INTERNATIONAL MONETARY FUND

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

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WP/23/160

2023
AUG

WORKING PAPER

 WP/23/160

IMF Working Paper
Research Department

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Authorized for distribution by Petya Koeva Brooks
August 2023

ABSTRACT: We use structural scenario analysis to show that the climate policy mix—supply-side versus demand-side policies—can lead to different oil price paths with diverging distributional consequences in a net-zero emissions scenario. When emission reduction is driven by demand-side policies, prices would decline to around 25 USD per barrel in 2030, benefiting consuming countries. Vice versa, supply-side climate policies aimed at curbing oil production would push up prices to above 130 USD per barrel, benefiting those producing countries that take the political decision to keep on producing. Consequently, it is wrong to assume that oil prices will necessarily decline due to the clean energy transition. As policies are mostly formulated at the country level and hard to predict at the global level, the transition will raise uncertainty about the price outlook.

Keywords:	Conditional forecasts; structural vector autoregression; structural scenario analysis; energy transition; oil prices; climate change.
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*We are grateful to Christiane Baumeister, Lutz Kilian, Gregor Schwerhoff and Christoph Ungerer for helpful suggestions and to Juan Antolin-Diaz, Juan Rubio-Ramirez and Ivan Petrella for sharing their code with us. We thank Rachel Brasier and Wenchuan Dong for excellent research assistance. The views in this paper are those of the authors and do not necessarily reflect the views of the International Monetary Fund, its Executive Board, and IMF Management.

WORKING PAPERS

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1 Introduction

The economic literature has typically assumed that fossil fuel prices will be 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 demand shocks. Subsidies to electric cars, for instance, cause negative crude-oil specific demand shocks, as oil is substituted with electricity, leading to lower prices.

This paper shows that a declining global fossil fuel production path can also arise from curbing fossil fuel production (i.e., from negative supply shocks), leading to increasing oil prices over the long term. This is in line with theoretical models by Hoel (1994) and Harstad (2012), where oil prices can increase in the face of supply-side climate policies. For example, climate regulation may directly restrict oil production while public preferences may shift in favor of sustainable investment—thereby, increasing 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). Higher policy uncertainty could also lead to a decline in fossil fuel investment (Bogmans et al., 2023). Importantly, as policies are mostly formulated at the country level and the mix between demand side and supply side policies is hard to predict at the global level, the energy transition raises uncertainty about the price outlook.

We apply structural scenario analysis following Antolín-Díaz et al. (2021) to model the impact of the energy transition on oil prices as a sequence of either oil-specific demand or oil supply shocks. 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 supply and demand shocks, which have substantially different implications for prices.

We find that if we only consider demand-side policies, oil prices could decline to $25 (inflation-adjusted) in 2030. This would have 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 changing its current geographical distribution and moving towards a more concentrated market.

Reductions in oil production that are driven only by supply-side measures would put strong upward pressures taking prices to roughly $130 per barrel. 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 price scenarios show that it is wrong to assume that fossil fuel prices will necessarily decline because of the energy transition. Instead, supply side policies could exert upward price pressures, while demand side 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 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.

We also show how structural scenario analysis can be used for longer forecast horizons. Based on our analysis, prices could decline to \$15 per barrel in 2050 in the demand-led scenario or increase to \$300 per barrel in a supply-led 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 on oil consumption. Expanding on Kilian and Murphy (2014), we fully identify the model relying on two types of oil-specific demand shocks: a contemporaneous and expectational oil-specific demand shock. The former leads to a contemporaneous fall in oil-specific demand that increases inventories while the latter leads to a fall in demand that lowers inventories. In the demand-driven structural scenarios, we assume that both shocks jointly drive the fall in crude oil demand resulting from the energy transition.

We also examine the sensitivity of our results to changes in the frequency of the data, elasticity bounds, and a variety different economic activity measures.

Our results suggest that if countries' climate policies are unpredictable and uncoordinated, the price effects of the energy transition are ultimately hard to determine, and this raises uncertainty about the price outlook. Countries will need to prepare for this higher price uncertainty and adjust their macroeconomic and fiscal policies accordingly.

A coordinated climate policy effort among net-consumer and net producer countries of fossil fuels and a pace of divestment from fossil fuels commensurate to the speed of adoption of renewable energy would help reduce the risk of high and volatile energy prices. Reducing policy uncertainty helps countries make necessary adjustments.

To our knowledge we are the first to show the different impact of the climate policy mix on future oil price trajectories from an empirical perspective. Hoel (1994) and Harstad (2012) provide theoretical models to explain that fossil fuel prices can increase in the face of supply-side climate policies.

Our findings imply that integrated assessment models that introduce climate change and the energy transition into dynamic stochastic general equilibrium models need to take into account policies on both the supply and demand sides (see also McKibbin et al. 2021). They are currently mostly focused on the demand side, assuming declining fossil fuel prices as a result of the clean 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 and (e.g., Alquist et al., 2013, Baumeister and Kilian, 2014b, 2015) and scenarios (e.g., Baumeister and Kilian, 2014a, Kilian and Lewis, 2011, Kilian, 2017 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 the medium to longer time horizon. In contrast to the prior literature our focus is on long-term price forecasts that are conditional both on economic observables and specific series of structural shocks.

We showcase some of the limitations of the methodology and provide robustness checks. First, the forecasts span a relative long horizon of several years under contrasting 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 under the influence of the scenario data. Waggoner and Zha (1999) discuss this in more detail. The implied different elasticities are warranted to some extent as, for instance, a purely demand-side driven scenario should imply a higher price elasticity of supply as the supply curve is not so likely to shift, based on historical data, to meet such a declining oil production path. It seems also reasonable to assume higher supply elasticities during the energy transition as it should be easier to reduce production rather than increase it.[1] Second, we model the energy transition as an historically unprecedented upward shift in the distribution of shocks (see critique in Lucas, 1976; Leeper and Zha, 2003). Agents could change their decision rule, partly anticipating the oil demand or supply declines and front-load the price effect. Finally, innovation, the technology mix, and policy-making lead to large

[1] 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.

uncertainty surrounding the consumption scenarios.

The remainder of the paper is structured as follows. Section 2 provides a short description of the scenarios and the data. Section 3 lays out the econometric model including the identification strategy and the setup of the structural scenario. Section 4 presents the results. Section 5 draws implications for the oil production across countries, looking at market shares. Section 6 looks at scenarios until 2050, and section 7 presents robustness checks. Finally, section 8 concludes.

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 assumes that there are net-zero CO2 emissions in 2050, including the energy sector. It implies that renewable energies become the leading source of electricity worldwide before 2030. In the transportation sector, the scenario assumes that electricity will cover 60 percent of energy consumption in addition to the broad use of hydrogen for trucks and shipping. Battery demand is expected to increase from 0.16 TWh in 2020 to 14 TWh in 2050, with 86 percent of the stock of cars being powered by electricity. We concentrate on this scenario which is the most ambitious with the highest chance of limiting global warming to 1.5°C (IPPC 2021). The total production

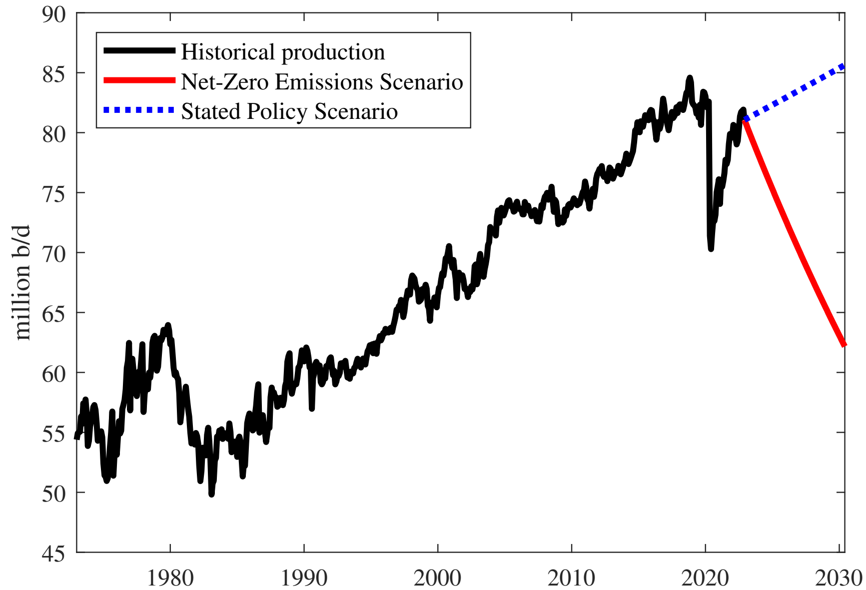


Figure 1: Global Oil Output Scenarios. Source: International Energy Agency (2022)

of oil would decline by about 23 percent until 2030 and by roughly 80 percent until 2050 when compared to 2022 production levels (see Figures 1 and 7).

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, annualized data and different types of measures for global economic activity.

For our baseline we use the 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) as a sensitivity check.

We employ global crude oil production data from the US Energy Information Administration. The data also includes condensates. We use monthly US WTI price data from FRED that is adjusted with the U.S. all urban consumers price index to adjust for inflation, also taken from FRED.[2]

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 $\mathbf{y}_t = (\mathbf{REA}_t, \mathbf{Q}_t, \mathbf{P}_t)'$, namely a measure of global economic activity $\mathbf{REA}_t$, the percentage change of global oil production $\mathbf{\Delta Q}_t$, and the log of the real price of crude oil (WTI) $\mathbf{P}_t$. 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. These errors have no economic interpretation. The matrix of deterministic terms $\mathbf{D}_t$ consists of a constant.

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

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.

	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 positive shock increases global economic activity, global oil production and its real price.[3]

We label the second shock as an oil supply shock, capturing, for example, production outages and stronger than expected declines in production. These can be caused by a broad variety of factors including supply-led climate policies and shifts in capital costs due to sustainable investment criteria. 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.

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 a shift in the demand curve due to factors that affect the demand for mainly oil 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-

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

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, 2013).

We assume an upper bound on the IRF-based impact supply elasticity of 0.2.[4]

This bound includes the estimate from Caldara et al. (2019) and Baumeister and Hamilton (2019)—which are around 0.1 and 0.15, respectively—but allows for potentially higher elasticities during the course of the energy transition as it should be easier to reduce production facing low oil prices (as also witnessed during the pandemic when US and OPEC+'s oil production dropped by about 30 percent and 20 percent, respectively, withing two months). It is higher than the elasticity bound of 0.026 from Kilian and Murphy (2014). We also discuss results for an upper 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).

Narrative sign restrictions following Antolín-Díaz and Rubio-Ramírez (2018) help us to sharpen the identification of the different structural shocks, and thus, the distinction

[4] More specifically, this concept is an impulse response-based ratio of equilibrium impacts. It is defined as the oil output response relative to the price response given an oil-specific or aggregate demand shock as defined by Kilian and Murphy (2014). 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 turns out to be 0.198 across draws in our empirical exercise.

between them. These restrictions are imposed on the importance of specific shocks during specific historical episodes. Following Antolín-Díaz and Rubio-Ramírez (2018) we impose 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. Their paper find that this single restriction, an accepted interpretation of the 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 price of crude oil 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 $\varepsilon_{T+1,T+h}$, thereby linking the path of future variables directly to certain shocks. We briefly lay out the underlying intuition tailored to the oil consumption scenarios from the International Energy Agency (2022) while appendix A provides technical details.

We take the oil consumption scenario as given, thus pre-specifying the oil quantities in the conditional forecasts $\mathbf{y}_{T+1,T+h}$. We set global consumption equal to global oil production in the scenarios from the International Energy Agency (2022), assuming that there are 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 then finds a series of oil-specific demand shocks that incentivizes the oil production path needed for the energy transition. We can then 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 a supply-side driven 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 oil-specific demand shocks or from oil supply shocks.

For example, 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, incentivising 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 in the scenario.

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). The aim is to draw from a joint posterior distribution of both 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. Note that the structural scenario restrictions depend on the structural VAR parameters via equation (11) shown in the appendix.

To draw from this distribution, we use the algorithm from Antolín-Díaz et al. (2021) that builds on Waggoner and Zha (1999). The algorithm uses a Gibbs sampler procedure that iterates between draws from the conditional distributions of the structural parameters and the conditional forecast.[5]

Hence, we pick a random draw of structural parameters out of 10,000 potential draws that relies both on the actual data and on a structural forecast. We use the structural parameters from this randomly picked draw to then draw the scenario paths of the price

[5] 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.

series and the economic activity index for the structural scenario that fits the specified oil production path. The next 10,000 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 (see Giannone et al., 2015) in combination 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.[6]

Identification via sign restrictions does not yield point estimates but instead sets of possible parameter intervals 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 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 recent progress on inference in Bayesian models, 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

[6]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, in which we are particularly interested.

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 rather 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 demand-side 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 that is supply side driven, demand elasticities become larger in absolute terms as consumers would be more likely to adapt to such a high price environment, eventually.[7]

4 Empirical Results

4.1 Price Scenarios

We use the case of crude oil prices to highlight quantitatively how the two different driving forces work in the Net-Zero Emissions Scenario by the International Energy Agency (2022).

We first consider a structural scenario, where only shocks from demand-side policies are considered. In this scenario, oil prices could decline to around $25 per barrel in 2030

[7] The dependency of parameter estimates to the scenario is an advantage for constructing scenarios that have not 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.

(figure 2, blue line).[8]

In the opposite scenario, where reductions in oil production only result from supply-side measures, prices would experience substantial upward pressures. They could climb to roughly $135 per barrel until 2030.

Consequently, the two price scenarios show that it is wrong to assume that fossil fuel prices will necessarily decline because of the energy transition. Instead, supply side policies could exert upward price pressures, while demand side policies would do the opposite.

The reality is likely a mix of a demand and a supply-led energy transition. Figure 3 shows a price scenario, where supply and demand side policy shocks equally drive the reductions in oil production until 2030. Prices increase slightly until 2030 but stay in the historical range of about $80 per barrel in inflation adjusted terms.

As a benchmark we also show scenario price paths for the stated policy scenario by the International Energy Agency (2022) that is based on announced climate policies in 2021 assuming a slightly increasing oil production until 2030. Prices would hover around $70 as figure 4 shows. This is true for both the demand-led and the supply led scenarios. There is not much of 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 demand shocks are needed to incentivize downwards adjustments in supply. The same is the case on the supply side.

[8]Figures B.1 and B.2 in the appendix show the underlying impulse responses.

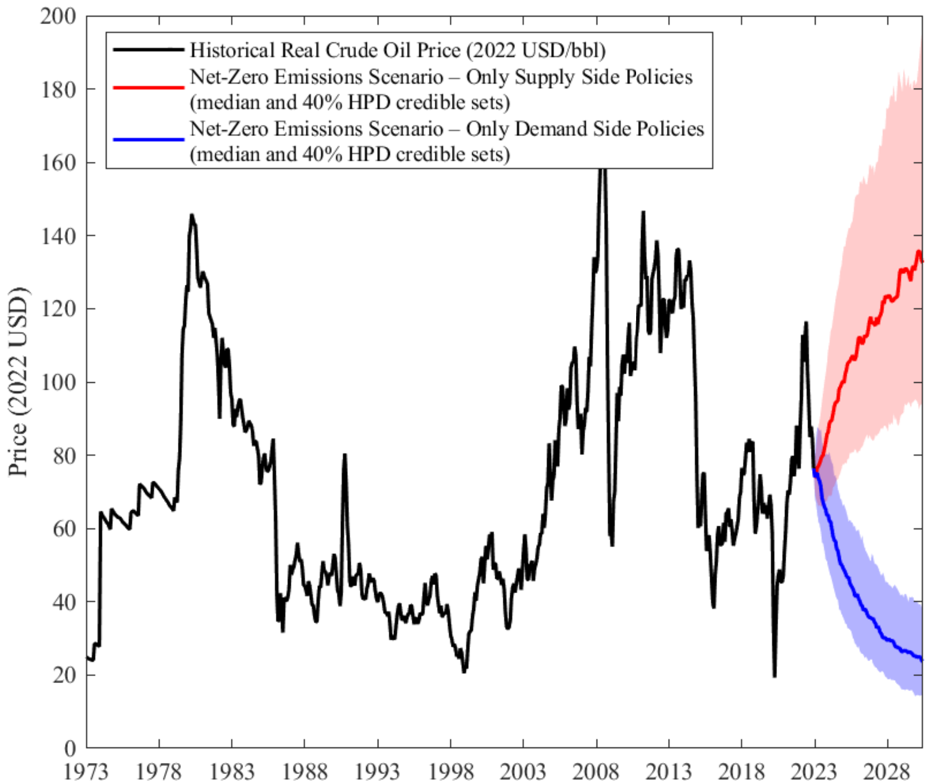


Figure 2: Oil prices in the supply and demand-side driven net-zero emissions scenario.

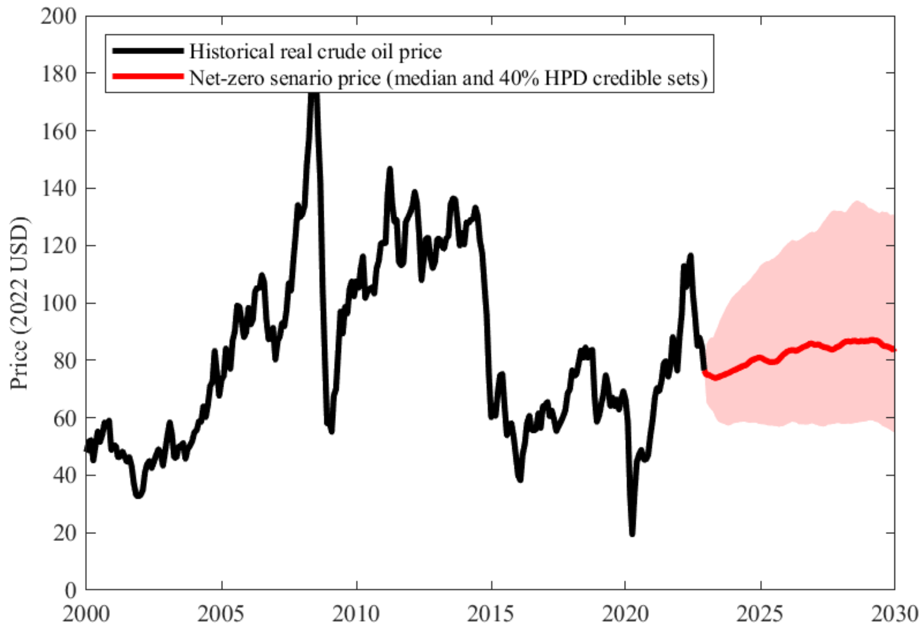


Figure 3: Oil prices in the net-zero emissions scenario with equally important supply and demand side policies

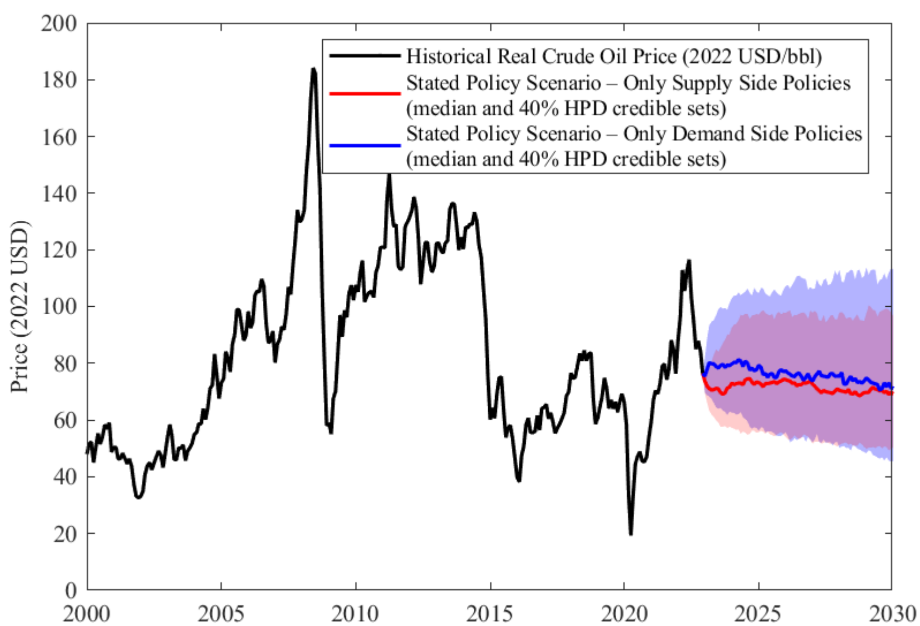


Figure 4: Oil prices in the supply and demand-side driven stated policy scenarios.

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.[9] 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.

[9]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 $z = D_{KL}(\mathcal{N}_{SS}||\mathcal{N}_{UF})$.

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.[10] The scenario of a completely demand-side driven energy transition is less plausible compared to historical precedent. This indicates that oil-specific demand shocks have played a smaller role in explaining oil price fluctuations compared to oil supply shocks, in the historical sample.

	Calibrated KL Statistic	
	Net-Zero Emissions Scenario	Stated Policy Scenario
Supply-side driven transition	0.67	0.65
Demand-side driven transition	0.83	0.82

Table 2: Scenario Plausibility Statistics

Figure C.8 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.[11]

[10] 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 $q = 0.9$.

[11] We also report the scenario shock series for the stated policy scenario for comparison (see Figure C.9 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.

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 scenario, oil prices are predicted to decline substantially. In a low-price and low-consumption scenario scarcity rents would decline and oil production in high cost regions would come under pressure. This will 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.[12] Oil production costs, however, vary significantly depending of geology and location with onshore conventional oil being one of the cheapest. So, as oil prices decline, some oil fields would become unprofitable, including some US shale oil patches, 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.[13] Breakeven prices are estimated

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

[13]The breakeven oil price indicates at which flat real Brent oil prices the continued operation of the 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 a government intake is subtracted, this includes: (1) royalty effects including royalty and oil and export duties; (2) government profits which are the PSA equivalent to petroleum taxes, but paid in kind (it reduces the company's entitlement production and is thus treated as a royalty effect in company reports); (3) income tax which is a corporate tax that is a sum of all profit based taxes, where the tax rate is equal to the country's corporate tax rate, and special petroleum taxes. The tax

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 oil assets with higher breakeven prices than the projected oil price (in the demand-side scenario) are unprofitable and, thus, assumed to be not producing. Production volumes at the oil field level come from geological information and are estimated at today's technology (Rystad).

Our results in figure 5 indicate that when oil prices reach $25 per barrel in 2030, under the net-zero demand-side scenario, the oil market will become much more concentrated with about 66 percent of the global oil production coming 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 increase even more, with the Persian Gulf's countries reaching a 95 percent market share (see Appendix).[14] Some of the countries experiencing the highest declines in production would be the United States, Russia and Canada. Interestingly, oil production would concentrate in regions that traditionally have shown high geopolitical instability.

Finally, reductions in emissions that are driven hypothetically only by supply-side measures would exert strong upward pressure on oil prices (see section 4.1), benefiting producing countries at the expense of consuming countries.[15] Since oil production would

base is the net sales revenue minus OPEX and depreciation. For petroleum taxes there may be applied an additional deduction called uplift. In many cases, some profit based taxes can be deducted in the tax base for other profit taxes. Interest expenses are not included.

[14]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 distribution would alter our estimated market shares.

[15]IMF (2012); Luca and Puyo (2016); Baunsgaard and Vernon (2022) provide a fiscal framework to tax windfalls in the energy sector.

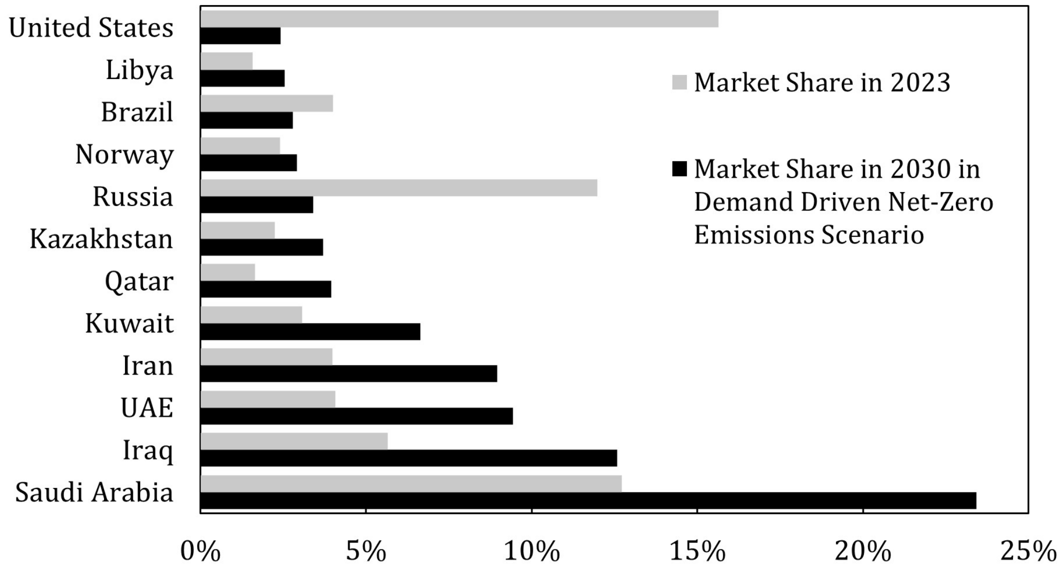


Figure 5: Market shares 2023 vs 2030 in the demand driven net-zero scenario.

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.

A scenario equally driven by supply and demand side policies would see revenues gradually taper off while production volumes decrease such that fewer producers see larger revenues individually (see figure 6).

Globally, the different scenarios have also major implications for the value of the oil market. In a demand-led net-zero scenario oil revenues would fall to historical lows where only the lowest cost producers stay profitable while in the opposite case, the price increase will more than offset the decline in volumes leading to an increase in global oil revenues (see figure 6), especially for some low-cost oil producing countries which would see only a modest decline in oil production given the higher market share.

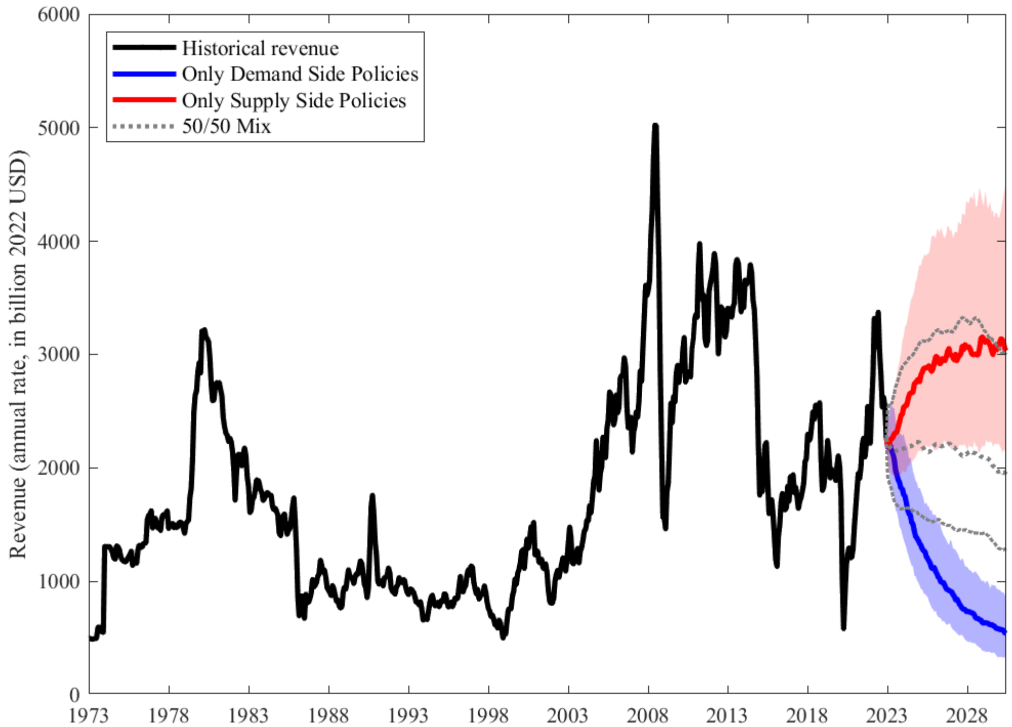


Figure 6: Oil revenues in the different net-zero emissions scenarios. Median estimates and 40% HPD credible sets. Oil revenues are calculated as quantity times price.

6 Can We Come Up With 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 and possibilities 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

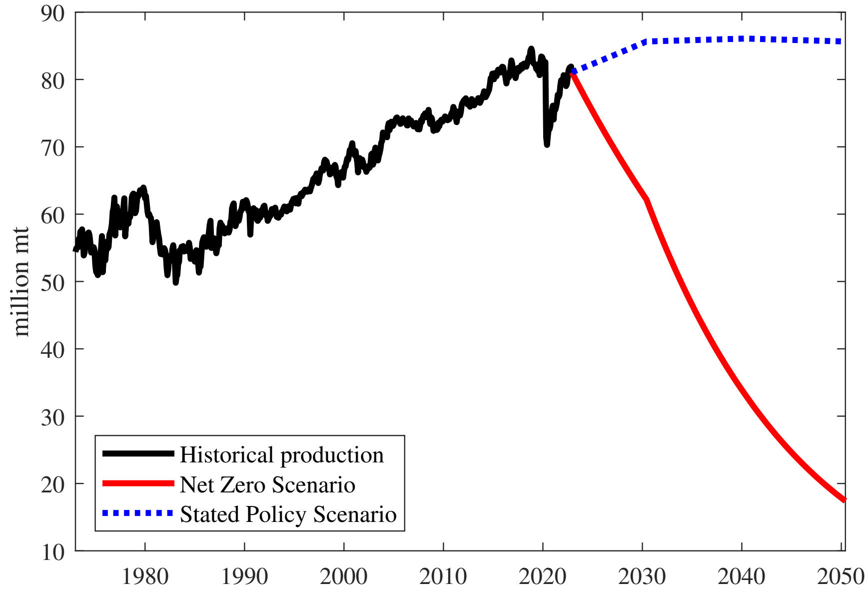


Figure 7: Global Oil Output Scenarios Until 2050 (Source: International Energy Agency (2022))

(see figure 7). 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 supply-led and demand-led scenarios.[16]

Figure 8 panel (a) shows the scenario oil price paths for the two policy cases in the

[16]Altering the algorithm such that it does not take the forecast horizon into account when estimating the structural parameters, we obtain an upper price of USD 120 in 2030 in the supply-side driven net-zero emissions scenario and USD 33 in the demand-side driven scenario. Somewhat less strong price changes compared to USD 135 and USD 25 in our baseline.

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.[17] For this long horizon we again rely on the model using global industrial production as the global economic activity index model produces implausible impulse responses even implying a slightly increasing price trend under the demand side driven policies scenario.

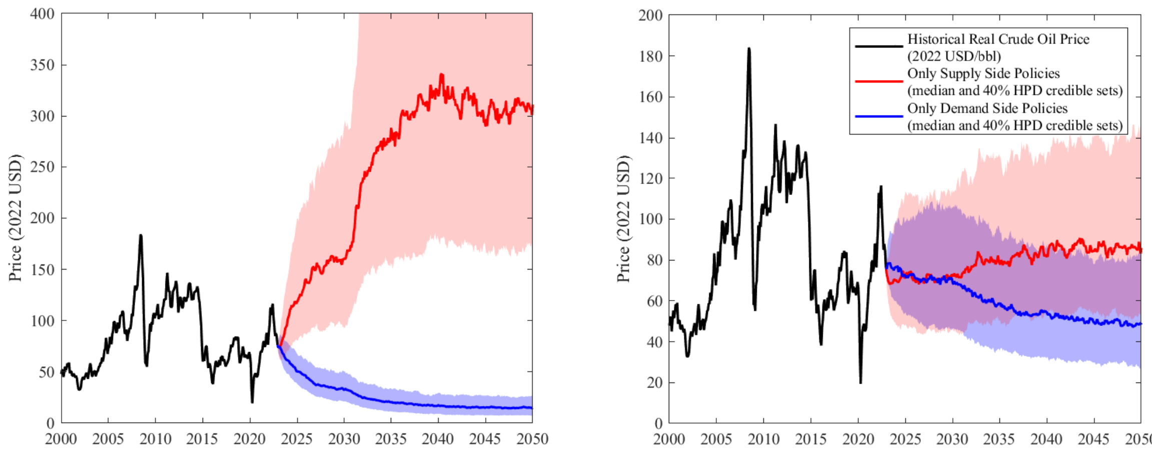
In the demand-led scenario, prices fall to around \$ 30 per barrel by 2030, reaching a level of around around USD 15 by 2040 and stay around that level until 2050. The scenario price path during the initial period until 2030 is broadly in line with our baseline scenario. A KL statistic of 0.72 indicates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

In the supply-led scenario prices increase strongly to around USD 300 in the mid 2030s and stay around those levels until 2050.[18] 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-led scenario and \$ 80 per barrel by 2050 in the supply-led scenarios (see panel (b) of figure 8). While prices are close across the two scenarios until 2030, there is an

[17] 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.

[18] 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 8: Supply and demand-side driven scenarios until 2050.

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, higher elasticity bounds as well as annual data (see also table C.1 in the appendix).

7.1 Inventories and Expectational Demand Shocks

One of the shortcomings of the three variable model is that the identified oil-specific demand shock groups together contemporaneous and expectational demand components and cannot differentiate between them. Concerning the energy transition, it is plausible to assume that agents anticipate the potential future decrease of oil demand, at least in part. 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 demand components.[19]

We identify two types of oil-specific demand shocks, a contemporaneous one and an expectational one, using sign restrictions as shown in table 3 following the approach in Boer et al. (2023). Both shocks are assumed to increase oil production and prices, while decreasing economic activity as a result of a positive 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 above-ground inventory due to forward-looking behavior.[20]

[19]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).

[20]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.

	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 policies driven 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, similar as in our baseline model (see figure C.1 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 decrease to around $30 (see figure C.2 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 USD 50 in 2030 under the demand-side driven scenario and a price of around USD 120 in the supply-side driven scenario (see figure C.3 in the appendix). In the scenario with an equally driven policy mix of supply and demand side shocks the median price in 2030 is around USD 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, among others economic activity, commodity prices, uncertainty, transportation demand and financial indicators. Relying on this measure yields median 2030 real prices of USD 14 in the demand-side driven scenario, USD 120 in the supply-side driven scenario (see figure C.5) and USD 73 in the equally driven net-zero scenario.

7.3 Higher Elasticity Bound

In our baseline analysis we assume an upper bound of 0.2 for the IRF-based impact elasticity of supply, i.e., the supply response to an oil-specific demand shock within the first month. This bound is in line with the literature, which has largely settled on a first-month elasticity of around 0.1 (see Caldara et al., 2019). 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.[21] 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, production is curbed more strongly when reacting to negative demand shocks. Under this higher upper bound we obtain a minimum price of USD 33 in 2030 in the demand side policies driven scenario (see figure C.6 in the appendix).

7.4 Annual data

We estimate scenarios for annual data, where we use monthly averages of oil production growth and prices and industrial production to have comparable results to our monthly baseline model. Sign restrictions are analogous to the monthly setup from Table 1. For the yearly model we specify no upper bound for the supply elasticity which is usually only applied within the first month (see Kilian, 2022). As narrative sign restrictions we

[21] This bound implies a realized upper bound of 0.28 of the ceteris paribus 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.

use the outbreak of the Iran-Iraq War in 1980, where we assume a negative supply shock contributing most to the 5% shortfall in global oil production in that year (see Antolín-Díaz and Rubio-Ramírez, 2018) and we assume that a negative aggregate demand shock was the most important contributor to the fall in oil prices during the Great Recession.

Oil prices reach around $ 45 per barrel in 2030 in the demand side policies driven net-zero emission scenario and close to $ 150 per barrel in the supply side policies driven scenario (see figure C.7 in the appendix) . In the stated policy scenario prices fall to around $ 70-75 per barrel by 2030 depending on the policy mix.

Relying on annual data, we loose estimation precision and, hence, the set of admissible models of the underlying impulse responses and the scenario price paths are broader. This is due to the smaller sample that implies less variation but also due to the somewhat different identification. We lose narrative restrictions that the literature places on specific months as they are difficult to defend when specifying them for a whole year. Also a bound on the supply elasticity over a whole year would be more difficult to defend.

8 Conclusion

This paper highlights that the impact of the energy transition on fossil fuel markets can be quite different depending on the policy shocks driving it at the example of oil.

We typically think about the energy transition as a negative demand shock to crude oil, coal and natural gas, and its producing countries. For example, subsidies to electric cars are a negative crude-oil specific demand shock, as crude oil is substituted by electricity, 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. Another recent example are the restrictions on coal mining in China.

We show that if we only consider demand-side policies in a scenario, oil prices could decline to the $20s in 2030. This would have negative consequences for oil exporters. Rents would diminish and oil production would come under pressure in high-cost regions. In contrast, reductions in oil production that are driven only by supply-side measures would, instead, put strong upward pressures taking prices to roughly $130 per barrel, benefiting producing countries at the expense of consuming 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.

If country policies are 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 effort among consumer and producer countries of fossil fuels and a pace of divestment from fossil fuels commensurate to the speed of adoption of renewable energy would help reduce the risk of high and volatile energy prices. Reducing policy uncertainty helps countries to make necessary policy adjustments during the energy transition.

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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.[22] 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

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

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

[22] 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.

yielding

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

where $\underline{\mathbf{C}} = \boldsymbol{\Xi}(\mathbf{M}')^{-1}$ and $\underline{\boldsymbol{\Omega}}_f = \boldsymbol{\Omega}_g$. 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 $\boldsymbol{\Xi}\widetilde{\boldsymbol{\varepsilon}}_{T+1,T+h} \sim \mathcal{N}(\mathbf{0}_{k_s}, \mathbf{I}_{k_s})$ 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

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

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.

B Impulse Responses

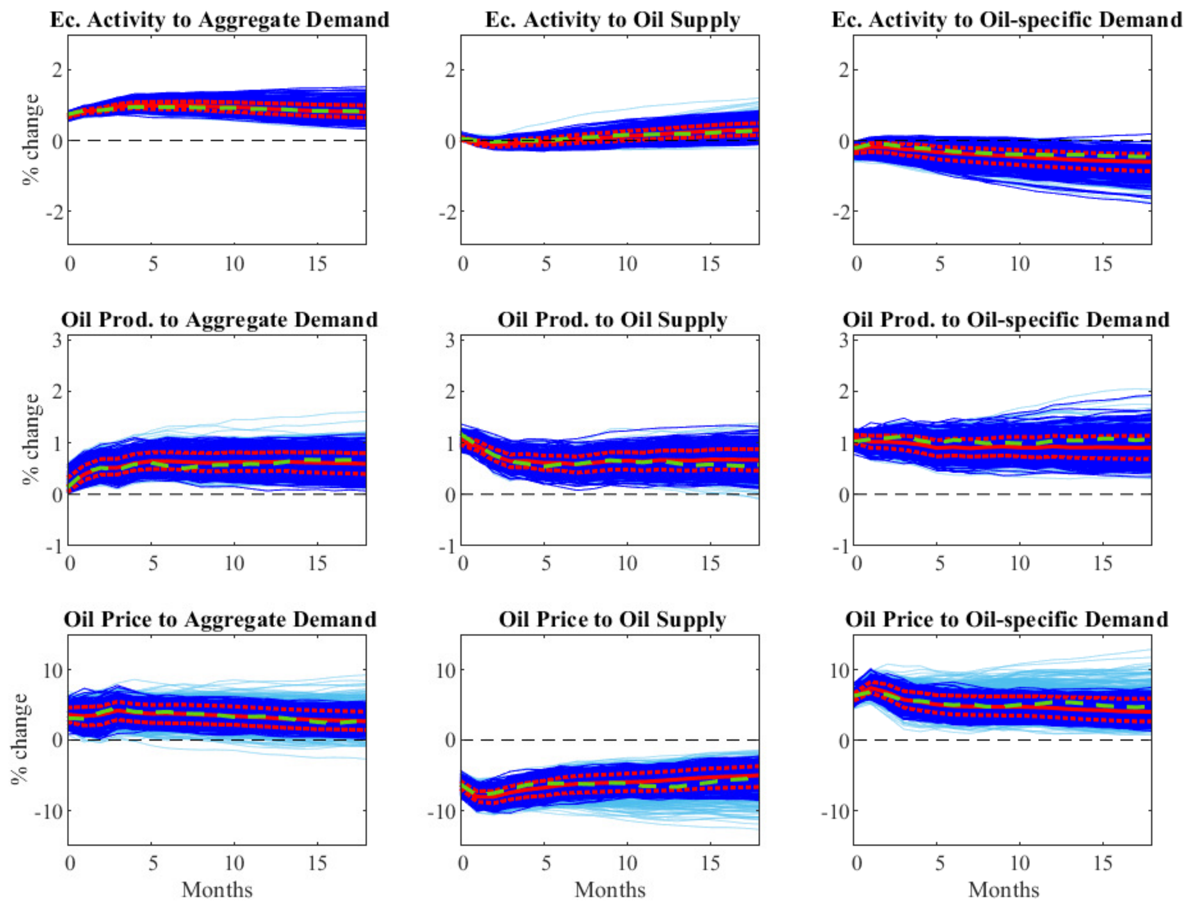


Figure B.1: Impulse Responses for the Demand-Side Driven Scenario

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.

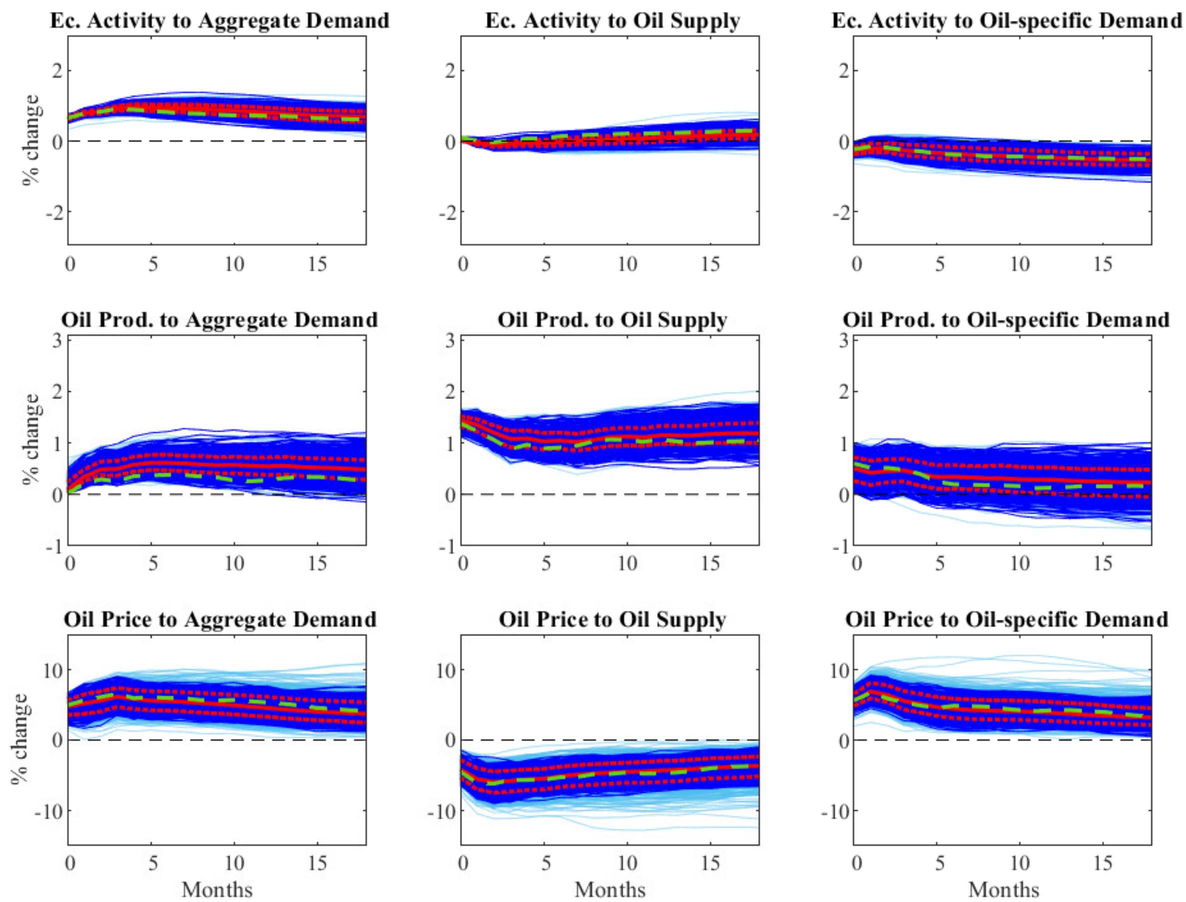


Figure B.2: Impulse Responses for the Supply-Side Driven Scenario

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.

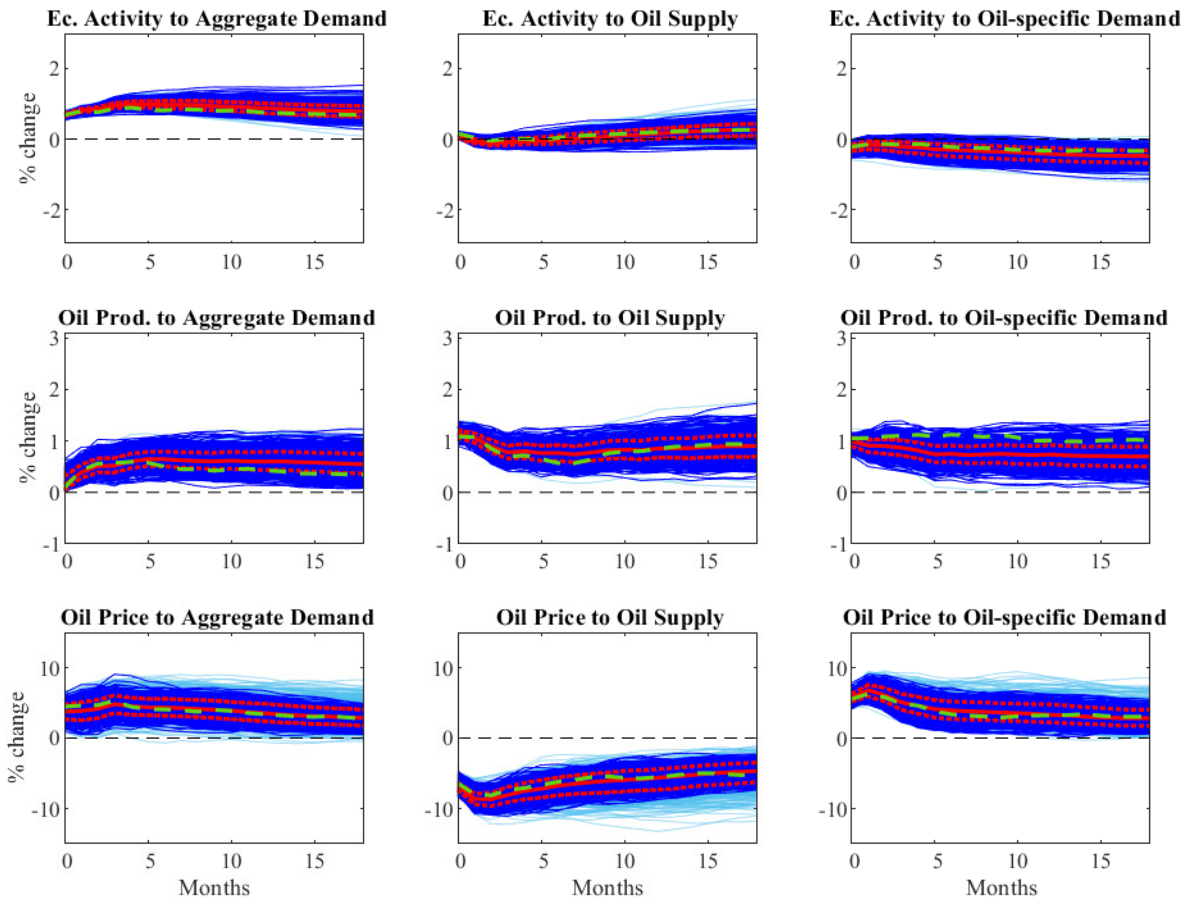


Figure B.3: Impulse Responses for the Equally Supply- and Demand-Side Driven Scenario

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.

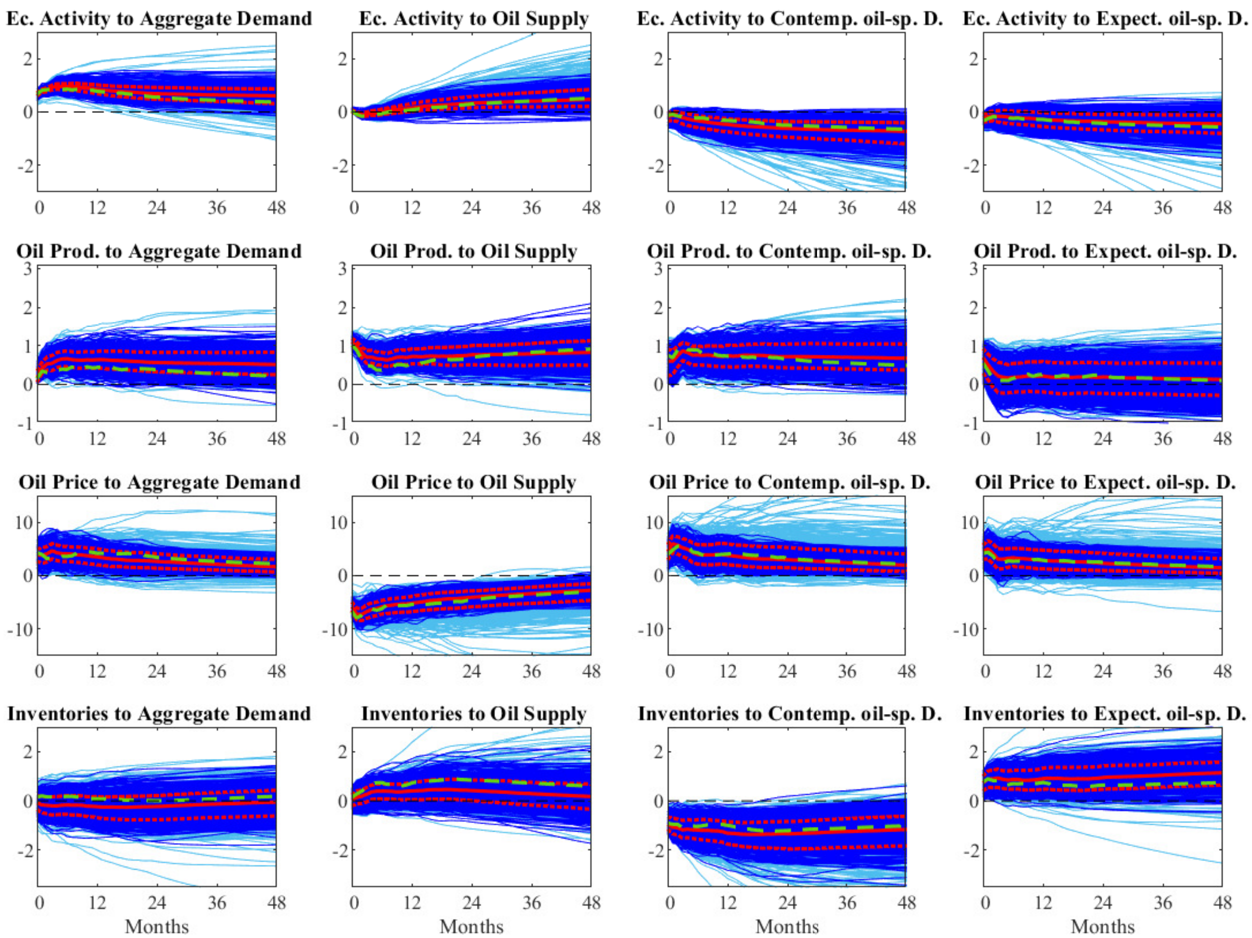


Figure B.4: Impulse Responses for the Demand-Side Driven Scenario in the 4-Variables Model with Expectational and Contemporaneous Oil-Specific Demand Shocks.

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.

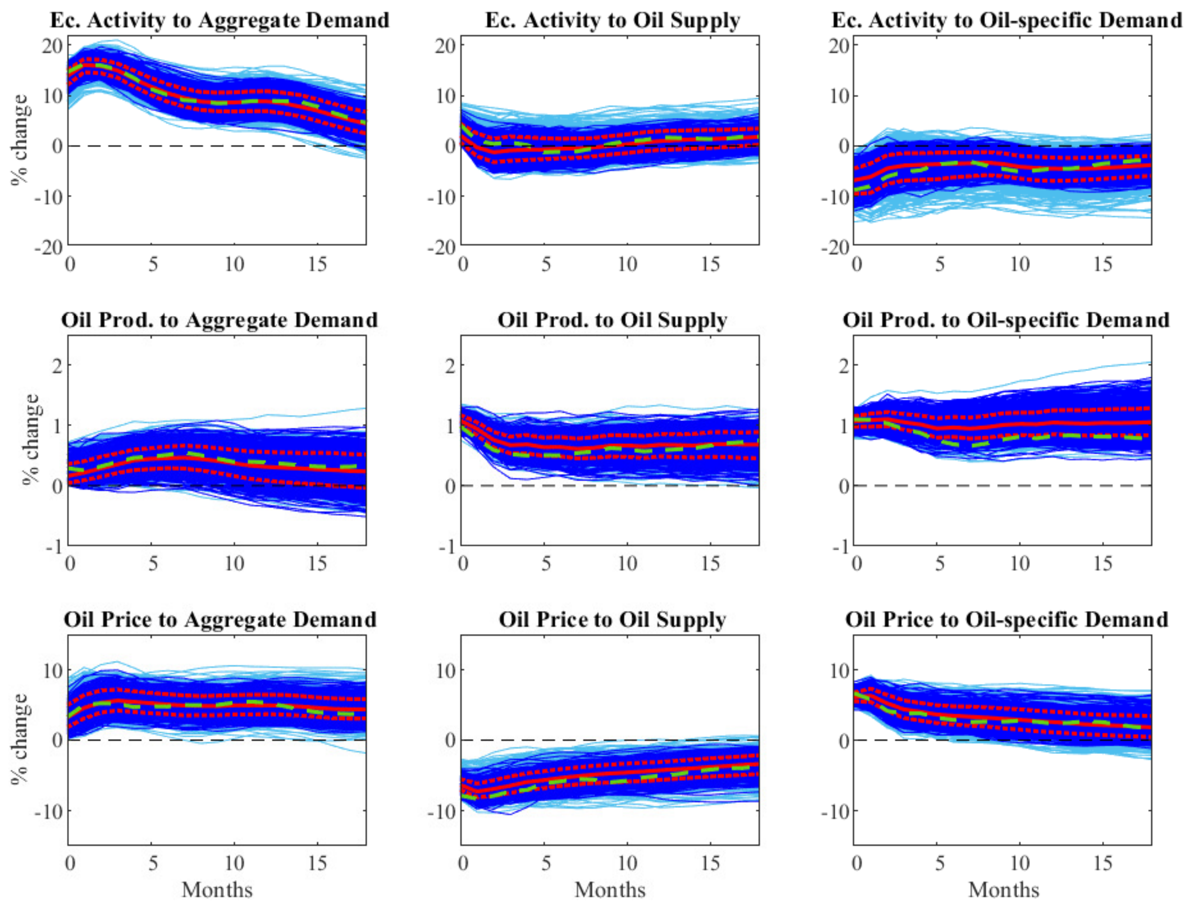


Figure B.5: Impulse Responses for the Demand-Side Driven Scenario Including the Global Economic Activity Index from Kilian (2009).

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.

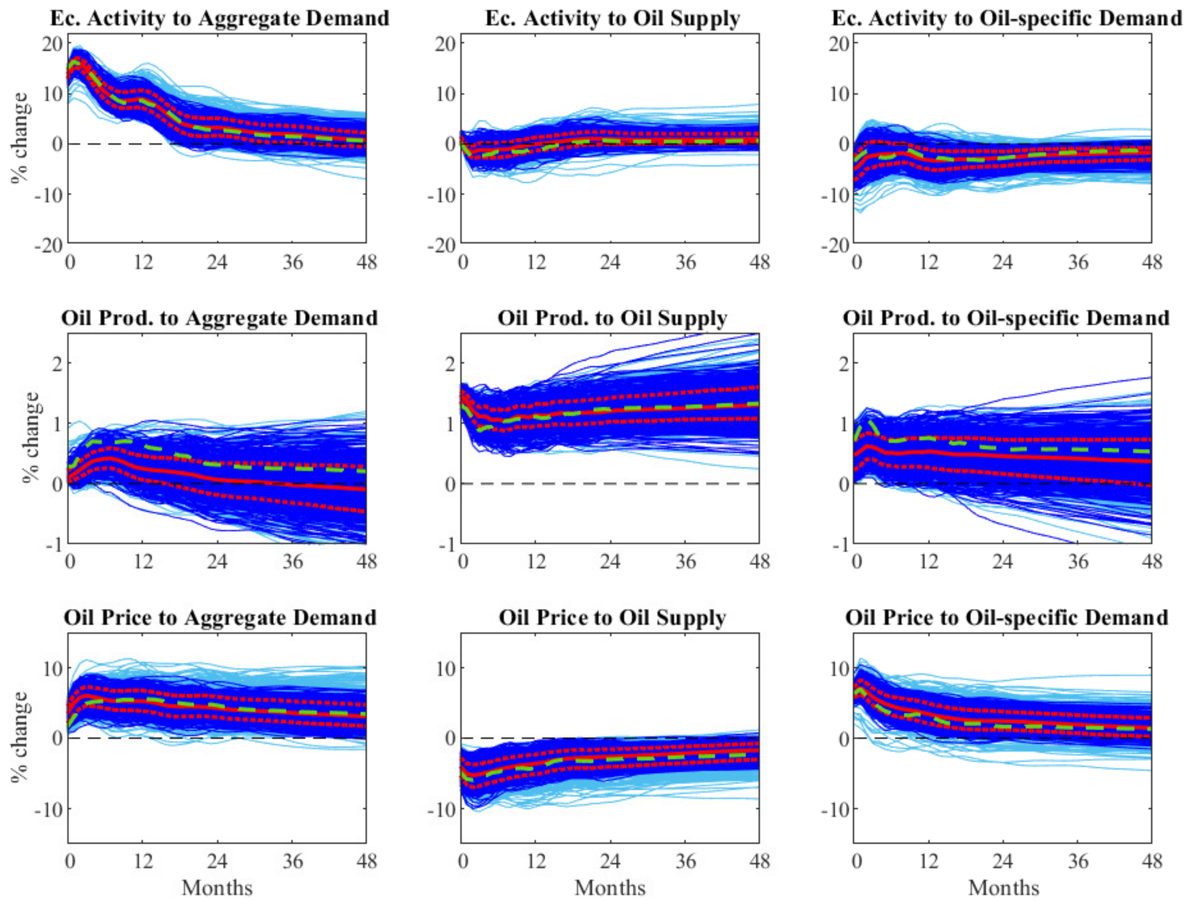


Figure B.6: Impulse Responses for the Supply-Side Driven Scenario Including the Global Economic Activity Index from Kilian (2009).

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.

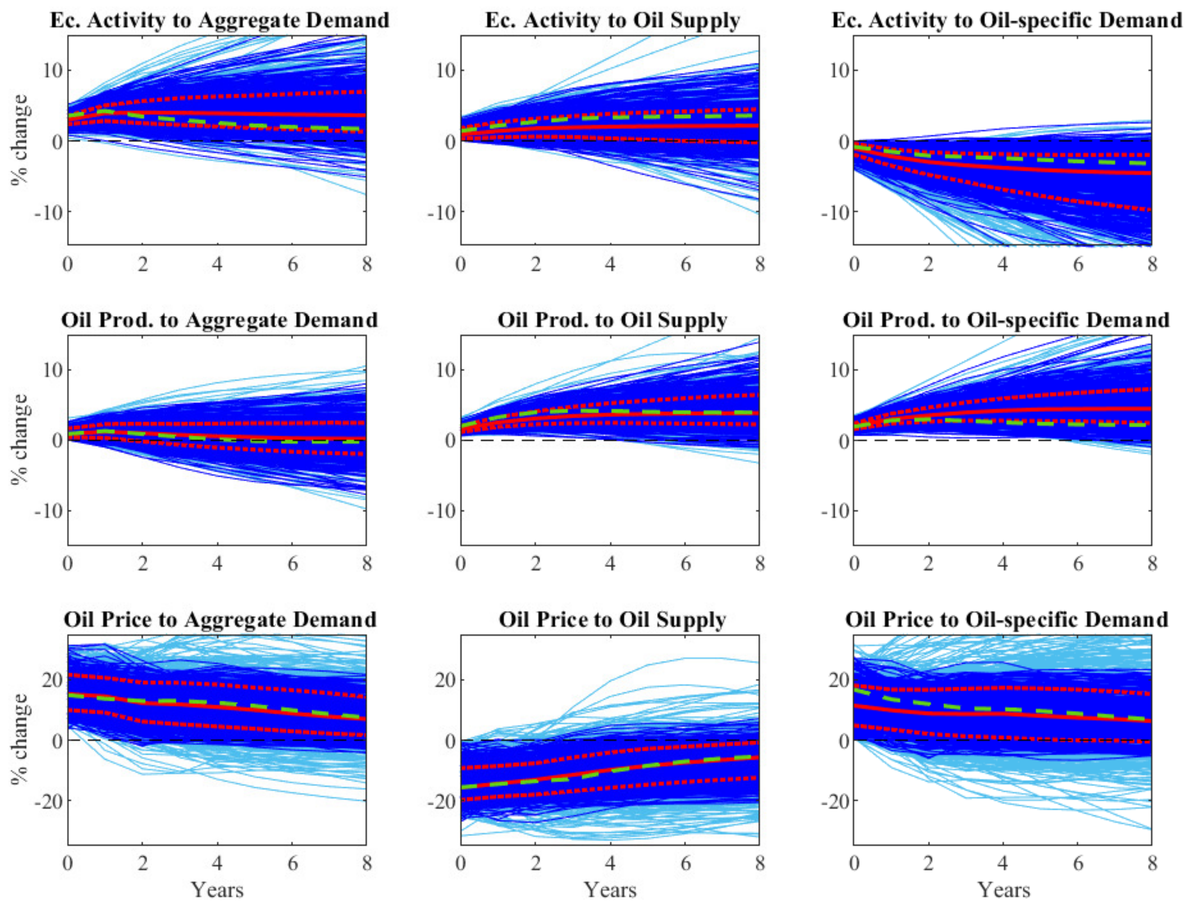


Figure B.7: Impulse Responses for the Demand-Side Driven Scenario in the Model Using Annual Data.

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.

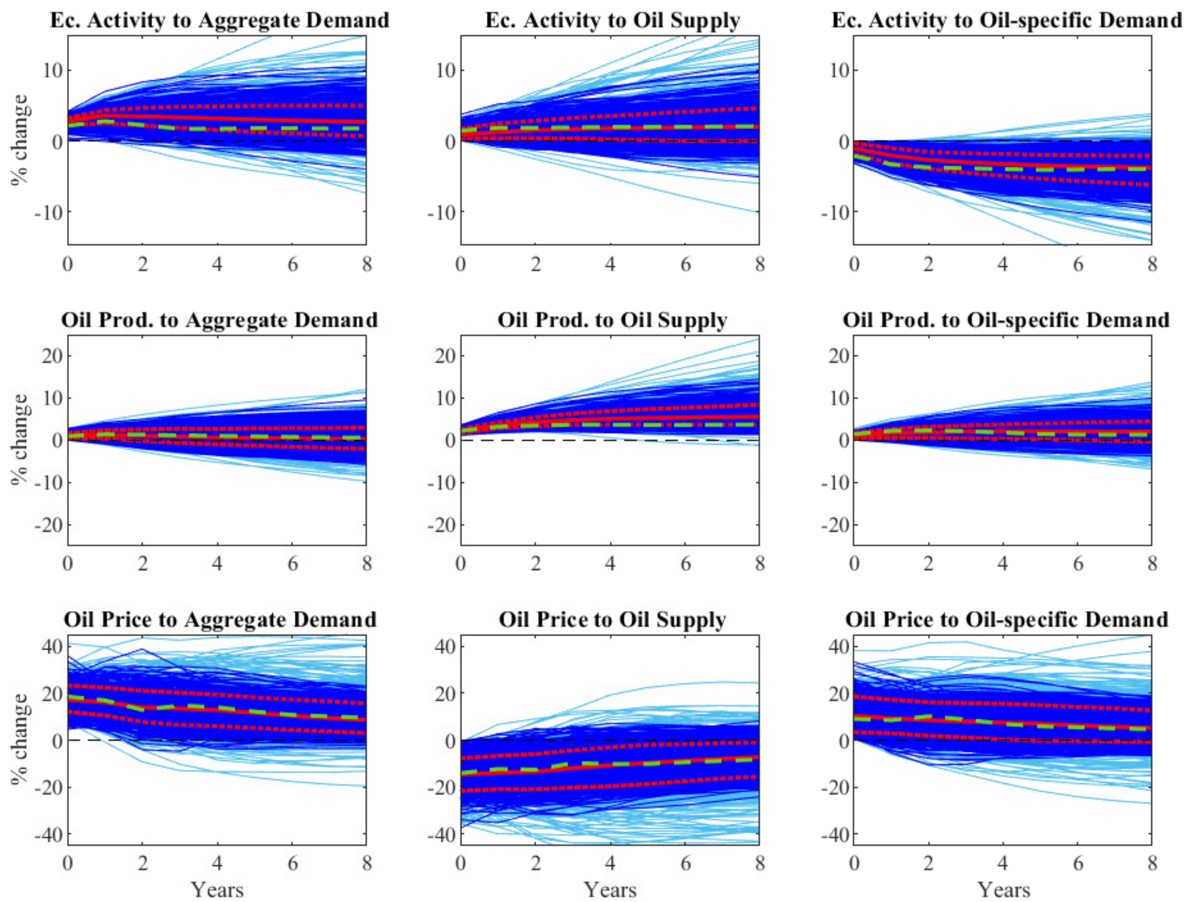


Figure B.8: Impulse Responses for the Supply-Side Driven Scenario in the Model Using Annual Data.

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.

C Robustness

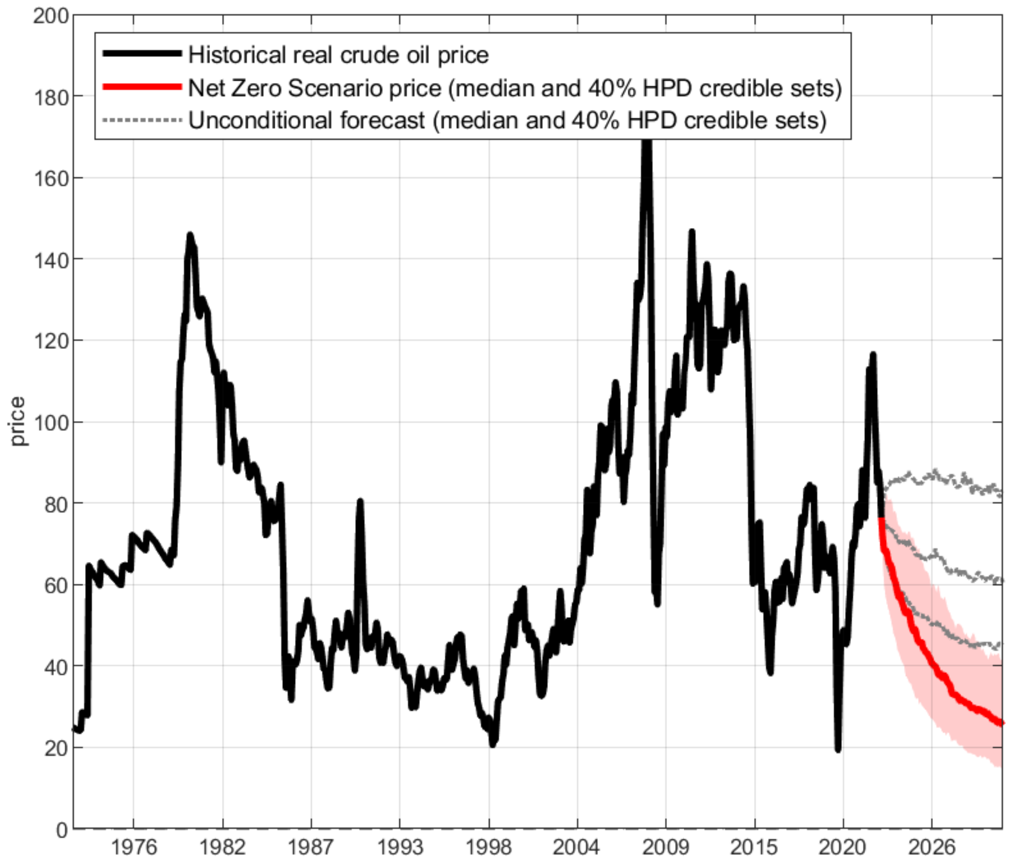


Figure C.1: Oil price scenarios in the model including inventories and differentiating between contemporaneous and expectational oil-specific demand shocks.

Figure C.2: Oil price scenarios in the model including inventories. Sign restrictions as in Kilian and Murphy (2014).

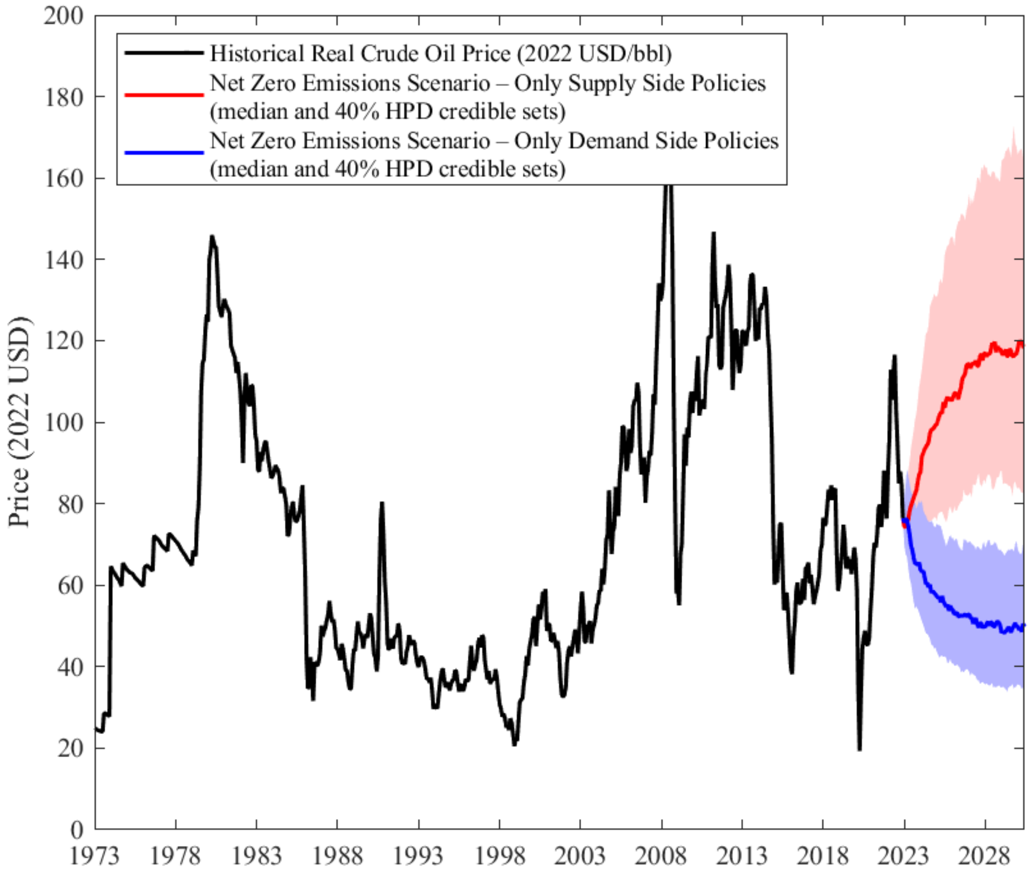


Figure C.3: Oil price scenarios in the net-zero emissions scenario model including the global economic activity index from Kilian (2009).

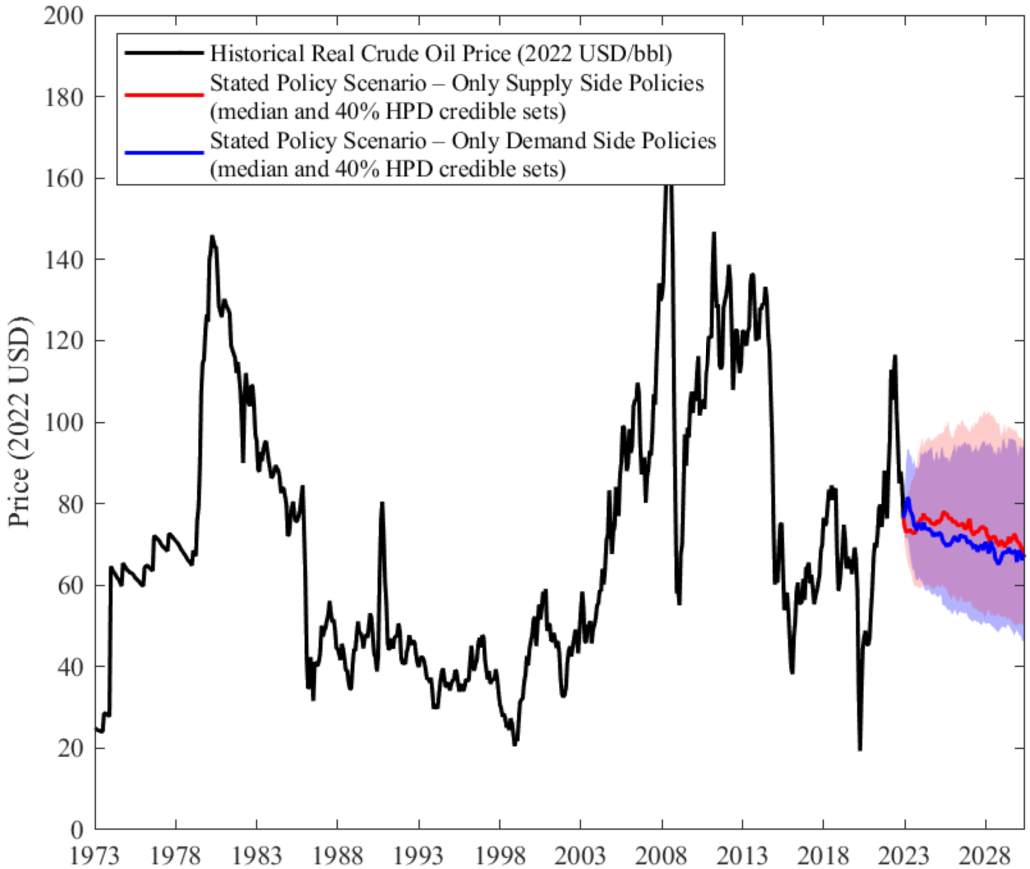


Figure C.4: Oil Price Scenarios in the stated policy scenario from the model including the global economic activity index from Kilian (2009).

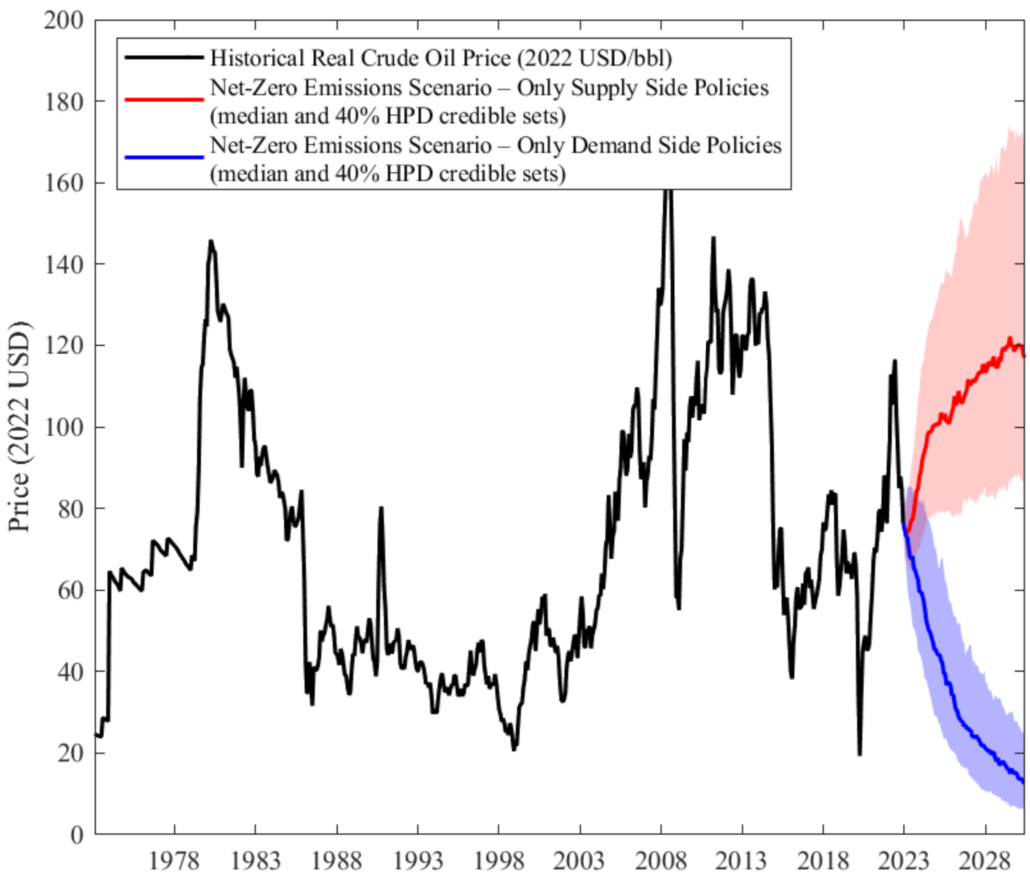


Figure C.5: Oil Price Scenarios in the stated policy scenario from the model including the global economic conditions index from Baumeister et al. (2022).

Figure C.6: Oil price scenarios in the model specifying an upper bound on the impact supply elasticity of 0.3.

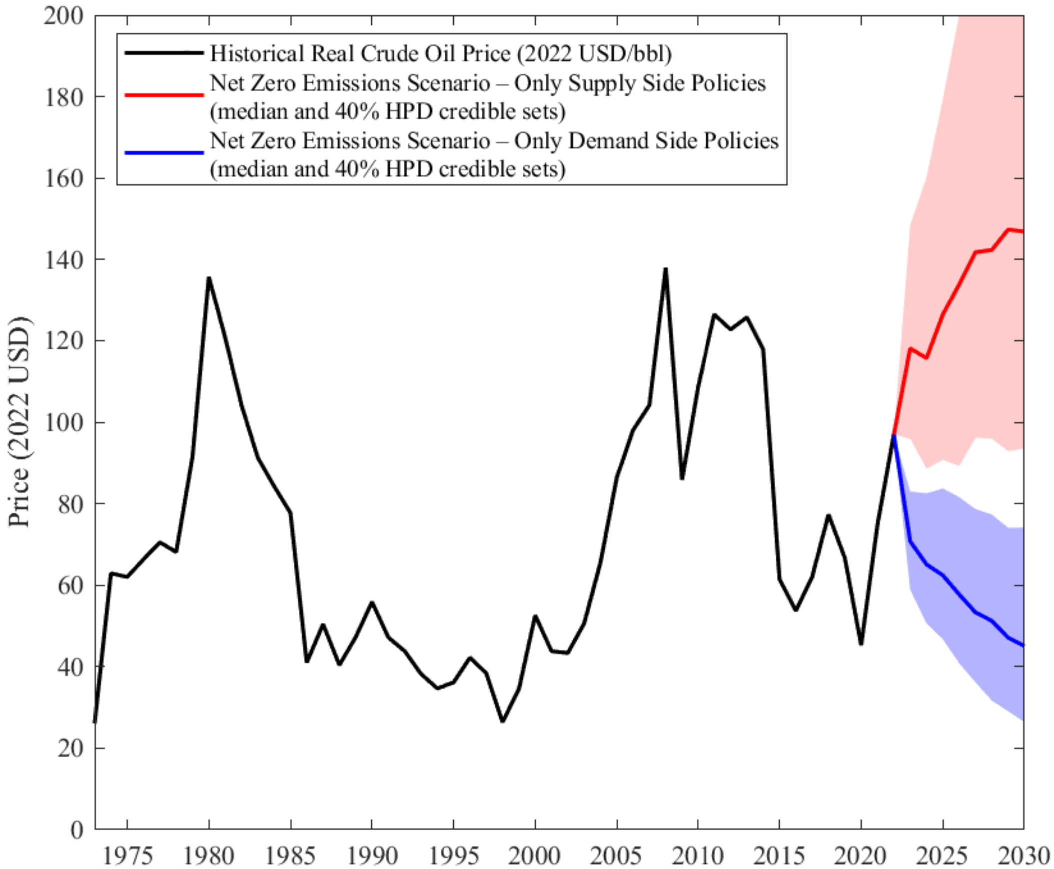
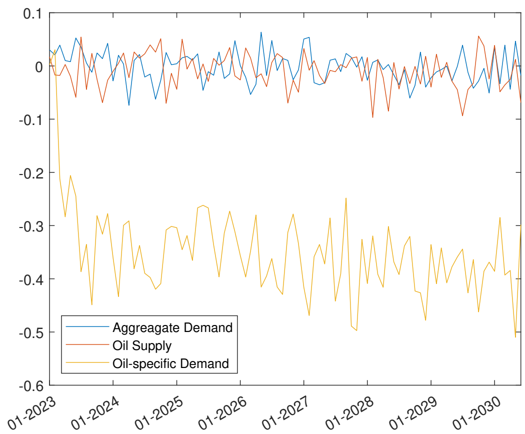
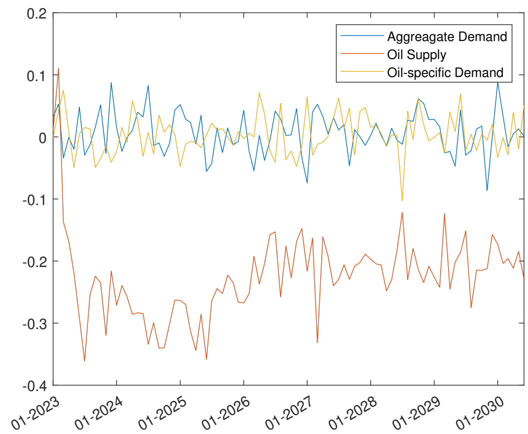


Figure C.7: Oil price scenarios in the model using annual data and global industrial production.

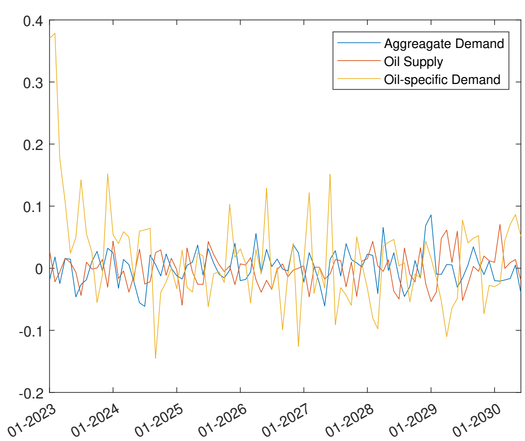


(a) Demand-side policies scenario

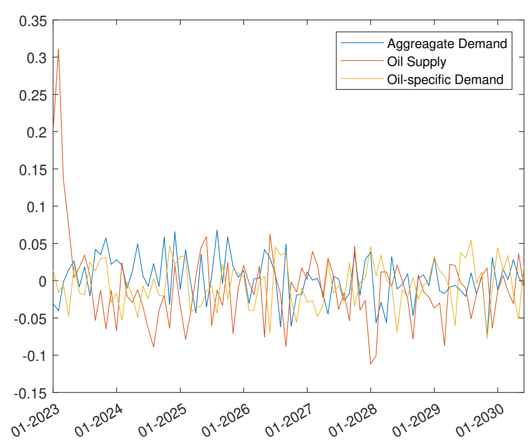


(b) Supply-side policies scenario

Figure C.8: Point-wise means of the shock series (in standard deviations) over the scenario horizon in the net-zero emissions scenario.



(a) Demand-side policies scenario



(b) Supply-side policies scenario

Figure C.9: Point-wise means of the shock series (in standard deviations) over the scenario horizon in the stated policy scenario.

		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 Production	Demand side policies	25	8.17	69	17.36
	Supply side policies	135	21.47	73	16.27
	50/50 mix	85	16.04	67	15.79
Global Economic Activity Index	Demand side policies	50	10.90	67	16.19
	Supply side policies	120	20.44	67	16.82
	50/50 mix	90	16.46		
Higher Elasticity Bound					
Industrial Production	Demand side policies	33	9.56	70	16.84
	Supply side policies	136	22.03	75	16.34
	50/50 mix	98	17.61		
Global Economic Activity Index	Demand side policies	56	12.12		
	Supply side policies	138	22.32		
	50/50 mix	98	17.59		
2050 Scenario Higher Elasticity Bound					
Industrial Production	Demand side policies	15	14.14	48	50.24
	Supply side policies	304	97.95	90	68.33

Table C.1: Sensitivity

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.

		Supply Elasticity		Demand Elasticity	
		IRF	Impact	IRF	Impact
Baseline 2030					
Industrial Production	Demand side policies	0.18	0.14	-0.16	-0.18
	Supply side policies	0.09	0.07	-0.34	-0.33
	50/50 mix	0.18	0.13	-0.17	-0.18
IP and Inventories	Demand side policies	0.15	0.13	-0.19	-0.15
Global Economic Activity	Demand side policies	0.18	0.12	-0.17	-0.18
	Supply side policies	0.07	0.03	-0.37	-0.52
	50/50 mix	0.12	0.14	-0.37	-0.16
Higher Elasticity Bound					
Industrial Production	Demand side policies	0.26	0.20	-0.14	-0.15
	Supply side policies	0.10	0.08	-0.30	-0.29
	50/50 mix	0.23	0.18	-0.15	-0.13
IP and Inventories	Demand side policies	0.20	0.16	-0.17	-0.13
Global Economic Activity	Demand side policies	0.26	0.18	-0.13	-0.14
	Supply side policies	0.10	0.09	-0.28	-0.27
	50/50 mix	0.23	0.19	-0.14	-0.12
2050 Scenario Higher El. Bound					
Industrial Production	Demand side policies	0.24	0.17	-0.10	-0.07
	Supply side policies	0.14	0.09	-0.17	-0.14

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

Notes: The impulse response function-based (IRF) supply and demand elasticities are estimated as the impact production response relative to the impact price response after an oil-specific demand and oil supply shock, respectively (see Kilian and Murphy, 2014). The impact demand and supply elasticities are obtained directly from the B_0 matrix (see Baumeister and Hamilton, 2023). The models including inventories in rows four and nine display the IRF supply elasticities as the average supply elasticities based on the contemporaneous (0.146 and 0.19) and expectational oil-specific demand shocks (0.155 and 0.21).

C.1 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

PUBLICATIONS

Not All Energy Transitions Are Alike: Disentangling the Effects of Demand- and Supply-Side Policies on Future Oil Prices
Working Paper No. WP/2023/160