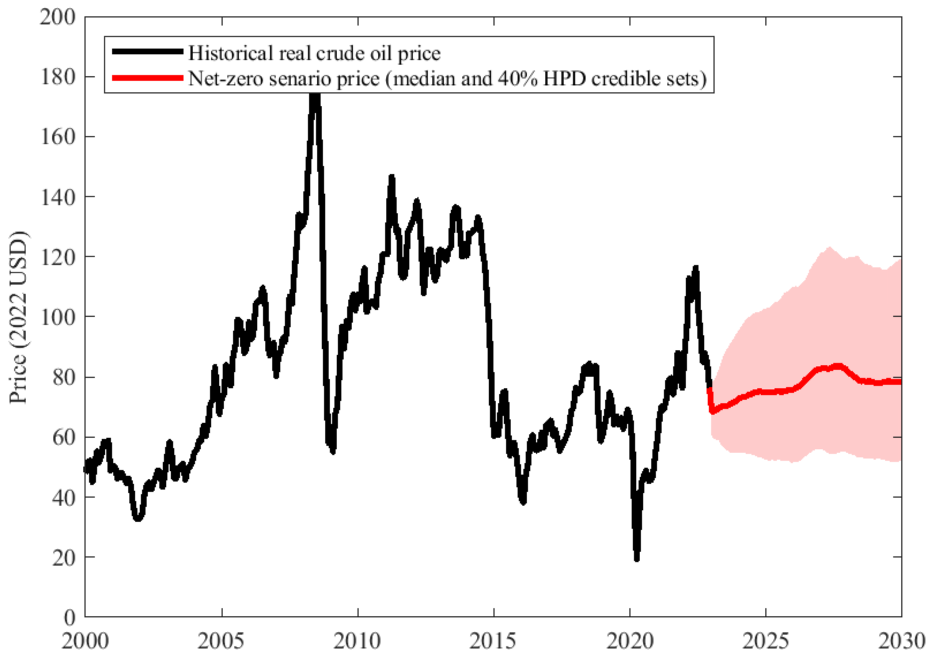


Figure B.13: Oil prices in the net-zero emissions scenario with equally important supply and demand side policies (4-variables model).

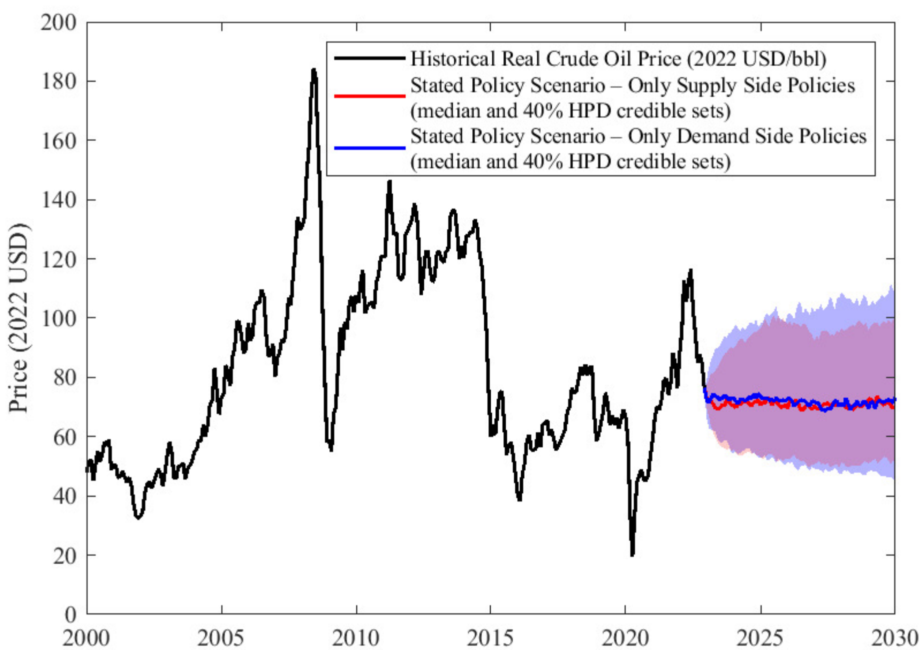


Figure B.14: Oil prices in the supply and demand-side climate policies scenarios (Stated Policy Scenarios, 4-variables model).

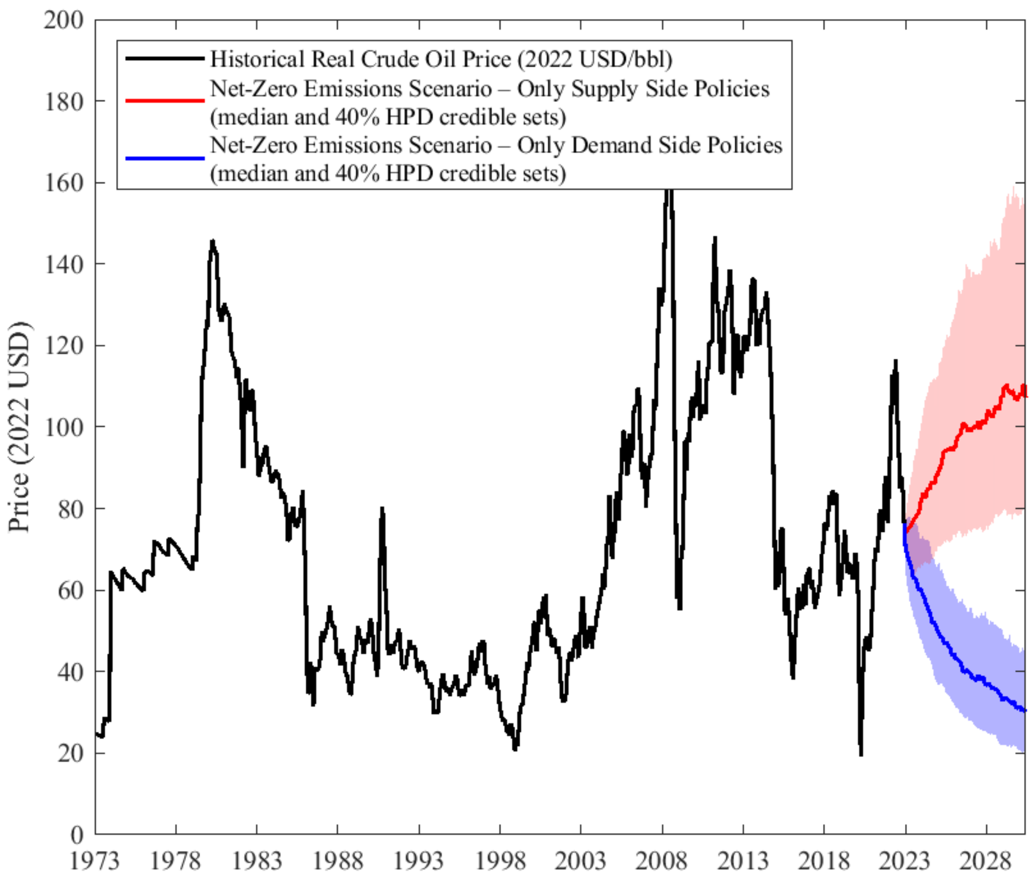


Figure B.15: Oil price scenarios in the model including inventories and three identified shocks from sign restrictions as in Kilian and Murphy (2014).

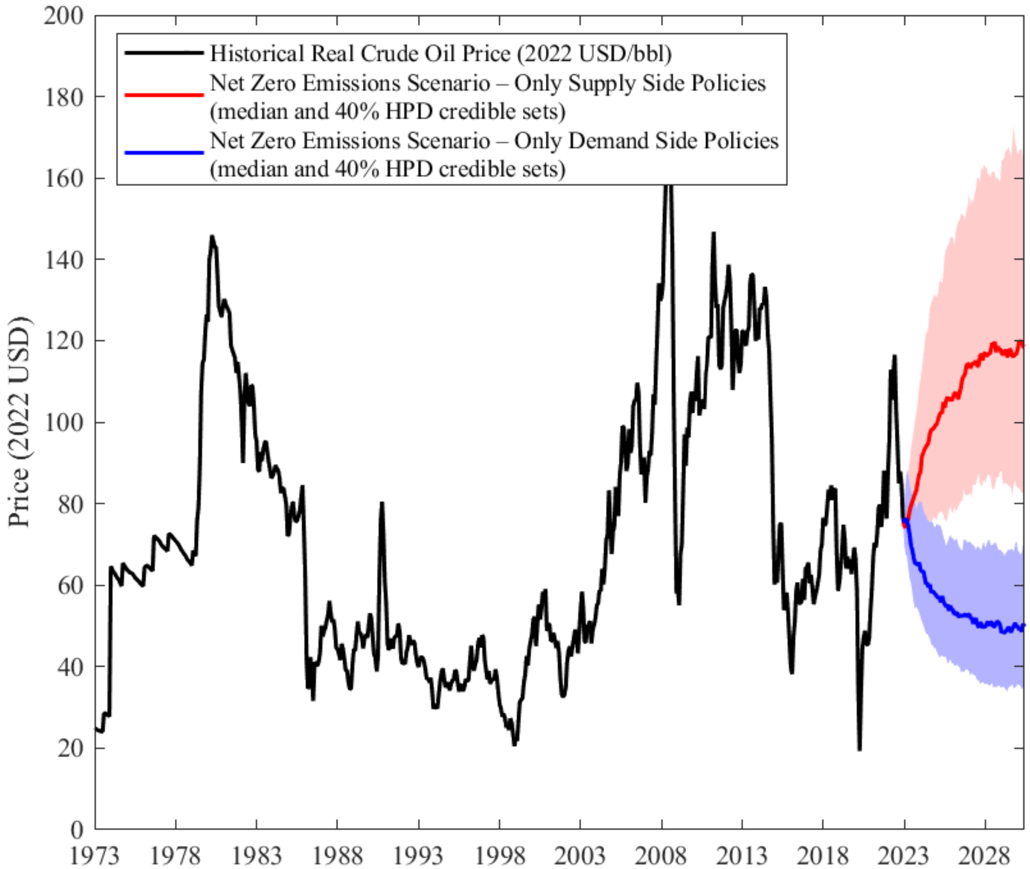


Figure B.16: Oil price scenarios in the net-zero emissions scenario model including the global real economic activity index from Kilian (2009).

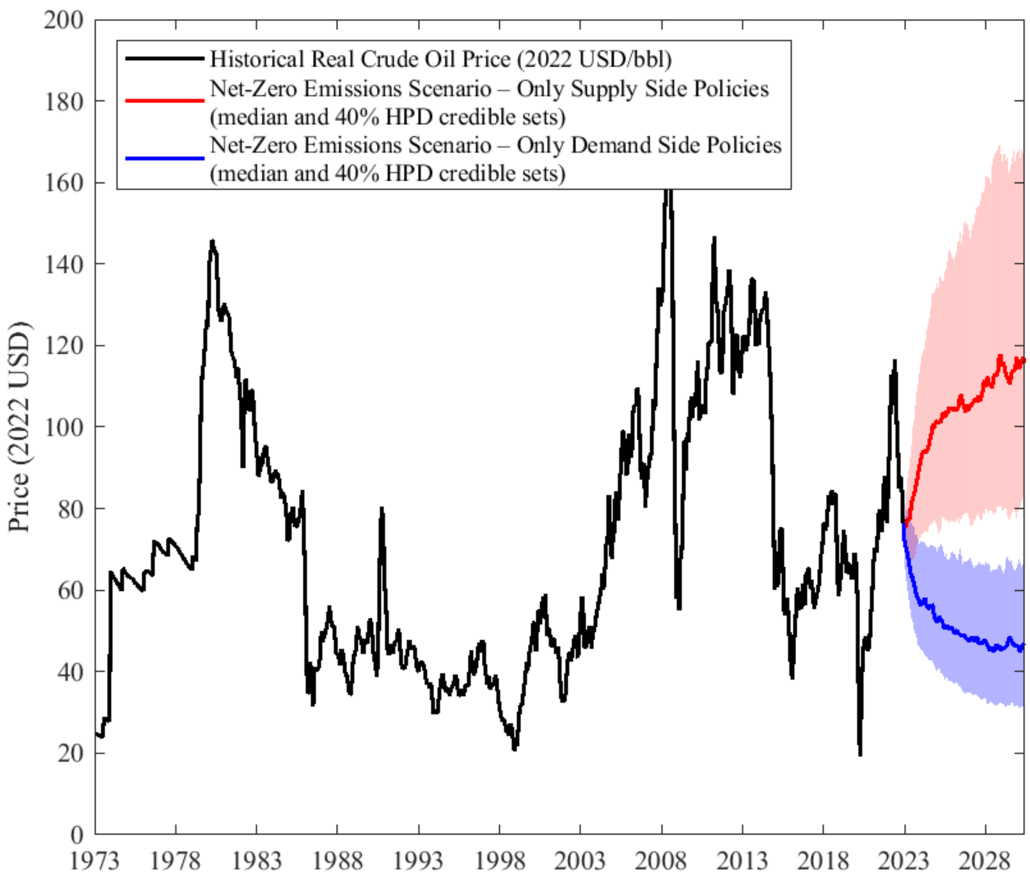


Figure B.17: Oil price scenarios in the net-zero emissions scenario model including the global real economic activity index from Kilian (2009) (4-variables model).

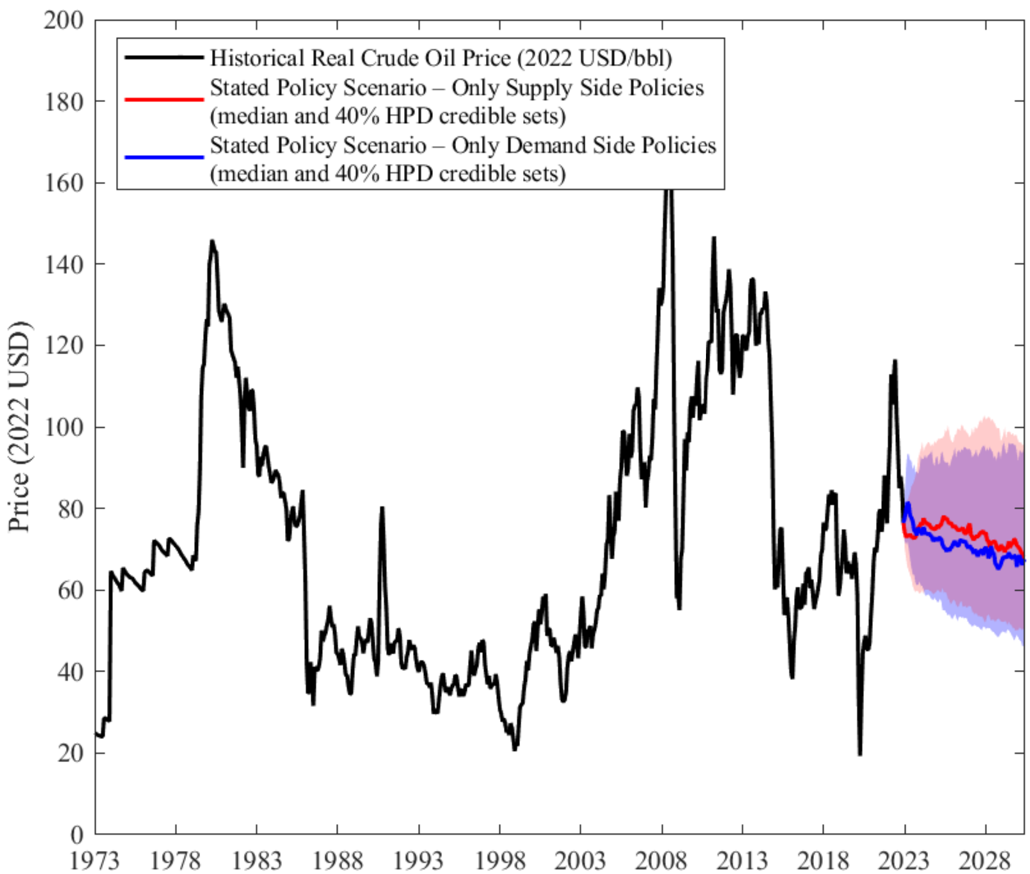


Figure B.18: Oil Price Scenarios in the stated policy scenario model including the global real economic activity index from Kilian (2009).

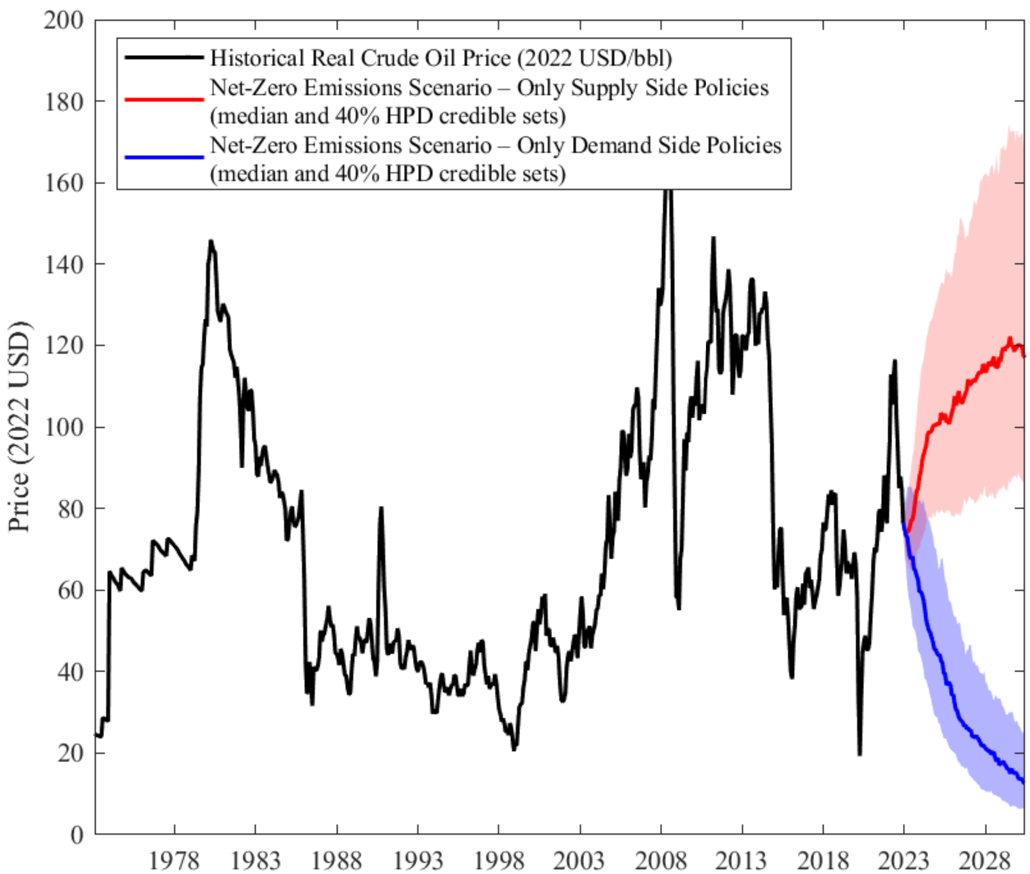


Figure B.19: Oil Price Scenarios in the net-zero emissions scenario model including the global economic conditions index from Baumeister et al. (2022).

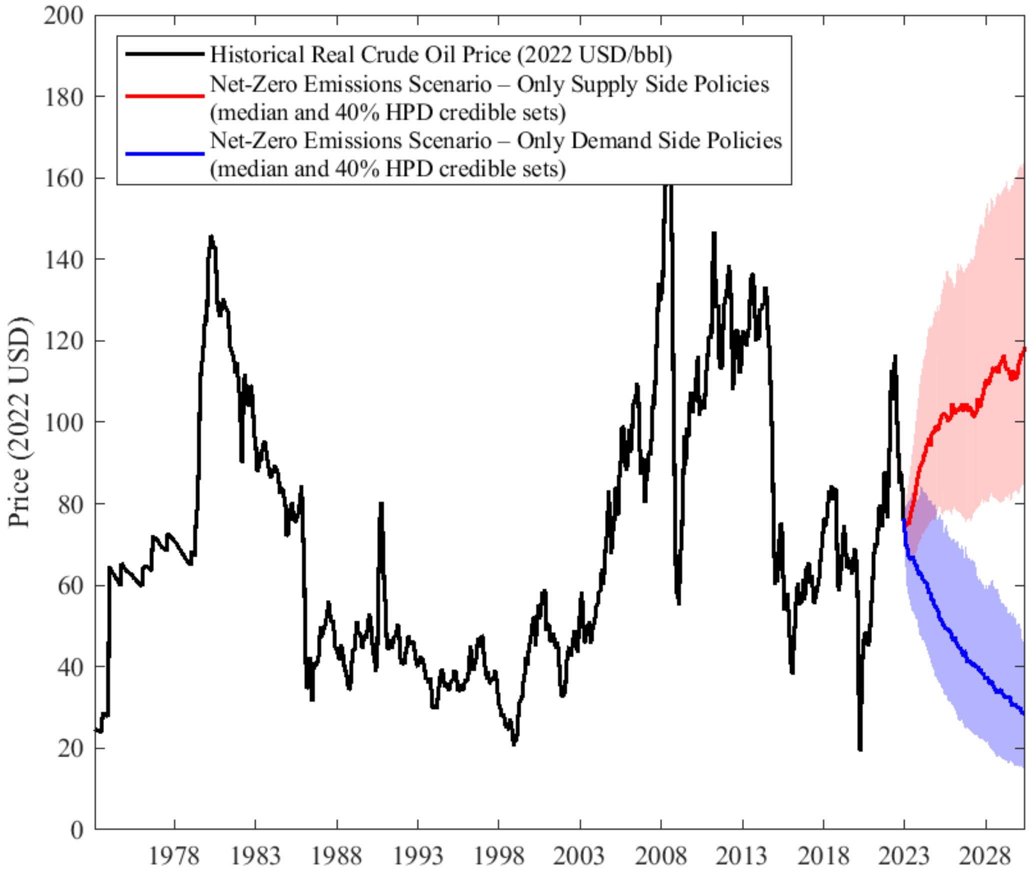


Figure B.20: Oil Price Scenarios in the net-zero emissions scenario model including the global economic conditions index from Baumeister et al. (2022) (4-variables model).

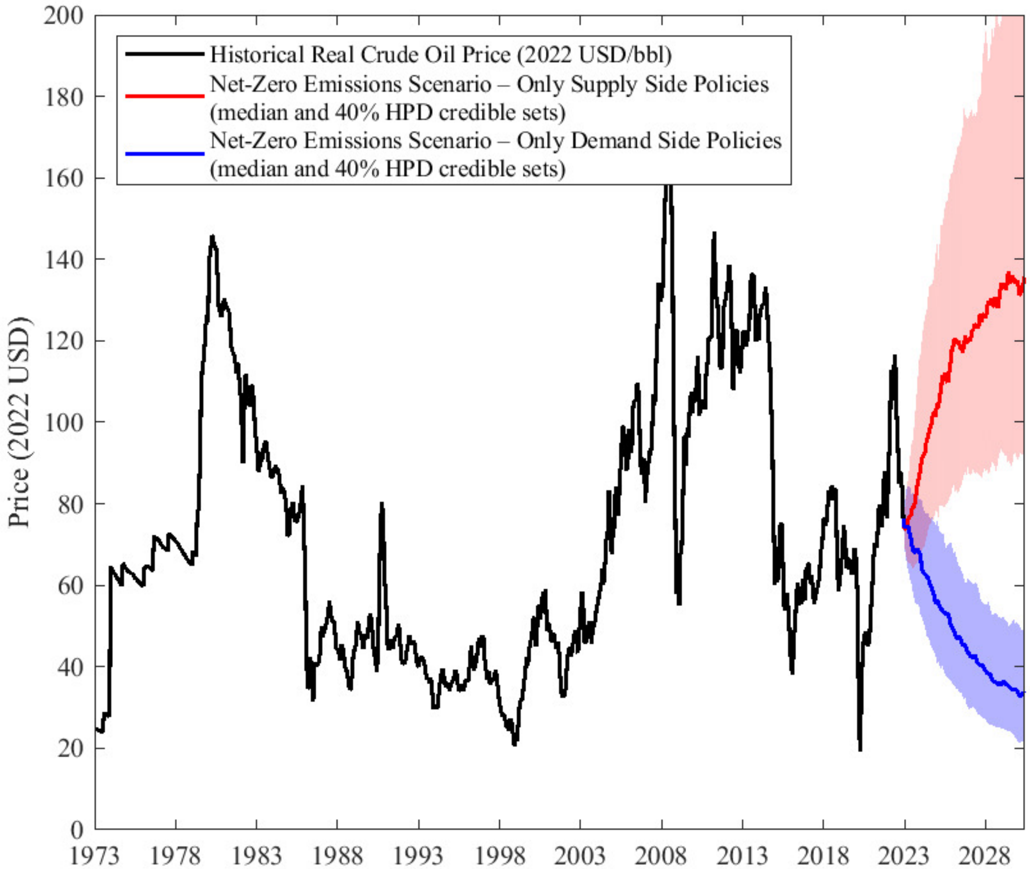


Figure B.21: Oil price scenarios in the model specifying an upper bound on the impact supply elasticity of 0.3.

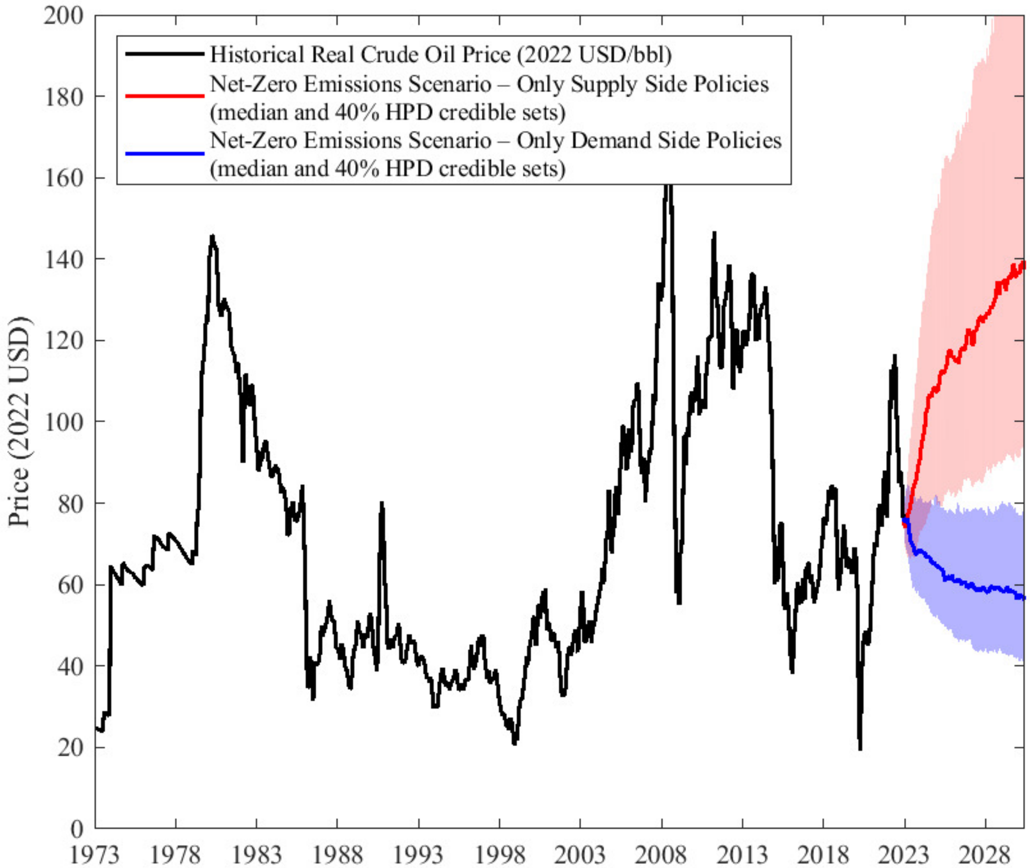


Figure B.22: Oil price scenarios in the model specifying an upper bound on the impact supply elasticity of 0.3 and including the global real economic activity index from Kilian (2009).

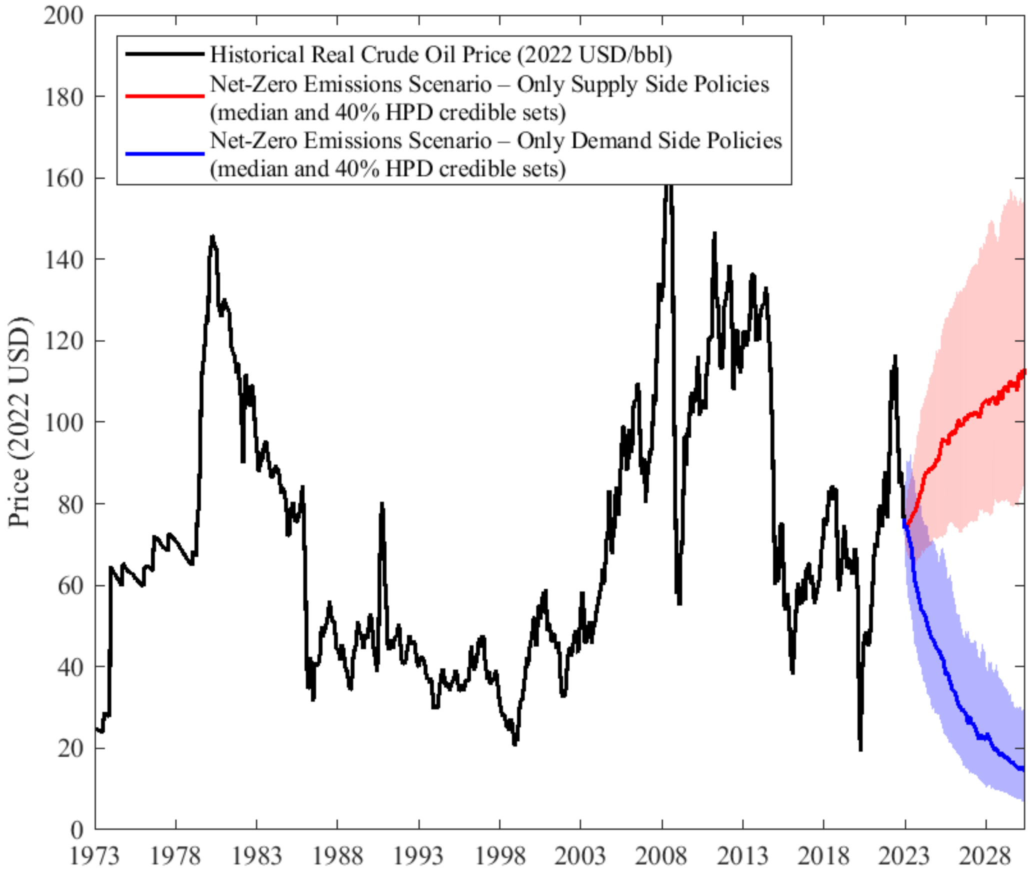


Figure B.23: Oil price scenarios in the net-zero emissions scenario model specifying an upper bound on the impact supply elasticity of 0.1.

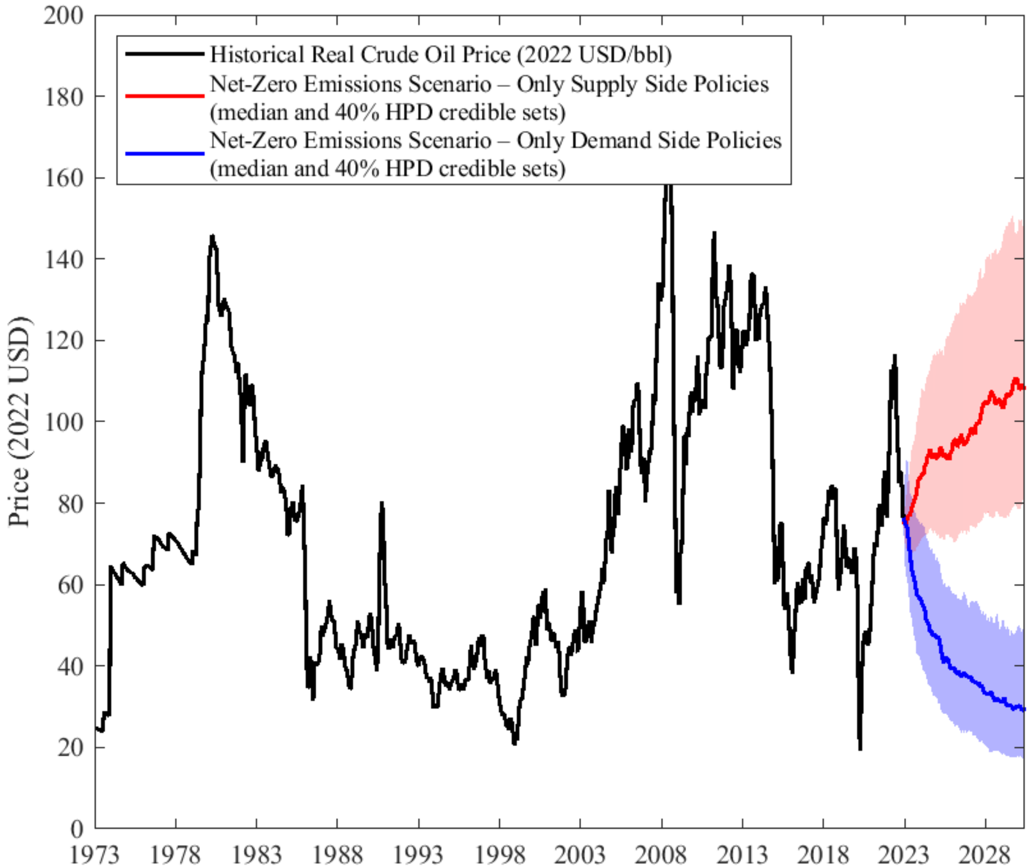


Figure B.24: Oil price scenarios in the net-zero emissions scenario model specifying an upper bound on the impact supply elasticity of 0.1 and including the global real economic activity index from Kilian (2009).

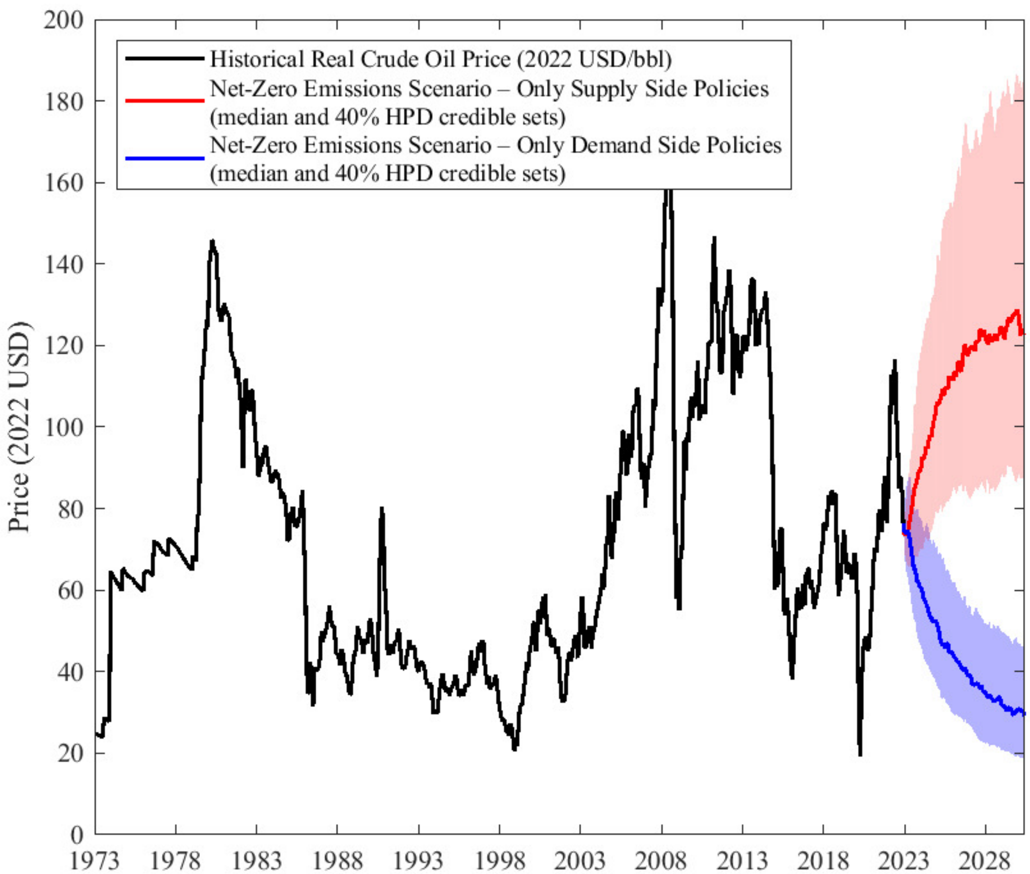


Figure B.25: Oil Price Scenarios in the net-zero emissions scenario based on the baseline model using a lag lengths of 12 months.

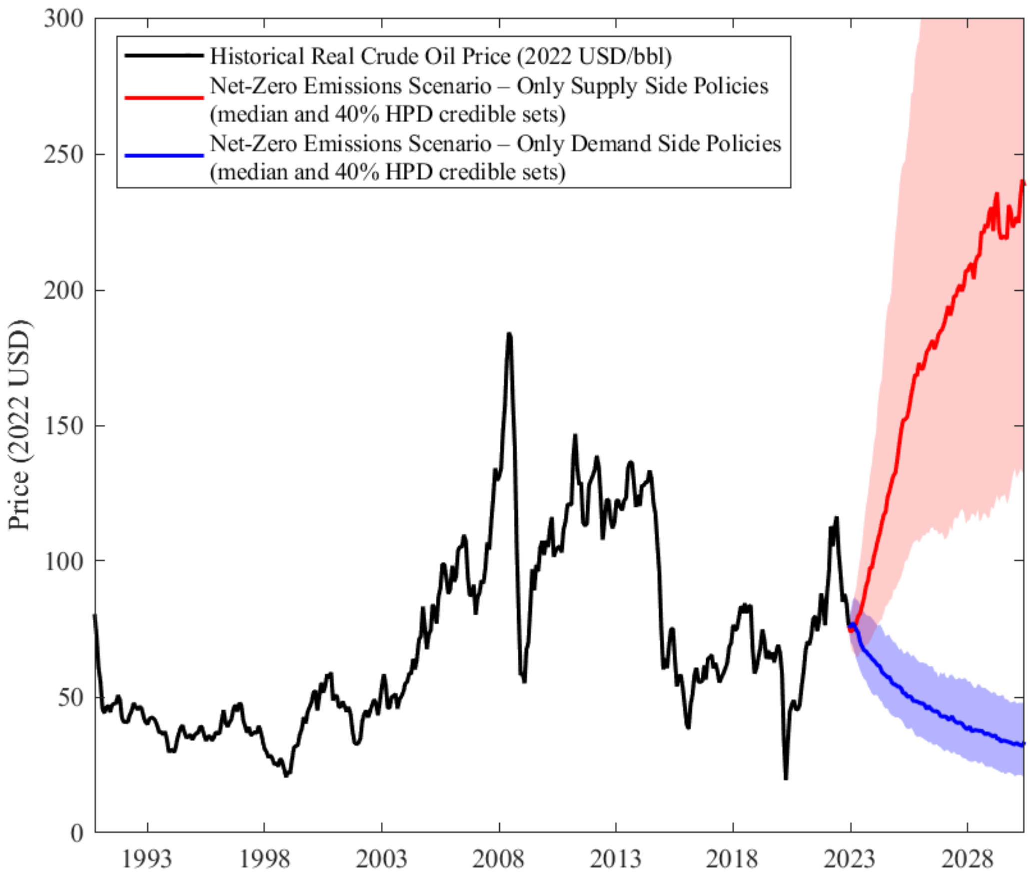
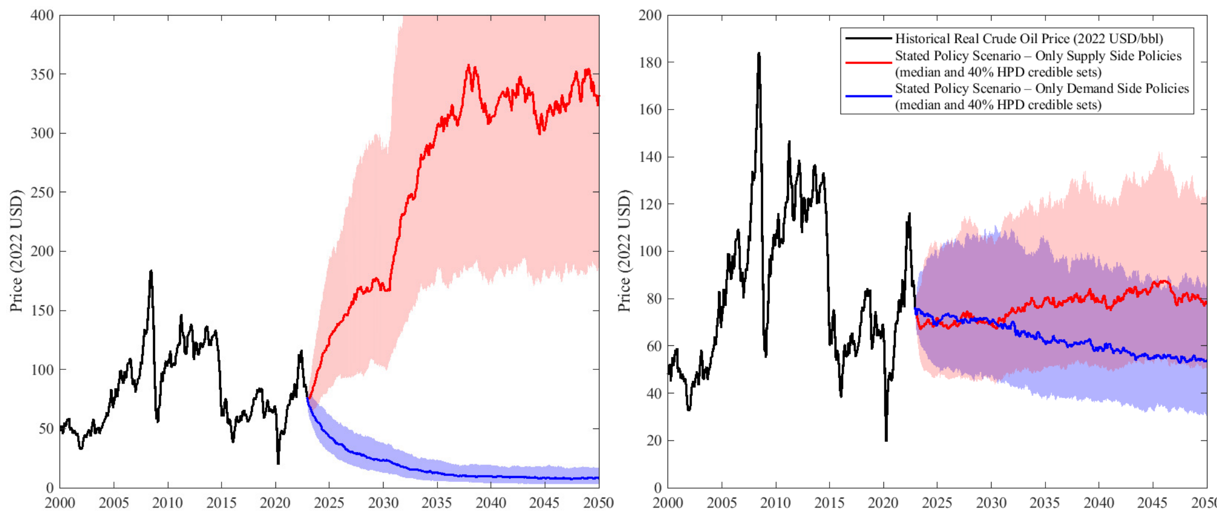


Figure B.26: Oil price scenarios when the sample starts in 1990m10.

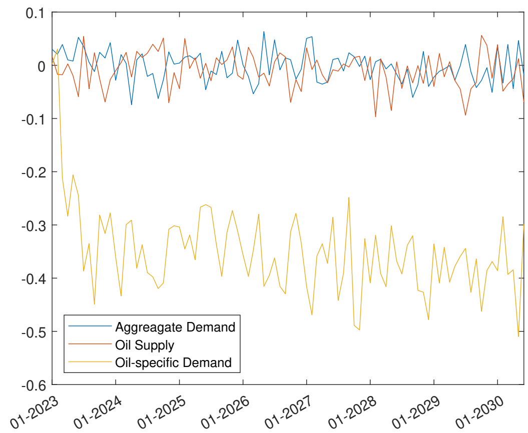


(a) Net-zero emissions scenario

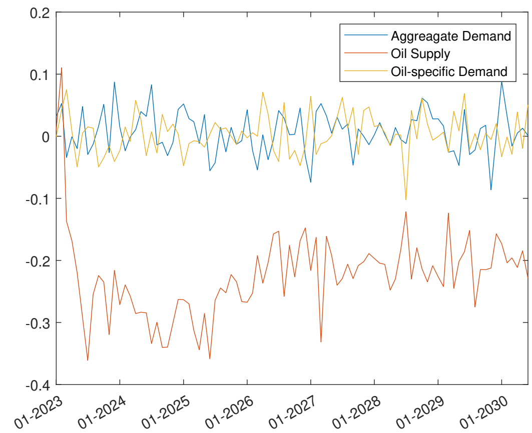
(b) Stated policy scenario

Figure B.27: Supply and demand side climate policies scenarios until 2050 (4-variables model).

B.4 Scenario Shock Series

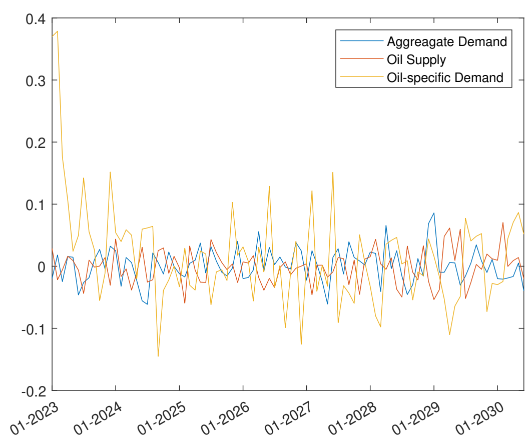


(a) Demand-side climate policy scenario

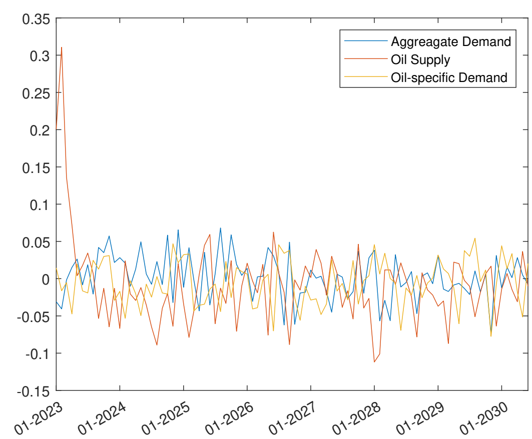


(b) Supply-side climate policy scenario

Figure B.28: Point-wise means of the shock series (in standard deviations) over the scenario horizon in the net-zero emissions scenario.



(a) Demand-side climate policy scenario



(b) Supply-side climate policy scenario

Figure B.29: Point-wise means of the shock series (in standard deviations) over the scenario horizon in the stated policy scenario.

C Additional Tables

C.1 Sensitivity

		Net-Zero Emissions Scenario		Stated Policy Scenario	
		Scenario End Price, USD per barrel	Cumulated Revenue Tril. USD	Scenario End Price, USD per barrel	Cumulated Revenue Tril. USD
Baseline 2030					
Industrial	Demand side pol.	25	8.17	69	17.36
Production	Supply side pol.	135	21.47	73	16.27
	50/50 mix	85	16.04	67	15.79
Global Economic	Demand side pol.	50	10.90	67	16.19
Activity Index	Supply side pol.	120	20.44	67	16.82
	50/50 mix	90	16.46		
4-Variables Model					
Industrial	Demand side pol.	25	8.12	71	16.43
Production	Supply side pol.	135	21.69	71	16.21
	50/50 mix	77	15.05		
Higher Elasticity Bound					
Industrial	Demand side pol.	33	9.56	70	16.84
Production	Supply side pol.	136	22.03	75	16.34
	50/50 mix	98	17.61	70	15.86
Global Economic	Demand side pol.	56	12.12	68	16.16
Activity Index	Supply side pol.	138	22.32	73	16.59
	50/50 mix	98	17.59		
Lower Elasticity Bound					
Industrial	Demand side pol.				
Production	Supply side pol.				
Lag Length 12 Months					
Industrial	Demand side pol.	29	8.78		
Production	Supply side pol.	124	21.20		
2050 Scenario Higher Elasticity Bound					
Industrial	Demand side pol.	15	14.14	48	50.24
Production	Supply side pol.	304	97.95	90	68.33

Notes: US Dollar (USD) refers to real 2022 prices, adjusted for inflation based on the December 2022 US-CPI. The inventories model shows the supply elasticites for the contemporaneous oil-specific demand shock and the elasticities for the expectational shock as both shocks are used simultaneously to drive oil production.

Table C.1: Sensitivity Analysis.

		Supply Elasticity	Demand Elasticity
Baseline 2030			
Industrial Production	Demand side policies	0.14	-0.18
	Supply side policies	0.07	-0.33
	50/50 mix	0.13	-0.18
IP and Inventories	Demand side policies	0.13	-0.15
Global Economic Activity	Demand side policies	0.12	-0.18
	Supply side policies	0.03	-0.52
	50/50 mix	0.14	-0.16
Higher Elasticity Bound			
Industrial Production	Demand side policies	0.20	-0.15
	Supply side policies	0.08	-0.29
	50/50 mix	0.18	-0.13
IP and Inventories	Demand side policies	0.16	-0.13
Global Economic Activity	Demand side policies	0.18	-0.14
	Supply side policies	0.09	-0.27
	50/50 mix	0.19	-0.12
4-Variables Model			
Industrial Production	Demand side policies		
	Supply side policies	0.08	-0.28
	50/50 mix	0.12	-0.16
2050 Scenario Higher El. Bound			
Industrial Production	Demand side policies	0.17	-0.07
	Supply side policies	0.09	-0.14

Note: The impact price elasticities of demand and supply are obtained directly from the B_0 matrix. All estimates are based on the net-zero scenario.

Table C.2: Estimated elasticities in the different scenarios.

C.2 Oil Market Shares

The additional tables below give the oil production volume, its value, and the market share by country, conditional on global oil volumes under the demand-side policy scenarios described in section 2.1 and 6, and the associated oil prices. Rystad data are used to calculate production shares and volumes.

Rank	Country	Production (mb/d)	Market Share	Value (bil. USD)
1	Saudi Arabia	10.3	23%	93.5
2	Iraq	5.5	13%	50.2
3	UAE	4.1	9%	37.6
4	Iran	3.9	9%	35.8
5	Kuwait	2.9	7%	26.5
6	Qatar	1.7	4%	15.8
7	Kazakhstan	1.6	4%	14.8
8	Russia	1.5	3%	13.6
9	Norway	1.3	3%	11.7
10	Brazil	1.2	3%	11.1
11	Libya	1.1	3%	10.1
12	United States	1.1	2%	9.7
13	China	1.0	2%	9.3
14	Algeria	0.8	2%	7.0
15	Guyana	0.6	1%	5.9
16	Canada	0.6	1%	5.7
17	Oman	0.6	1%	5.4
18	Azerbaijan	0.6	1%	5.0
19	Neutral Zone	0.5	1%	4.5
20	United Kingdom	0.4	1%	3.6

Notes: Scenario: NZE, 2030, Production at $25/bbl.

Table C.3: Oil market share under demand-side policies, Net-Zero scenario, 2030

Rank	Country	Production (mb/d)	Market Share	Value (bil. USD)
1	Saudi Arabia	10.3	19%	112.6
2	Iraq	5.6	11%	61.5
3	UAE	4.2	8%	46.5
4	Iran	4.0	7%	43.9
5	United States	3.6	7%	39.5
6	Russia	3.0	6%	32.8
7	Kuwait	2.9	5%	31.8
8	Brazil	2.6	5%	28.2
9	Qatar	1.7	3%	18.9
10	Kazakhstan	1.7	3%	18.5
11	Norway	1.5	3%	16.6
12	China	1.4	3%	15.8
13	Canada	1.2	2%	13.6
14	Libya	1.1	2%	12.5
15	Algeria	0.9	2%	10.3
16	Mexico	0.9	2%	9.9
17	Guyana	0.8	2%	9.2
18	Oman	0.6	1%	6.8
19	Neutral Zone	0.6	1%	6.1
20	Azerbaijan	0.6	1%	6.1

Notes: Scenario: NZE (up to 2050), 2030, Production at $30/bbl.

Table C.4: Oil market share under demand-side policies, Net-Zero scenario, 2030

Rank	Country	Production (mb/d)	Market Share	Value (bil. USD)
1	Saudi Arabia	6.3	39%	34.4
2	Iraq	2.6	16%	14.4
3	Iran	2.1	13%	11.3
4	UAE	1.9	12%	10.5
5	Kuwait	1.7	11%	9.4
6	Qatar	0.4	3%	2.3
7	Kazakhstan	0.4	2%	2.2
8	Neutral Zone	0.3	2%	1.4
9	China	0.1	1%	0.7
10	Russia	0.1	0%	0.3
11	Libya	0.1	0%	0.3
12	Azerbaijan	0.1	0%	0.3
13	Brazil	0.0	0%	0.1
14	Algeria	0.0	0%	0.1
15	Venezuela	0.0	0%	0.1
16	Oman	0.0	0%	0.1
17	Brunei	0.0	0%	0.1
18	Nigeria	0.0	0%	$\sim$
19	United States	0.0	0%	$\sim$
20	Angola	0.0	0%	$\sim$

Notes: Scenario: NZE, 2050, Production at $15/bbl.
$\sim$ denotes smaller than 0.05 bil. USD value.

Table C.5: Oil market share under demand-side policies, Net-Zero scenario, 2050

Rank	Country	Production (mb/d)	Market Share	Value (bil. USD)
1	United States	14.2	17%	352.5
2	Saudi Arabia	10.5	12%	260.5
3	Russia	8.8	10%	214.0
4	Iraq	5.7	7%	140.7
5	Canada	5.1	6%	127.4
6	Brazil	5.1	6%	125.8
7	UAE	4.6	5%	113.1
8	Iran	4.2	5%	103.2
9	China	3.4	4%	80.8
10	Kuwait	3.0	4%	74.2
11	Kazakhstan	2.0	2%	49.3
12	Qatar	1.8	2%	45.4
13	Norway	1.8	2%	43.9
14	Libya	1.5	2%	37.3
15	Mexico	1.4	2%	34.4
16	Guyana	1.2	1%	30.0
17	Algeria	1.0	1%	25.2
18	Nigeria	0.9	1%	21.2
19	Oman	0.8	1%	20.5
20	Argentina	0.7	1%	17.2

Notes: Scenario: STEPS, 2030, Production at $68/bbl.

Table C.6: Oil market share under demand-side policies, STEP scenario, 2030

Rank	Country	Production (mb/d)	Market Share	Value (bil. USD)
1	Saudi Arabia	9.0	18%	154.9
2	United States	6.0	12%	90.8
3	Canada	4.7	10%	63.5
4	Russia	4.3	9%	59.5
5	Iran	3.5	7%	56.6
6	Iraq	3.5	7%	55.4
7	UAE	2.7	6%	47.1
8	Kuwait	2.1	4%	33.9
9	Brazil	1.9	4%	18.9
10	China	1.5	3%	17.5
11	Venezuela	1.2	2%	17.3
12	Qatar	1.1	2%	17.1
13	Kazakhstan	1.0	2%	12.3
14	Argentina	0.7	1%	11.8
15	Mexico	0.6	1%	7.7
16	Norway	0.5	1%	7.5
17	Neutral Zone	0.4	1%	6.2
18	Guyana	0.4	1%	5.0
19	Libya	0.4	1%	5.0
20	Nigeria	0.3	1%	3.1

Notes: Scenario: STEPS, 2050, Production at $85/bbl.

Table C.7: Oil market share under demand-side policies, STEP scenario, 2050

Rank	Country	Production (mb/d)	Market Share	Value (bil. USD)
1	United States	12.8	16%	372.9
2	Saudi Arabia	10.4	13%	303.6
3	Russia	9.8	12%	285.6
4	Canada	4.8	6%	139.5
5	Iraq	4.6	6%	134.8
6	China	3.9	5%	114.6
7	UAE	3.3	4%	97.0
8	Brazil	3.3	4%	95.5
9	Iran	3.3	4%	95.0
10	Kuwait	2.5	3%	73.0
11	Norway	2.0	2%	57.4
12	Kazakhstan	1.8	2%	53.3
13	Mexico	1.8	2%	52.3
14	Nigeria	1.6	2%	45.9
15	Qatar	1.3	2%	39.4
16	Libya	1.3	2%	37.3
17	Algeria	1.3	2%	36.7
18	Angola	1.1	1%	32.3
19	Oman	1.1	1%	30.7
20	Venezuela	0.9	1%	25.0

Table C.8: Market shares in 2023