# Oil Prices and Global Activity in a General Equilibrium Model with Dynamic Elasticities*

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**Abstract**

This paper develops a dynamic general equilibrium model of the global crude oil market that delivers horizon-dependent price elasticities of oil supply and demand, arising from the gradual adjustment of oil producers and consumers over time. We refer to elasticities beyond the impact horizon as dynamic elasticities. We derive closed-form expressions for the elasticities, which allow us to impose transparent prior restrictions in the empirical analysis and to quantify how dynamic elasticities shape the propagation of structural shocks to oil prices and global real activity. We estimate the model with Bayesian methods using monthly data on industrial production and key oil-market indicators—production, inventories, and prices. Diffuse priors on dynamic elasticities imply elasticity profiles that are essentially flat across horizons. By contrast, informative priors (or an expanded information set including drilling activity under diffuse elasticity priors) yield (supply) elasticities that rise with the horizon, increase the contribution of supply shocks to fluctuations in oil prices and real activity, and reduce that of oil-consumption demand shocks.

**JEL classifications:** C32, C11, E32, Q41, Q43

**Keywords:** Oil market, Real Business Cycle (RBC), Bayesian estimation, dynamic elasticities, oil supply and demand.

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# 1 Introduction

What drives commodity price fluctuations, and what are their macroeconomic effects? This question is central to both academic research and policy. We study it in the context of crude oil, one of the world's most important traded commodities. From the oil shocks of the 1970s to the commodity boom of the 2000s and the more recent spikes associated with wars, geopolitical tensions, and supply disruptions, oil prices have exhibited large and recurrent swings, with important consequences for firms, households, and governments in both oil-importing and oil-exporting economies.

A central challenge is to quantify the relative contributions of demand and supply disturbances to oil price fluctuations. A large body of work addresses this question using structural vector autoregressive (SVAR) models (e.g., Kilian, 2009; Kilian and Murphy, 2012, 2014; Baumeister and Hamilton, 2019; Caldara et al., 2019, hereafter K09, KM12, KM14, BH19 and CCI19). Identification in these models typically hinges on restrictions on the short-run (impact) price elasticities of oil demand (SRED) and supply (SRES). Inference about the sources of oil price fluctuations is highly sensitive to the assumed values of the elasticities. For instance, assuming a lower SRES implies a higher SRED and, in turn, attributes a smaller role to supply shocks in explaining oil price fluctuations (e.g., Herrera and Rangaraju, 2020).

More generally, however, the importance assigned to structural shocks depends not only on impact effects but also on their dynamic propagation, which is governed by how oil demand and supply adjust over time. Prior information may therefore justify imposing restrictions not only on short-run elasticities but also on elasticities at longer horizons. For instance, the evidence summarized in Section 2.1 suggests a supply elasticity of about 0.17 at a one-year horizon and about 0.52 in the long run. This motivates our focus on horizon-dependent elasticities and on quantifying how alternative restrictions across horizons shape the dynamics of oil prices and real activity.

This paper develops a Real Business Cycle (RBC) framework for the global oil market that generates horizon-dependent price elasticities of oil supply and demand through the gradual adjustment of oil producers and consumers over time. Oil demand arises from final-goods production and inventory accumulation by competitive storage firms. Oil supply comes from existing wells, whose productive capacity declines over time, and from new drilling, which combines capital with exploitable land. Solving the relevant optimization problems yields closed-form expressions for horizon-specific supply and demand elasticities. Supply

elasticities are governed by factor shares, input substitutability, and the well depreciation rate. Demand elasticities are governed by substitution between oil services and other inputs, together with the depreciation rate and cost structure of oil-saving capital.

To clearly distinguish between impact and longer-horizon responses, we introduce the concept of *dynamic elasticities*. Henceforth, the dynamic elasticities of oil supply and demand denote the horizon-dependent percentage responses of oil production and consumption, respectively, to a permanent one-percent increase in the oil price at horizons beyond one month. In contrast, short-run elasticities refer to their contemporaneous (within-month) responses.

Our framework delivers clear theoretical predictions about how dynamic elasticities shape the propagation of shocks to oil prices and real activity. Varying only the SRES, while holding the longer-horizon elasticities fixed, mainly affects the contemporaneous responses of oil prices and real activity, with little effect on their subsequent dynamics. For example, imposing a perfectly inelastic short-run supply amplifies the impact response of oil prices to demand shocks relative to a calibration with a SRES of 0.10. However, this gap is short-lived and is partly offset by endogenous inventory demand, which smooths the delayed adjustment of supply. Beyond the impact period, the responses are therefore essentially identical across the two scenarios, since longer-horizon elasticities are held constant.

In contrast, varying the dynamic elasticities of oil supply and demand has much stronger effects on oil prices and real activity at all horizons. When the dynamic elasticity of oil supply is higher, a positive demand shock induces producers to expand supply more at medium and long horizons, thereby dampening the increase in oil prices and reducing its persistence. By the same logic, a higher dynamic elasticity of demand dampens and shortens the oil-price responses to oil supply shocks. Because oil prices enter final-goods production costs, the persistence of oil-price dynamics also affects real activity directly. Mischaracterizing dynamic elasticities can therefore bias the inferred propagation of shocks and distort the relative importance assigned to demand and supply disturbances. Jointly accounting for dynamic demand and supply elasticities is thus crucial for understanding the dynamics of oil prices and real activity.

We then quantify how dynamic elasticities govern the propagation and persistence of global crude oil prices and global real activity in response to four structural shocks at the center of the SVAR literature: aggregate demand shocks, oil-consumption demand shocks, oil supply shocks, and oil-inventory demand shocks. We estimate four versions of the RBC model that

differ in the priors imposed on short-run and dynamic elasticities, using Bayesian methods and monthly data on industrial production and oil market indicators—production, inventories, and prices—spanning 1975–2019. We also expand the information set with drilling activity in model-validation exercises.

These four specifications combine short-run restrictions inspired by KM14 and BH19 with priors on dynamic elasticities that are either diffuse or informative. In two benchmark models, we impose short-run restrictions inspired by KM14 and BH19 together with diffuse priors on dynamic elasticities, consistent with the fact that these studies are agnostic about medium- and long-run elasticities. In the KM-benchmark, SRES is restricted to lie in $[0, 0.026]$, while the prior for SRED is centered around 0.26. In the BH-benchmark, by contrast, the priors for both SRES and SRED are centered around 0.10.[1] We compare these two benchmark specifications with two alternative models that maintain the same short-run restrictions but impose informative priors on dynamic elasticities.

Our empirical results show that diffuse priors on dynamic elasticities imply elasticity profiles that are essentially flat across horizons in both the KM and BH benchmark models. In these specifications, the posterior modes of the medium- and long-run elasticities of oil supply remain very low—about 0.03 to 0.06 in the KM benchmark and about 0.10 in the BH benchmark. These values are difficult to reconcile with the evidence and imply a substantially smaller contribution of supply shocks to fluctuations in oil prices and real activity. This finding also helps explain why SVAR studies that impose very low priors on the impact supply elasticity tend to assign a limited role to supply shocks, as the same restrictions are associated with low supply elasticities at longer horizons.

By contrast, informative priors yield elasticities that rise with the horizon, increase the role of supply shocks in fluctuations in oil prices and real activity, and reduce the role of oil-consumption demand shocks. In the KM-informed model, the implied one-year supply elasticity is about 0.15 and the implied long-run supply elasticity is about 0.46. As a result, the share of oil price fluctuations attributed to supply shocks rises from about 6% in the KM benchmark to 16% in the KM-informed model, even though the prior on SRES remains bounded above by 0.026 in both specifications. This is a key result of the paper: oil supply plays a non-negligible role even when the short-run elasticity of oil supply is constrained to be very low. At the same time, the contribution of oil-consumption demand shocks to real

[1] In KM14, the SRED is restricted to lie in $[0, 0.8]$. In our application inspired by these authors, we center our prior around their estimated mode.

activity declines from 13% in the KM benchmark to 7% in the KM-informed model.

Our first contribution is to the SVAR literature on global crude oil markets (e.g., K09; KM12; KM14; BH19; CCI19; Juvenal and Petrella, 2015; Antolín-Díaz and Rubio-Ramírez, 2018; Herrera and Rangaraju, 2020; Zhou, 2020; Cross et al., 2022; Braun, 2023). We show that short-run and dynamic elasticities play distinct roles in the analysis of oil market fluctuations. While short-run elasticities are central to shock identification and impact responses, dynamic elasticities play a key role in shock propagation, so both matter for the attribution of fluctuations across demand and supply disturbances. We also show that under diffuse priors on dynamic elasticities, alternative assumptions about the short-run elasticities imply different medium- and long-run elasticities, both in SVAR and RBC frameworks. These differences in dynamic elasticities, in turn, may help explain why SVAR studies reach different conclusions about the relative importance of oil demand and supply disturbances. Simulations further assess the conditions under which SVAR elasticity proxies constructed from impulse response function (IRF) ratios can recover the true structural elasticities implied by our RBC model. Using data simulated from the calibrated RBC model, for which the true structural elasticity profile is known, we show that the recovery improves when shocks are more persistent and the SVAR lag structure is sufficiently rich. Finally, our RBC model could be used to design priors about dynamic elasticities for SVAR models, along the lines of the DSGE-VAR approach of Del Negro and Schorfheide (2004).

Our second contribution is to the DSGE literature on oil markets and macroeconomic fluctuations (e.g., Kim and Loungani, 1992; Balke et al., 2010; Nakov and Pescatori, 2010; Bodenstein et al., 2011; Unalmis et al., 2012; Peersman and Stevens, 2013; Bergholt et al., 2019; Houssa et al., 2023; Gagliardone and Gertler, 2023; Kilian et al., 2024).[2] Existing DSGE models do not explicitly characterize how oil supply and demand elasticities evolve across horizons, despite evidence of gradual adjustment by both producers and consumers. Some studies capture specific components of this adjustment—for example, exploration or drilling-based capacity expansion on the supply side (e.g., Anderson et al., 2018; Bornstein et al., 2023), or investment in oil-saving capital on the demand side (e.g., Balke and Brown, 2018). We build on these contributions by developing a framework that integrates both sides of the market, derives closed-form expressions for dynamic elasticities, and quantifies how

[2] Our framework builds on the standard RBC environment (e.g., King and Rebelo, 2000; King et al., 1988) with external habit formation in consumption (Abel, 1990), investment adjustment costs (Christiano et al., 2005), oil as an input in final-goods production (Kim and Loungani, 1992) and oil inventories (Unalmis et al., 2012). Oil storage is competitive (e.g., Wright and Williams, 1984; Deaton and Laroque, 1992) and brings a convenience yield (e.g., Williams, 1987; Pindyck, 1994; Alquist and Kilian, 2010).

they shape the propagation of shocks. This delivers a unified and tractable way to bring empirical knowledge about medium- and long-run elasticities into DSGE models, where such a discipline is largely absent.

Our findings are robust along three dimensions. First, we replace industrial production with the Index of Global Real Economic Activity (IGREA) proposed by K09 and used in KM12 and KM14 as an alternative measure of global demand for industrial commodities. Second, we re-estimate the model over the 1995M1-2019M12 subsample, rather than the 1975M1-2019M12 baseline sample. Third, we relax the prior discipline on short-run elasticities imposed in the BH and KM benchmark specifications. This yields a new benchmark in which both short-run and dynamic elasticities are assigned diffuse priors. We compare this specification with an alternative in which short-run elasticities remain diffuse while dynamic elasticities are assigned informative priors. This exercise helps to isolate the role of dynamic elasticities. Finally, we validate the framework using drilling activity data, which is not directly targeted in the baseline estimation, and show that this additional information supports dynamic supply elasticities that rise with the horizon.

The remainder of the paper is organized as follows. Section 2 presents evidence on dynamic elasticities. Section 3 develops our RBC model of the global oil market. Section 4 shows how short-run and dynamic supply and demand elasticities shape the transmission of structural shocks. Section 5 uses the framework to revisit the causes and macroeconomic consequences of fluctuations in oil prices and global activity. Section 6 discusses the implications of the framework and presents validation and simulation exercises. Section 7 concludes.

# 2 Evidence on dynamic elasticities

This section has two closely related objectives that motivate and guide the specification and interpretation of our RBC model for the global oil market. First, we review the existing evidence on dynamic price elasticities of oil demand and supply (Section 2.1). Second, we construct IRF-based proxies for these dynamic elasticities in SVAR models using the identifying restrictions in KM12–KM14 and BH19 (Section 2.2).

## 2.1 Prior knowledge about dynamic elasticities

We conducted a systematic search of Google Scholar, EconLit, and NBER for literature reviews and studies estimating oil demand and supply elasticities at different horizons. We retained studies that report or allow us to infer elasticities on impact (short run), at a one-year horizon (medium run), and at a five-year horizon or longer (long run). For each included study, we report the values of the elasticity estimates and key characteristics (including geographical coverage, sample period, and estimation approach). For studies reporting both conventional and unconventional supply elasticities, we report weighted averages, assigning a 6% weight to unconventional wells (as in Kilian, 2022). We exclude studies focusing only on unconventional technology (e.g. Storrøsten, 2024; Aastveit et al., 2026). For demand elasticities, the literature provides relatively few studies for crude oil (e.g., Caldara et al., 2019). To broaden coverage, we also include evidence on gasoline elasticities and, following Hamilton (2009), assume that the price elasticity of crude oil demand is approximately one-half that of gasoline.

Table 1: Prior knowledge about oil supply elasticity

| Crude oil | Method | Short-run | 1 year | Long-run |
|---|---|---|---|---|
| Greene and Leiby (2006) | Literature review | 0.07 | | 0.20-0.66 |
| Fally and Sayre (2018) | Literature review | 0.15 | | 0.29-0.60 |
| Caldara et al. (2019) | Literature review | 0.13 | | |
| Anderson et al. (2018) | Texan Wells (functioning), 1998/99 | 0.00 | | |
| Newell and Prest (2019) | US wells (5 States), 2000-2015 | 0.02 | | 1.11 |
| Bjørnland et al. (2021) | North Dakota wells | 0.04 | | |
| Kilian and Murphy (2012) | World (excluding Iraq and Kuwait), Gulf War | 0.03 | | |
| Caldara et al. (2019) | Country panel (IV=supply disruptions) | 0.08 | | |
| Bornstein et al. (2023) | Fields (world), 1971-2015, IV=world GDP | | 0.20 | |
| Bogmans et al. (2024) | Country panel, 1960-2021, IV=country shock | | 0.14 | 0.46 |
| Golombek et al. (2018) | Structural model, 1986-2016, non-OPEC | | | 0.32 |
| Rao (2018) | Californian wells, after-tax elasticity | | | 0.38 |
| Averages | | 0.06 | 0.17 | 0.52 |

Notes: For ranges, we compute averages of lower and upper bound values. Newell and Prest (2019) and Bjørnland et al. (2021) provide estimates for both conventional and unconventional wells separately. We thus report a weighted average, assigning a 6% weight to unconventional wells to reflect their approximate share in global oil production over the sample (as in Kilian (2022)). For example, in Bjørnland et al. (2021), the short-run elasticity is estimated at 0.7 for unconventional wells and at zero for the others. The weighted average is 0.06*0.7 + 0.94*0 = 0.04.

Tables 1 and 2 summarize oil supply and demand elasticities at three horizons—impact, 1-year, and the long run. Two patterns stand out. First, the data confirm the well-known fact that oil demand and supply are highly inelastic in the short run. Second, elasticities increase with the horizon, although long-run elasticities remain well below unity in most cases.

The long-run elasticity of oil supply exceeds its short-run counterpart for two reasons (An-

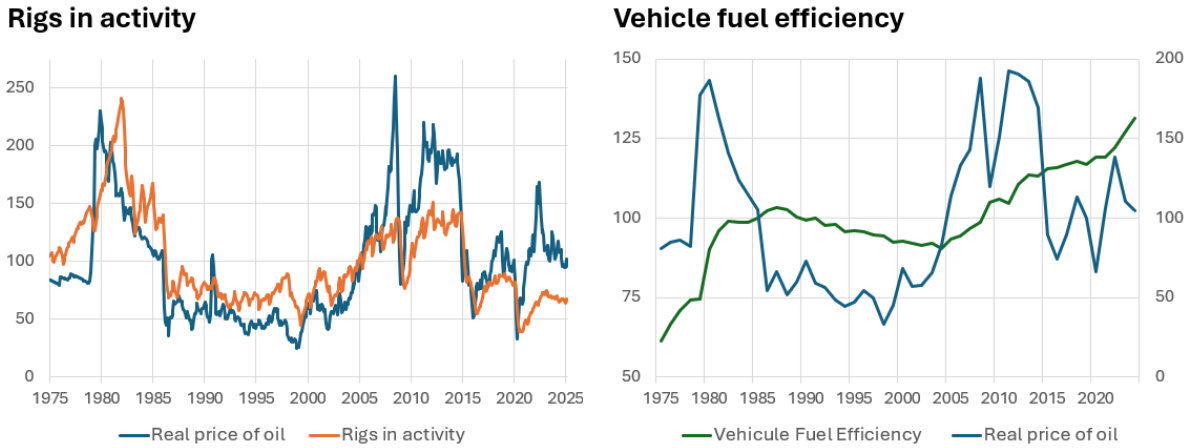
Table 2: Prior knowledge about gasoline demand elasticity

| Gasoline studies | Method | Short-run | Long-run |
|---|---|---|---|
| Dahl and Sterner (1991) | Literature survey | -0.26 | -0.86 |
| Espey (1996) | Meta-analysis | | -0.58 |
| Espey (1998) | Meta-analysis | -0.26 | -0.58 |
| Graham and Glaister (2003) | Literature survey | -0.25 | -0.77 |
| Brons et al. (2008) | Meta-analysis | -0.34 | -0.84 |
| Kouris (1983) | Literature survey | -0.26 | -0.68 |
| Goodwin et al. (2003) | Meta-analysis | -0.25 | -0.64 |
| Havranek et al. (2012) | Meta-analysis | -0.09 | -0.31 |
| Basso and Oum (2007) | Meta-analysis | -0.26 | -0.71 |
| Kilian and Zhou (2024) | Panel of US states | -0.25 | |
| Small and Van Dender (2007) | Panel of US states | -0.09 | -0.43 |
| Bento et al. (2009) | Survey of US households | | -0.35 |
| Davis and Kilian (2011) | Panel of US states | -0.46 | |
| Hughes et al. (2008) | Time series for the US | -0.05 | |
| Knittel and Tanaka (2021) | Micro data on fuel consumption in Japan | -0.37 | |
| Levin et al. (2017) | Panel of US cities | -0.28 | |
| Li et al. (2014) | Panel of US states & households survey | -0.13 | |
| Liu (2014) | Panel of US states | -0.08 | |
| Coglianese et al. (2017) | Panel of US states (event study) | -0.37 | |
| Gelman et al. (2023) | Micro data on US consumers spending | -0.22 | |
| **Average** | | -0.24 | -0.61 |

derson et al., 2018). First, production from existing oil wells is constrained by reservoir conditions: as extraction proceeds, reservoir pressure declines and well productivity naturally falls over time. Second, when prices are high, oil firms increase drilling activity, as reflected in the strong co-movement between the real price of oil and the number of active drilling rigs worldwide (Figure 1, left panel). However, drilling and bringing a new well online takes time—typically a few months. As a result, increases in the number of wells raise oil production primarily at medium and long horizons.

Gasoline demand also becomes more elastic at longer horizons. When gasoline prices are high, households and firms can reduce fuel use not only by adjusting utilization (e.g. driving fewer miles) but also by changing technology and capital choices (e.g. purchasing more fuel-efficient vehicles). The right panel of Figure 1 shows that new vehicles purchased in the United States tend to be more fuel efficient when the real price of oil is high. As these purchases gradually change the vehicle stock toward higher efficiency, oil demand becomes more responsive to prices in the medium and long runs.

Figure 1: Rigs in activity, vehicle fuel efficiency, and the real price of oil




*Sources: Baker Hughes (international rig count), U.S. Environmental Protection Agency (miles per gallon for new light duty vehicles in the United States) and World Bank Pink Sheet (average oil prices). All data are divided by their historical mean.*

## 2.2 Dynamic elasticities of oil demand and supply from SVARs

We compare the dynamic price elasticities of oil supply and demand in two SVAR models that only differ in their SRES. Our objective is to quantify how differences in impact elasticities translate into different longer-horizon elasticities in the SVAR framework. For this purpose, we re-estimate the SVAR model of BH19, comparing their original results (henceforth the BH model) with those obtained using the same monthly data (1975-2016) under an alternative prior inspired by KM12 and KM14 (the KM-inspired model). The BH prior is centered around 0.1, while the KM-inspired prior imposes an upper bound of 0.026 on the short-run supply elasticity.[3]

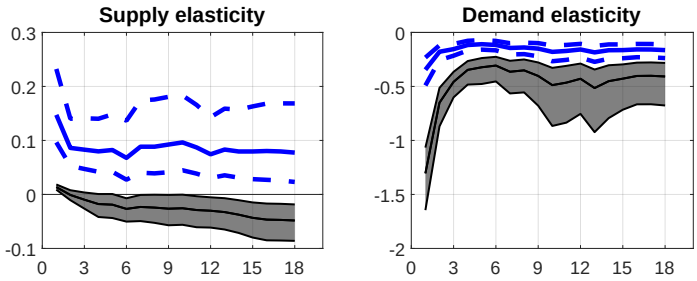
We proxy these dynamic elasticities using ratios of IRFs. Because they are constructed from IRFs, these ratios should be interpreted as approximations rather than structural elasticities. A structural dynamic elasticity measures the percentage change in oil production or consumption resulting from a permanent one-percent increase in the oil price, holding all other determinants of supply or demand constant. IRFs measure equilibrium responses following a shock that do not necessarily produce permanent changes in prices and that may violate the ceteris paribus condition. Nonetheless, they provide a useful gauge of differences in the dynamic adjustment of oil demand and supply across models at short and medium

[3] Details on these priors are provided in Appendix A. We are grateful to BH for sharing their data and replication codes, which we adapt for our analysis; see https://sites.google.com/site/cjsbaumeister/research.

horizons. In Section 6.3, we exploit our RBC model to discuss the conditions under which IRF-based proxies can match the true structural dynamic elasticities.

For oil supply, we proxy the elasticity at horizon $h$ as the ratio of the IRFs of oil production to the real oil price following an oil-specific demand shock (Figure 2, left panel). We focus on an oil-specific demand shock because it provides a clean demand shifter that traces out the supply response along the supply curve, and because it produces a persistent increase in oil prices, allowing us to evaluate the elasticity in the short and medium runs. Empirically, this shock is also the key driver of oil-price fluctuations. For oil demand, we proxy the elasticity at horizon $h$ as the ratio of the IRFs of oil consumption to the real oil price following an oil supply shock (Figure 2, right panel). We construct the IRFs of oil consumption from the IRFs of oil production and inventories.[4] We show our results for horizons of 1 to 18 months.

Figure 2: Approximated demand and supply elasticities at different horizons: BH (blue) vs KM-inspired (grey) SVAR models. Mode and 16-84 percentiles.




Three main facts emerge. First, as expected, the estimated one-month price elasticities of oil supply differ sharply between the BH and KM-inspired models, reflecting the different priors imposed in these studies. The posterior mode is 0.15 in the BH model and 0.01 in the KM-inspired model. Moreover, imposing a lower SRES is associated with a higher (in absolute value) SRED: the posterior mode of the one-month demand elasticity is about $-0.35$ in the BH model and about $-1.3$ in the KM-inspired model.

Second, the disagreement in impact supply and demand elasticities persists into the medium run. In the KM-inspired model, the IRF-based proxy of the dynamic elasticity of supply quickly becomes statistically not different from zero beyond impact, and the median drifts below zero after about one year. By contrast, in the BH specification the supply elasticity hovers around 0.1 and remains significantly greater than zero at all horizons. In both cases,

[4] We use the following identity $V_t - V_{t-1} = Y_t(o) - O_t$, where $V$ is oil inventory, $Y(o)$ is oil production, and $O$ is oil consumption demand.

the median profiles are relatively flat, suggesting that imposing a prior on impact elasticity also disciplines elasticities at longer horizons. The IRF-based proxies of demand elasticities also differ across horizons, with the KM-inspired model implying more elastic demand (in absolute value) at medium and long horizons than the BH model.[5]

Third, these relatively flat elasticity profiles in both SVAR models contrast with the evidence summarized in Section 2.1, which suggests instead that both demand and supply elasticities increase with the horizon. These features motivate the RBC framework developed in Section 3, which embeds slow adjustment mechanisms—drilling-driven capacity expansion on the supply side and oil-saving investment on the demand side—that generate rising dynamic elasticities and allow us to impose economically meaningful cross-horizon restrictions in the empirical analysis. In turn, this framework helps to reassess the drivers of global oil prices and real activity.

# 3 RBC model with oil

We develop a dynamic general equilibrium model of the global crude oil market with four types of agents: households, oil producers, final-goods producers, and inventory firms. The framework builds on the standard RBC framework and is augmented with external habit formation in consumption, investment adjustment costs, oil as an input in final-goods production, and competitive oil storage. These features allow us to derive closed-form expressions for the dynamic elasticities of oil demand, oil supply, and inventory adjustment, which we use to discipline the prior restrictions imposed in the empirical analysis.

Section 3.1 studies the optimization problem of oil producers and derives closed-form expressions for the dynamic elasticities of oil supply. Section 3.2 analyzes the final-goods producers and derives closed-form expressions for the dynamic price elasticities and income elasticity of oil demand. Sections 3.3 and 3.4 characterize inventory demand and the household problem,

[5] These results are consistent with a careful analysis of the IRFs presented in the original papers of KM14 and BH19. Restrictions imposed on short-run elasticities primarily shape impact responses. For example, positive demand shocks generate essentially no contemporaneous increase in oil production in KM14, whereas production rises on impact in BH19. These differences in impact responses are central to the SVAR debate on global oil markets. Importantly, the IRFs in KM14 and BH19 also display markedly different medium-run supply responses to demand-driven oil price changes. In BH19, oil production gradually rises following a positive economic activity shock, whereas in KM14 it remains muted for roughly 18 months, despite similarly persistent oil-price responses in both specifications. See the IRFs in Appendix A.3.

respectively. Time is discrete and one period corresponds to one month.

## 3.1 Oil supply

Oil production takes place in two stages that capture the key features of the oil extraction industry.[6] In the first stage, oil producers drill new wells using capital and land newly available for drilling (Section 3.1.1). In the second stage, oil is extracted from the existing stock of wells using labor (Section 3.1.2). Solving the oil producer's problem (described in Section 3.1.3), we derive closed-form expressions for the short- and long-run price elasticities of oil supply (Sections 3.1.4-3.1.5). The dynamic price elasticity can then be expressed as a function of its short- and long-run counterparts and of the production decay rate of oil wells (Section 3.1.6).

### 3.1.1 Drilling

New wells ($\Lambda_t^{new}$) are drilled on available land using investment in physical capital

$$\Lambda_t^{new} = a(o)\left[(1-\gamma)^{\frac{1}{\theta}} I_t(o)^{\frac{\theta-1}{\theta}} + (\gamma)^{\frac{1}{\theta}} L^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{1}$$

where $\theta$ is the elasticity of substitution between capital investment ($I_t(o)$) and land ($L$) in the production of new wells and $\gamma$ is the income share of land. The stock of new exploitable land ($L$) available in each period is fixed.[7] The parameter $a(o)$ is a scaling constant.

These newly drilled wells are added to the stock of producing wells with a one-period lag[8]

$$\Lambda_t = (1-\delta_\Lambda)\Lambda_{t-1} + \Lambda_{t-1}^{new}, \tag{2}$$

where existing wells depreciate at a rate $\delta_\Lambda$, capturing the decline in productive capacity of existing wells as reservoir pressure gradually declines over time (see e.g. Chapter 3 of Dake, 1978).

[6] We abstract from the exploration and permitting stage, which we treat as exogenous and do not model explicitly.

[7] This assumption captures the length, complexity, and uncertainty associated with exploration.

[8] This one-period lag ensures that a change in drilling activity cannot affect oil supply within a month and does not affect the short-run elasticity (more details shortly). Also, note that the drilling stage usually takes 50 to 60 days on suitable locations where permits have already been obtained.

### 3.1.2 Oil extraction

Oil is produced by operating existing wells using labor

$$Y_t(o) = \varepsilon_t^{os} \left[ (1-\lambda)^{\frac{1}{\phi}} H_t(o)^{\frac{\phi-1}{\phi}} + (\lambda)^{\frac{1}{\phi}} \Lambda_t^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \tag{3}$$

where $\phi$ is the elasticity of substitution between labor ($H_t(o)$) and wells ($\Lambda_t$) in oil production, $1-\lambda$ is the labor share, and $\varepsilon_t^{os}$ is an exogenous oil-supply shock. Labor is the only short-run adjustment margin in our model. The assumption reflects the idea that, in the short run, production can be adjusted.[9]

### 3.1.3 Oil producers' objective

Oil producers are assumed to be risk-neutral. They maximize the present value of profits

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left[ p_t Y_t(o) - I_t(o) - w H_t(o) \right], \tag{4}$$

where $\beta$ is their discount factor and $p_t$ is the real price of oil, i.e. the nominal price divided by the final good price. We assume that $w$ is a constant unit labor cost and that investment goods are produced with one unit of the final good. The oil producer's problem is thus to maximize their profits given by Eq. (4) with respect to $H_t(o)$ and $I_t(o)$ under their production technology given by Eqs. (1)-(3).

### 3.1.4 The short-run elasticity of oil supply

Solving the oil producer's problem yields two first-order conditions, with respect to hours worked and investment in new wells. We linearize these conditions together with Eqs. (1)-(3), which jointly characterize the dynamics of oil supply. To derive an analytical expression for the short-run supply elasticity, we exploit the assumption that new wells start producing

[9] One interpretation is that, in response to unexpectedly high prices, producers may postpone the planned closure of low productivity or nearly depleted wells by increasing labor input. More broadly, this input should be interpreted as a composite variable input, that captures short-run operating margins at existing wells, including the energy used to inject water or gas to maintain the reservoir pressure and sustain production at wells that might otherwise be closed.

with a one-period lag. As a result, on impact, $\Lambda_t$ remains at its steady-state value and the system collapses to a single expression linking oil production to oil prices. This expression defines the short-run supply elasticity, $\sigma_{\text{SR}}$, as:

$$\sigma_{\text{SR}} = \frac{\phi(1-\lambda)}{\lambda}. \tag{5}$$

The short-run elasticity is increasing in the elasticity of substitution between labor and wells, $\phi$, and in the labor share, $(1-\lambda)$. Because labor is the only short-run adjustment margin, the parameter $\phi$ captures the technical feasibility of raising oil production with more labor at existing wells. In the limit case as $\phi \to 0$, supply becomes perfectly inelastic in the short run. The details are presented in Appendix B.1.

### 3.1.5 The long-run elasticity of oil supply

In the long run, both labor and the stock of producing wells have adjusted. To derive a closed-form expression for the long-run elasticity of oil supply, we analyze the response of oil supply to a permanent increase in the oil price (details in Appendix B.3). To proceed, we start from the system of linear equations governing the dynamic response of oil supply. We simplify this system knowing that all variables must converge to some equilibrium in the long run (formally, $x_t = x_{t+s}\ \forall x$). The system then simplifies to a single equation linking the long-run response of oil production to a change in oil price. This expression defines the long-run elasticity of oil supply, $\sigma_{\text{LR}}$, as:

$$\sigma_{\text{LR}} \quad = \quad \sigma_{\text{SR}} + \frac{\theta(1-\gamma)}{\lambda\gamma}. \tag{6}$$

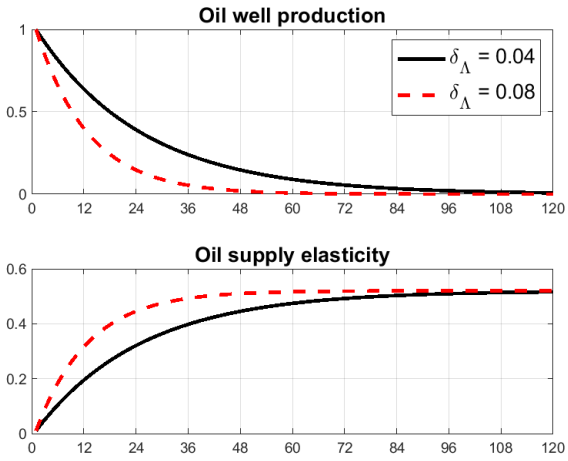
The long-run elasticity is bounded below by the level of the short-run elasticity, because labor can adjust at both horizons. In addition, $\sigma_{\text{LR}}$ is increasing in the elasticity of substitution between land and capital investment, $\theta$, and in the capital share, $1-\gamma$, since capital is adjustable in the long run whereas land is fixed. In the limiting case without land, $\gamma = 0$, the long-run elasticity becomes infinite. A fixed production factor such as land is therefore crucial for ensuring a finite $\sigma_{\text{LR}}$.[10]

[10] To study oil price dynamics at business cycle frequencies, it is reasonable to treat land as fixed, since exploration often takes years or even decades.

### 3.1.6 The adjustment speed and dynamic oil supply elasticities

The well-depreciation rate, $\delta_\Lambda$, governs the speed with which the elasticity of oil supply converges from its short-run to its long-run value. Because the productive capacity of existing oil wells declines only gradually over time, the effects of past drilling investment decisions persist, implying a gradual response of oil supply to unexpected price changes. The adjustment speed is increasing in $\delta_\Lambda$, since a higher depreciation rate shortens the life of existing wells and thereby weakens the influence of past investment decisions on current productive capacity.

Figure 3: Adjustment speed towards the long-run elasticity




This pattern yields a closed-form expression for the price elasticity of oil supply at horizon $h$, which we label the *dynamic oil supply elasticity*, as a function of the short-run elasticity, $\sigma_{\text{SR}}$, the long-run elasticity, $\sigma_{\text{LR}}$, and the depreciation rate that governs the adjustment speed of oil supply, $\delta_\Lambda$; see Appendix B.4 for the derivation[11]:

$$\sigma(h) = (1-\delta_\Lambda)^h \sigma_{\text{SR}} + (1-(1-\delta_\Lambda)^h)\sigma_{\text{LR}}. \tag{7}$$

Figure 3 illustrates how the well-depreciation rate governs the adjustment speed of oil supply. The upper panel compares well-level production patterns across alternative depreciation

[11] The dynamic elasticity given in Eq. (7) implies a geometric convergence between $\sigma_{\text{SR}}$ and $\sigma_{\text{LR}}$ as the gap between $\sigma(h)$ and $\sigma_{\text{LR}}$ reduces each period by a factor 1-$\delta_\Lambda$: $\frac{\sigma(h+1)-\sigma_{\text{LR}}}{\sigma(h)-\sigma_{\text{LR}}} = 1-\delta_\Lambda$. The speed of convergence can be characterized by a half-life, i.e. the number of periods required to halve the gap between $\sigma_{\text{SR}}$ and $\sigma_{\text{LR}}$: $h_{1/2} = \frac{\ln(0.5)}{\ln(1-\delta_\Lambda)}$.

rates, while the lower panel shows the implied dynamic oil supply elasticities (using Eq. (7)) where $\sigma_{\text{SR}}$ and $\sigma_{\text{LR}}$ are calibrated to 0.01 and 0.52.

This closed-form solution for the dynamic elasticity of oil supply measures the horizon-dependent percentage change in oil production resulting from a permanent one-percent increase in the oil price, holding all other determinants of supply constant. We thus make the following assumptions: (i) the change in oil price is unanticipated but permanent; (ii) the economy is initially at its steady state; (iii) we use a first-order approximation of the model; (iv) wages are constant; and (v) oil producers are risk-neutral.

## 3.2 Final good producers and oil consumption demand

Oil enters final-goods production as an input (Section 3.2.1), while final-goods producers can also invest in oil-saving capital (Section 3.2.2). Solving the final-goods producer's problem (Section 3.2.3), we derive closed-form expressions for the short-run and long-run price elasticities of oil demand (Sections 3.2.4-3.2.5). The dynamic price elasticity of oil demand can then be expressed as a function of its short-run and long-run counterparts and of the depreciation rate of oil-saving capital (Section 3.2.6).

### 3.2.1 Final goods production

Final-goods production takes place in two steps. First, firms combine labor and capital using a standard Cobb-Douglas technology to produce an intermediate good ($X_t$):

$$X_t = \varepsilon_t^{ea} K_t^{\alpha} H_t(f)^{1-\alpha}, \tag{8}$$

where $\varepsilon_t^{ea}$ is a productivity shock capturing exogenous shifts in global economic activity and $(1-\alpha)$ is the labor income share in the intermediate good.

Second, firms combine the intermediate good with oil services (defined shortly below) using a CES production function to produce final goods

$$Y_t(f) = \left[ (1-\omega)^{\frac{1}{\xi}} (X_t)^{\frac{\xi-1}{\xi}} + (\omega)^{\frac{1}{\xi}} \left(\varepsilon_t^{od} S_t\right)^{\frac{\xi-1}{\xi}} \right]^{\frac{\xi}{\xi-1}}, \tag{9}$$

where the parameter $\xi$ is the elasticity of substitution between oil services and the intermediate good; $\omega$ is the oil share in production; and $\varepsilon_t^{od}$ is an oil-specific demand shock.

Final goods are used for consumption and investment. The final-good market clears when output equals the sum of household demand for consumption, $C_t$; investment goods used in well production, $I_t(o)$; investment in the capital stock used to produce intermediate goods, $I_t(f)$; and investment in oil-efficiency capital, $I_t(z)$: $Y_t(f) = C_t + I_t(o) + I_t(f) + I_t(z)$.

### 3.2.2 Oil services and oil-saving capital

Oil services ($S_t$) are given by

$$S_t = O_t + Z_t - \bar{Z}, \tag{10}$$

where $O_t$ is oil consumption; $Z_t$ is oil-saving capital that turns one unit of oil into two units of oil services[12]; and $\bar{Z}$ is either a fixed oil-input cost (when $\bar{Z} > 0$) or an exogenously given endowment (when $\bar{Z} < 0$). When $Z_t = \bar{Z}$, we have a standard CES production function with oil consumption as input. In this case, the price and income elasticities of oil demand are constant over time, and equal to $\xi$ and 1, respectively.

Oil-saving capital evolves according to the following law of motion

$$Z_t = (1 - \delta_z)Z_{t-1} + I_{t-1}(z), \tag{11}$$

where $I_t(z)$ is an irreversible investment and $\delta_z$ is the depreciation rate of oil-saving capital. At every period, firms can decide how much to invest at a cost given by $a(z)\left(\frac{I_t(z)}{I(z)}\right)^{\frac{1}{\varphi}} I_t(z)$. The parameter $\varphi \geq 0$ implies that the marginal cost of investment in oil-saving capital is increasing in $I_t(z)$.[13]

[12] This assumption implies that $Z$ units of physical oil are combined with oil-saving capital to deliver $2 \times Z_t$ units of productive oil services: $S_t = O_t - Z_t + 2 \times Z_t - \bar{Z}$. In that sense, oil services reflect the effective oil input entering the final-goods production.

[13] Note that we treat the cost $a(z)\left(\frac{I_t(z)}{I(z)}\right)^{\frac{1}{\varphi}} I_t(z)$ as a pecuniary wedge (rebated to households), while only $I_t(z)$ units of final goods are used (see the market clearing condition in Section 3.2.1).

### 3.2.3 Final good producer's objective

Final-goods producers maximize their expected profits given by

$$\mathrm{E}_t \sum_{j=0}^{\infty} \beta^j \{Y_{t+j}(f) - w^f_{t+j} H_{t+j}(f) - r^k_{t+j} K_{t+j} - p_{t+j} O_{t+j} - a(z) \left( \frac{I_{t+j}(z)}{I(z)} \right)^{\frac{1}{\varphi}} I_{t+j}(z)\}, \quad (12)$$

where $w^f_{t+j}$ and $r^k_{t+j}$ are the wage and rental rates of labor and capital, respectively. The final-goods producer's problem is therefore to choose $H_t(f)$, $K_{t+1}$, $O_t$, and $I_t(z)$ so as to maximize the profit function in Eq. (12), subject to the production technologies in Eqs. (8)-(11).

### 3.2.4 The short-run elasticity of oil demand

Solving the final-goods producer's problem yields the first-order conditions for $H_t(f)$, $K_{t+1}$, $O_t$, and $I_t(z)$, see Appendix B.5. Linearizing these conditions together with Eqs. (8)-(11) gives a system that characterizes the dynamic response of oil consumption demand. To derive a closed-form expression for the short-run elasticity of oil demand, $\eta_{\text{SR}}$, we solve this system under the assumption that, on impact, the stocks of productive capital and oil-saving capital ($K_t$ and $Z_t$) are predetermined, and thus remain at their steady-state values. To isolate the difference between price and output elasticities, we also assume that production remains constant. This reduces the system to a single expression linking oil consumption demand to the oil price, which defines the short-run elasticity of oil demand (expressed in absolute value)

$$\eta_{\text{SR}} \quad = \quad \xi \frac{S}{O}, \quad (13)$$

where $O$ and $S$ denote steady-state values of $O_t$ and $S_t$, respectively. In this expression, the short-run price elasticity of demand, $\eta_{\text{SR}}$, is increasing in the elasticity of substitution between oil services and the intermediate input, $\xi$.

### 3.2.5 The long-run elasticity of oil demand

To derive a closed-form expression for the long-run elasticity of oil demand, $\eta_{\text{LR}}$, we analyze the response of oil consumption to a permanent increase in the oil price; see Appendix B.6 for details. We start from the system of linear equations governing the dynamic response of oil demand and impose the long-run equilibrium condition that $x_t = x_{t+s}\ \forall x$. This reduces the system to a single equation linking the long-run log deviation of oil consumption from its initial steady state to that of the oil price, which defines the long-run elasticity of oil demand as:

$$\eta_{\text{LR}} \quad = \quad \eta_{\text{SR}} + \varphi \frac{S}{O}. \tag{14}$$

The long-run price elasticity is bounded below by the short-run elasticity, $\eta_{\text{SR}}$, because final-goods firms can substitute oil services with the intermediate input, $X_t$, both in the short run and the long run. The long-run price elasticity of demand is increasing in $\varphi$. A rise in oil prices encourages final-goods firms to invest in oil-saving capital in order to reduce production costs, making oil demand more price-elastic in the long run. The lower the marginal cost of investing in oil-saving capital—i.e., the higher $\varphi$—the stronger this incentive and the larger the long-run price elasticity of oil demand. In the limiting case as $\varphi \to 0$, the marginal cost of investing in oil-saving capital is prohibitively high, so the stock of oil-saving capital is always fixed at its steady-state level and the short-run and long-run elasticities coincide.

Our framework also yields a closed-form expression for the output elasticity of oil demand, $\chi = \frac{S}{O}$, which we interpret as the income elasticity of oil demand. This elasticity is constant over time and is governed by the parameter $\bar{Z}$, which pins down the steady state ratio $\frac{S}{O}$.

### 3.2.6 The adjustment speed and the dynamic elasticity of oil demand

The oil-saving capital depreciation rate, $\delta_z$, governs the speed with which the elasticity of oil demand converges from its short-run to its long-run value. Because oil-saving capital depreciates only gradually over time, the effects of past investment decisions in this capital persist, implying a gradual response of oil demand to unexpected price changes. This in turn yields a closed-form expression for the price elasticity of oil demand at horizon h, which we label the *dynamic oil demand elasticity*, as a function of the short-run, $\eta_{\text{SR}}$, and long-run,

$\eta_{\text{LR}}$, elasticities and the depreciation rate that governs the adjustment speed of oil demand, $\delta_z$, see Appendix B.7 for the derivation:

$$\eta(h) = (1-\delta_z)^h \eta_{\text{SR}} + (1-(1-\delta_z)^h)\eta_{\text{LR}}. \tag{15}$$

## 3.3 Storage and oil-inventory demand

Competitive risk-neutral storage firms hold inventories. A firm $j$ maximizes its expected profit of carrying oil inventories, $V_{j,t}$, from one period to the next

$$\mathrm{E}_t p_{t+1} \varepsilon_t^v V_{j,t} - p_t V_{j,t} \Phi(V_t, p_t), \tag{16}$$

where $p_t$ denotes the real oil price, $\mathrm{E}_t p_{t+1}$ is the expected future real oil price, $\varepsilon_t^v$ is an exogenous storage-demand shock that captures speculation/precaution motives, and $\Phi(V_t, p_t)$[14] defines the storage cost function as:

$$\Phi(V_t, p_t) = \left(\frac{V_t}{V}\right)^{\frac{1}{\nu(1-\tau)}} \left(\frac{p_t}{p}\right)^{\frac{\tau}{1-\tau}}. \tag{17}$$

The parameter $\nu$ governs the curvature of the storage-cost function with respect to inventory holding. It captures increasing marginal storage costs due to limited physical storage capacity and/or the diminishing convenience yield as oil stocks increase. The parameter $\tau$ allows storage costs to vary with current oil prices, reflecting, for example, the financing, insurance, or opportunity costs of carrying inventories.[15]

Under these assumptions, the linearized FOC of the storage firm yields

$$\hat{V}_t = \nu\Big\{\mathrm{E}_t \Delta\hat{p}_{t+1} - \tau \mathrm{E}_t \hat{p}_{t+1}\Big\} + \hat{\varepsilon}_t^v \tag{18}$$

where $\Delta\hat{p}_{t+1} = \hat{p}_{t+1} - \hat{p}_t$. The implication is that $\nu$ captures the elasticity of storage demand

[14] A firm $j$ takes storage costs as given.

[15] It is common to assume that the marginal convenience yield declines with the total stock of inventories, while the marginal storage cost is constant. In that case, the marginal storage costs (net of a convenience yield) increase with inventories, as captured by our net cost function $\Phi(V_t)$, with $\nu \geq 0$. Allowing storage costs to depend on the current oil price helps to reconcile the SVAR literature, where demand shocks can generate a gradual increase in oil prices and an immediate fall in inventories, a pattern that can be reproduced when $0 \leq \tau < 1$.

to the expected price gains of holding oil inventories, while $\tau$ allows storage firms to place greater weight on current prices than on expected future prices when making inventory decisions (see the details in Appendix B.8). Finally, note that the oil market clears when the gap between demand and supply matches the change in inventories: $V_t - V_{t-1} = Y_t(o) - O_t$.

## 3.4 Households

Households derive utility from consumption, $C_t$, and disutility from labor, $H_t(f)$, in the final good sector. They maximize their utility given by

$$\mathrm{E}_0^j \sum_{t=0}^{\infty} \beta^t \left[ \frac{(C_{j,t} - \mathbf{b}C_{t-1})^{1-\sigma_c}}{1-\sigma_c} - A_h \frac{(H(f)_{j,t})^{1+\sigma_h}}{1+\sigma_h} \right], \tag{19}$$

where $\mathbf{b}$ is an external habit parameter, $\sigma_c$ is the inverse of the inter-temporal elasticity of substitution (IES) for consumption, and $\sigma_h$ is the inverse Frisch elasticity of labor supply in the final good sector.[16] Their budget constraint is

$$C_t + I_t(f) + B_{t+1} = R_{t-1}B_t + w_t H_t(f) + wH_t(o) + r_t^k K_t + \Pi_t + SC_t + OSIC_t, \tag{20}$$

where $R_t$ is the real gross rate of interest paid on bonds $B_t$. The term $\Pi_t$ represents the sum of profits transferred from oil producers, final good producers, and oil-inventory firms. We assume that part of the storage costs, $SC_t = p_t V_t(1 - \Phi(V_t, p_t))$, and part of the oil-saving investment costs, $OSIC_t = \left(1 - a(z)\left(\frac{I_t(z)}{I(z)}\right)^{\frac{1}{\varphi}}\right) I_t(z)$, are rebated to households and therefore do not constitute a net loss of resources. Productive capital, $K_t$, is accumulated with investment, $I_t(f)$

$$K_{t+1} = \left[1 - \frac{\psi}{2}\left(\frac{I_t(f)}{I_{t-1}(f)} - 1\right)^2\right] I_t(f) + (1-\delta_k)K_t, \tag{21}$$

where $\psi$ is the investment adjustment cost in the final good sector and $\delta_k$ is the depreciation rate of capital. Details on the derivation of the household optimality conditions are presented in Appendix B.9.

[16] We assume that the real wage in the oil sector is fixed to a constant $w$, so we do not need to introduce disutility from labor in the oil sector in the utility function.

# 4 Impact and dynamic elasticities in shock propagation

After presenting the calibrated model in Section 4.1, we show how the dynamic elasticities of oil supply (Section 4.2) and demand (Section 4.3) shape the propagation and persistence of global crude oil prices and economic activity in response to structural shocks.[17] We then isolate the role of the contemporaneous supply elasticity (Section 4.4).

## 4.1 Calibration

Throughout Sections 4.2-4.4, we vary the horizon-dependent elasticities of demand and supply. The remaining parameters are calibrated as follows (see Table 3). A first group of parameters ($\beta$, $\delta_k$, $\alpha$, $\psi$, $\sigma_c$, $\sigma_h$, $b$) is set to standard values from the literature, adjusted to the monthly frequency of data. A second group ($\omega$, $V$, $\gamma$, $\lambda$) is chosen to match long-run averages and steady-state ratios; additional details are provided in Appendix C.1. We discuss the third group below.

Table 3: Calibrated parameters

| Symbols | Parameters | Value |
|---|---|---|
| $\beta$ | Discount factor | $0.99^{\frac{1}{3}}$ |
| $\delta_k$ | Depreciation rate of capital | $0.025/3$ |
| $\alpha$ | Capital income share (final good) | 0.32 |
| $\psi$ | Investment adjust. cost (final good) | 12 |
| $\sigma_c$ | Inverse IES of consumption | 1 |
| $\sigma_h$ | Labour supply elasticity | 2 |
| $b$ | Habits in consumption | 0.85 |
| $\omega$ | Oil share in industrial production | 0.05 |
| $V/Y(o)$ | Oil inventories to production ratio | 1.00 |
| $\gamma$ | Land share in oil well production | 0.74 |
| $1-\lambda$ | Labor share in oil production | 0.10 |
| $\chi$ | Output elasticity of oil demand | 1 |
| $\nu$ | Storage demand elast. to $\mathrm{E}_t\Delta\hat{p}_{t+1}$ | 0.46 |
| $\tau$ | Storage demand: weight penalty for $\mathrm{E}_t\hat{p}_{t+1}$ | 0.13 |
| $\delta_\Lambda$ | Oil well decay rate | 0.038 |
| $\delta_z$ | Oil-saving K depreciation rate | 0.033 |

The output (or income) elasticity of oil demand, $\chi$, is set to one. This is the implicit assumption in much of the literature that relies on standard CES production or utility functions.

[17] Changes in the dynamic elasticities are implemented by adjusting the values of the long-run elasticities. We also experiment with changes in the adjustment speed and with joint shifts in the short and long-run elasticities (Appendix C).

Table 4: Oil wells production decay

| **Oil wells** | **Production half-life** | **Data** |
|---|---|---|
| Wachtmeister et al. (2017) | less than 6 months | TX, Unconventional |
| Kellogg (2014) | 7 months | TX (infill wells) |
| Anderson et al. (2018) | 6 to 24 months | TX (by period) |
| Newell and Prest (2019) | 6 to 12 months | TX, ND, CA, OK, CO, all types |
| Bjørnland et al. (2021) | 11 to 22 months | ND, all types |

This value also lies within the range of estimates reported in the literature (Hamilton, 2009; Havranek and Kokes, 2015; Golombek et al., 2018; Chang et al., 2019). Values close to one are typically supported by studies that do not control for the stock of vehicles and therefore capture a total long-run elasticity.[18]

We calibrate $\nu$ and $\tau$ using a regression of U.S. crude oil inventories at the Petroleum Administration for Defense District level, defined by the EIA, on two variables: (1) an interest-adjusted basis, defined as the difference between the price of a one-month forward contract and the spot price of oil, adjusted for a risk-free rate that captures the opportunity cost of holding oil inventories; and (2) the current oil price. Inventories are expressed as a percentage deviation from their trend, using the HP filter, to align the empirical specification as closely as possible with Eq. (18). We proxy the risk-free rate with the federal funds rate. The resulting OLS estimates ($\widehat{\beta}_1$ and $\widehat{\beta}_2$) are then used to calibrate $\nu = \widehat{\beta}_1 - \widehat{\beta}_2 = 0.46$ and $\tau = \frac{-\widehat{\beta}_2}{\widehat{\beta}_1 - \widehat{\beta}_2} = 0.13$.[19]

The oil well decay rate ($\delta_\Lambda$) is calibrated to 0.038 based on the actual production profile described in the studies summarized in Table 4. This value corresponds to a production half-life of 18 months. The depreciation rate of the oil-saving capital ($\delta_z$) is set to 0.033, corresponding to a half-life of 21 months.

The short and long-run elasticities of supply and demand ($\sigma_{\text{SR}}$, $\sigma_{\text{LR}}$, $\eta_{\text{SR}}$, $\eta_{\text{LR}}$) then pin down the values of input substitutability in the oil and final good production processes ($\phi$, $\theta$, $\xi$, $\varphi$), using Eqs. (5), (6), (13), (14), as reported in Table 5.

[18] The value of $\chi$ pins down that of $\bar{Z}$. We can easily find the value of $S$ at steady-state that is consistent with the calibrated value of the oil service income share $\omega$, and we can also make the convenient assumption that $Z = S$. Then, we obtain the steady-state value of $O$ that is consistent with the income elasticity: $O = \frac{S}{\chi}$. Finally, we recover $\bar{Z} = O + Z - S$.

[19] To the best of our knowledge, there are no prior studies that provide estimates of the elasticities of storage demand with respect to expected oil-price changes or current oil prices, which are needed to calibrate the parameters in Eq. (18).

Table 5: Elasticities and the structural parameters

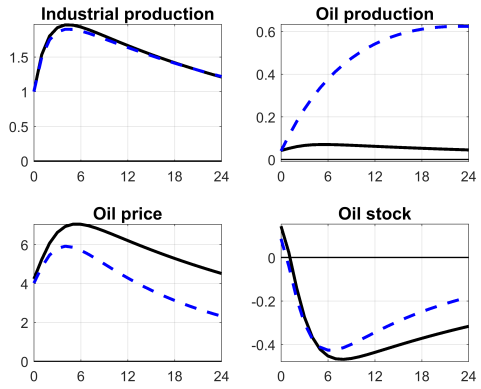
| Symbol | Structural parameters | Values implied by elasticities |
|---|---|---|
| $\phi$ | Labor/wells substitutability | $\phi = \frac{\lambda\sigma_{\text{SR}}}{1-\lambda}$ |
| $\theta$ | Capital/land substitutability | $\theta = (\sigma_{\text{LR}} - \sigma_{\text{SR}})\frac{\lambda\gamma}{(1-\gamma)}$ |
| $\xi$ | Oil-service/Labor-capital substitutability | $\xi = \eta_{\text{SR}}/\chi$ |
| $\varphi$ | Curvature in oil-saving capital cost | $\varphi = (\eta_{\text{LR}} - \eta_{\text{SR}})/\chi$ |

## 4.2 The dynamic elasticity of supply

We simulate the effects of a positive global economic activity shock (Figure 4, left panel) and a positive oil-consumption demand shock (Figure 4, right panel), under two scenarios that differ in their dynamic elasticities of oil supply. In the first scenario, motivated by KM12 and KM14, the short-run and long-run elasticities of supply are both set to 0.01, so the elasticity remains constant over horizons.[20] In the second scenario, we raise the long-run elasticity of supply to 0.52 and set the production half-life of oil wells to 18 months. As a result, the oil supply elasticity rises gradually with the horizon: it equals 0.01 on impact, reaches 0.20 after one year, and converges to 0.52 in the long run. These two scenarios thus differ in their dynamic elasticities of oil supply but have identical short-run elasticities. In both cases, the shock is calibrated to produce the same impact response of industrial production.

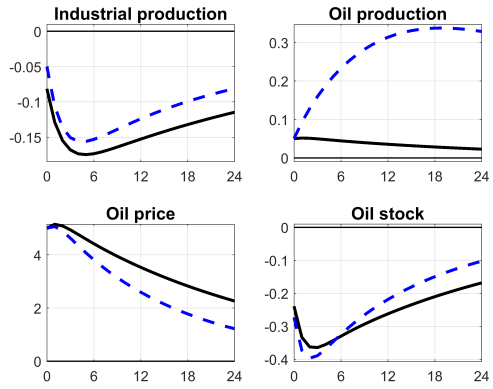
Figure 4: Demand shocks and the dynamic elasticity of supply

(a) Economic activity shock




*Black: KM14-inspired:* $\sigma_{SR} = \sigma_{LR} = 0.01$
*Blue:* $\sigma_{SR} = 0.01$, $\sigma_{LR} = 0.52$

(b) Oil consumption demand shock




*Black: KM14-inspired:* $\sigma_{SR} = \sigma_{LR} = 0.01$
*Blue:* $\sigma_{SR} = 0.01$, $\sigma_{LR} = 0.52$

[20] Note that in this case, the adjustment speed becomes irrelevant as the elasticities of supply and demand remain constant over time. The SRED and LRED are set to 0.26.

The favorable economic activity shock stimulates industrial production and the demand for oil inputs. The initial response of oil production is weak in both scenarios, owing to the identically low short-run elasticity imposed in both cases. In the KM-scenario, oil production remains muted in the medium and long runs as well. In the alternative scenario, by contrast, oil production rises gradually over time.

The dynamic elasticity of oil supply can substantially affect both the magnitude and the persistence of oil price responses to an economic activity shock. This shock generates a hump-shaped increase in industrial production and oil prices. When oil supply is more elastic over longer horizons, producers respond more strongly to higher expected oil prices by expanding future supply. This stronger response may reflect a larger drilling response driven by a greater ability to substitute capital investment for land in the drilling stage (Eqs. (1) and (6)). The resulting gradual increase in oil supply mitigates the imbalance between oil demand and supply caused by the shock, thereby lowering the peak in oil prices and speeding their return to the steady state. By contrast, the oil price response is more persistent when the supply is less elastic.

Similarly, the right panel of Figure 4 shows that a higher dynamic elasticity of oil supply mitigates the effects of an oil-consumption demand shock for both oil prices and global economic activity. In particular, the gradual expansion of supply reduces the persistence of the oil price increase and, in turn, dampens its adverse effects on economic activity, because oil prices enter final-goods producers' costs.

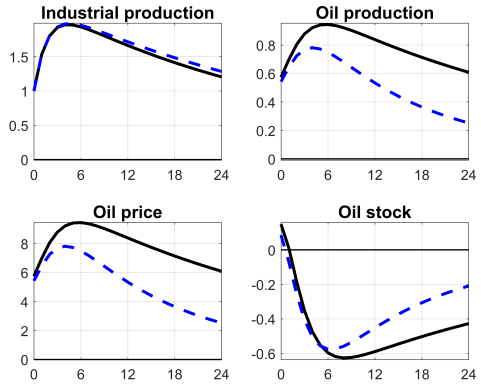
## 4.3 The dynamic elasticity of demand

We simulate the effects of a positive economic activity shock (Figure 5, left panel) and an adverse oil supply shock (Figure 5, right panel) under two scenarios that differ only in their dynamic oil demand elasticities. In the first scenario, the short-run and long-run demand elasticities are both set to 0.10, so the elasticity is constant across horizons. In the second scenario, we raise the long-run demand elasticity to 0.80.[21] We set the half-life of oil-efficiency capital to 21 months. The dynamic elasticity of oil demand thus rises gradually with the horizon: it equals 0.10 on impact, reaches 0.33 after one year, and converges to 0.80 in the long run.

[21] This value is higher than the available estimates presented in Section 5.2 but is chosen to clearly illustrate its effect on oil prices and real activity.

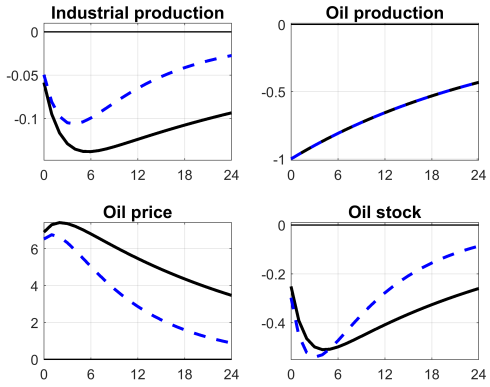
Figure 5: Shocks and the dynamic elasticity of demand

(a) Economic activity shock




*Black:* $\eta_{SR} = \eta_{LR} = 0.10$
*Blue:* $\eta_{SR} = 0.10$, $\eta_{LR} = 0.80$

(b) Oil supply shock




*Black:* $\eta_{SR} = \eta_{LR} = 0.10$
*Blue:* $\eta_{SR} = 0.10$, $\eta_{LR} = 0.80$

Following a favorable economic activity shock, oil prices rise less and return more quickly to steady state when the dynamic elasticity of oil demand is higher. In that scenario, firms respond to higher expected oil prices by increasing investment in oil-saving capital, which gradually lowers their dependence on oil inputs. The resulting improvement in oil-use efficiency reduces the imbalance between oil supply and demand, leading to a smaller and less persistent increase in oil prices.

Similarly, the dynamic elasticity of oil demand substantially affects both the magnitude and persistence of the response of oil prices and real activity to an oil supply shock.[22] An adverse oil supply shock raises oil prices and lowers industrial production, but these effects are smaller and less persistent when the dynamic elasticity of oil demand is higher. In that scenario, firms respond to higher expected oil prices by investing in oil-saving capital, which gradually reduces their dependence on oil inputs, and thereby speeds the adjustment of both oil prices and economic activity.

Looking at the contrasting IRFs to an oil supply shock in the original papers of KM12 and KM14 compared to BH19, a similar picture emerges. In all these studies, the oil supply shock affects oil production quite persistently, for at least 18 months. However, the persistence of the effect on prices strongly differs. In KM12 and KM14, the increases in oil prices are only

[22] For the oil supply shock, we set the supply elasticity to zero, so that the oil production follows exactly the same path in both scenarios. This allows us to isolate the role of the dynamic adjustment in demand by controlling for endogenous supply responses.

significantly different from zero for one month and one year, respectively. In both cases, the median oil price response quickly reverts to zero. The fact that prices quickly return to zero while oil production remains persistently lower hints at a stronger and quicker dynamic adjustment on the demand side. In contrast, in BH19, oil supply shocks have a strong and persistent effect on oil prices. Our analysis shows that differences in the dynamic elasticity of demand can potentially explain these contrasting results. Thus, a disagreement about the dynamic elasticity of oil demand in SVAR studies might also be playing an important role in identifying the contributions of demand and supply shocks.

## 4.4 The one-month price elasticities of oil supply

Finally, we simulate the effects of a positive global economic activity shock (Figure 6, left panel) and a positive oil-consumption demand shock (Figure 6, right panel) under two scenarios that differ only in their one-month oil supply elasticity. In the first scenario, this elasticity is set to 0.10, corresponding to the mode of the BH19 prior, whereas in the second scenario it is set to zero.[23] In both scenarios, the short-run and long-run price elasticities of demand are set to 0.26, and the long-run supply elasticity is set to 0.52.

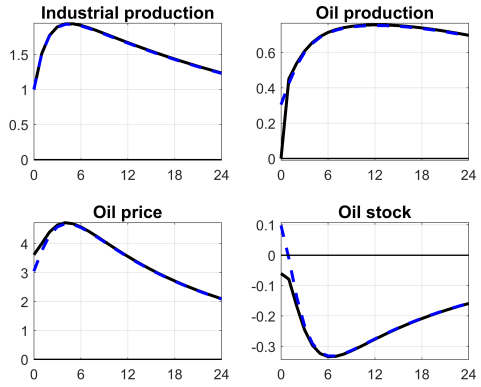
Imposing a perfectly inelastic oil supply in the very short run leads to only small deviations from the baseline responses of oil prices and real activity, with little effect on their longer-run dynamics, following any of the shocks. Oil prices rise more on impact when supply is not allowed to respond within the month, but this gap relative to the baseline dissipates quickly. Even on impact, the difference between the two scenarios remains limited, because inventories partially absorb the short-run imbalance created by the delayed supply response and agents anticipate that oil supply will begin adjusting after one month.

An important implication of these results is that varying the one-month elasticity of oil supply, while holding all other elasticities and parameters fixed, has only a limited direct effect on oil-price responses to demand shocks. This suggests that the widely used SVAR restrictions on that elasticity matter mainly to the extent they also alter other parameters of the model. Since the SVAR literature differs not only on the short-run drivers of oil prices,

[23] We implement the zero restriction by assuming that hours worked in the oil sector are fixed one month in advance, thereby shutting down only the impact response of oil supply. As a result, the one-month price elasticity of oil supply is zero in the second scenario, while the two-month elasticity is identical in both cases (see Appendix B.2 for details). The comparison allows us to isolate the role of contemporaneous supply elasticity.

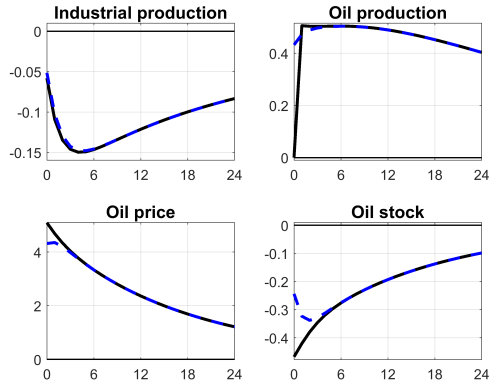
Figure 6: Demand shocks and the one-month elasticity of supply

(a) Economic activity shock




*Blue:* $\sigma_{SR} = 0.10$, $\sigma_{LR} = 0.52$
*Black: zero one-month elasticity of supply*

(b) Oil consumption demand shock




*Blue:* $\sigma_{SR} = 0.10$, $\sigma_{LR} = 0.52$
*Black: zero one-month elasticity of supply*

but also on the sources of oil-price fluctuations at medium to long horizons, the impact restrictions used in these studies may matter indirectly through their implications for other model parameters.[24] As discussed in Section 2, one important channel is that priors on the one-month price elasticities may also discipline demand and supply elasticities at longer horizons.

Overall, our theoretical results show that dynamic elasticities play a central structural role in the propagation and persistence of oil prices and real activity. The simulations in this section show that, even when the impact elasticity of supply is zero, changes in the horizon profiles of supply and demand elasticities alter the magnitude and persistence of responses to structural shocks. Dynamic elasticities govern the speed at which oil markets adjust over time and, by shaping expectations about future paths of supply and demand, also affect agents' current decisions. Our empirical analysis in the next section then demonstrates how these dynamic elasticities can be disciplined through prior restrictions.

[24] CCI19 reports the 24-month ahead forecast error variance decomposition of oil prices; KM12 up to 18 months; BH19 and K09 describe their cumulative effects with a historical decomposition.

# 5 Causes and macroeconomic consequences of oil price fluctuations

What drives oil price fluctuations, and what are their macroeconomic consequences? This section revisits these questions through the lens of our RBC model estimated with Bayesian methods (e.g., DeJong et al., 2000; Otrok, 2001; Schorfheide, 2000) in Dynare (Adjemian et al., 2011). We first describe our dataset (Section 5.1) and priors (Section 5.2). We then discuss the sign and magnitude restrictions implied by the model and show that they are comparable to those of SVAR models, with the additional advantage that our framework allows us to impose restrictions on dynamic elasticities (Section 5.3). We show that using prior information on the contemporaneous and dynamic elasticities materially changes the estimated contribution of oil supply and demand shocks to fluctuations in global oil prices and global economic activity and alters the interpretation of key historical episodes (Sections 5.4 and 5.5). Appendix D.8 reports additional sensitivity analysis based on alternative calibrations of the dynamic elasticities.

## 5.1 Data

In our benchmark estimation, we use four variables to characterize the global oil market: oil prices, oil inventories, oil production, and a world industrial production index, which proxies for global economic activity. The oil price measure is the average price index of crude oil from the World Bank Pink Sheet, deflated by the US CPI from the U.S. Bureau of Labor Statistics. The remaining three series are based on BH19 and updated by the authors.[25] Prior to estimation, the data are transformed as follows. Following BH19, we express changes in inventories as a fraction of lagged oil production. We transform the remaining three series into monthly growth rates. We also allow for measurement errors in inventories.

The data span the period from 1975M1 to 2019M12. The starting date is chosen to facilitate comparison with K09, KM12, KM14 and BH19, who estimate SVARs with 12 or 24 lags using monthly data beginning in 1973M1. The end date excludes the pandemic period. We also experimented with samples starting in 1985M1, at the beginning of the Great Moderation, as in CCI19, and in 1995M1 after oil supply became less volatile. These alternative starting

[25] Data are available at https://sites.google.com/site/cjsbaumeister/datasets.

dates allow us to account for potential time variation in the estimated parameters and to assess the drivers of oil prices over the most recent part of the sample.[26]

## 5.2 Prior distributions

We estimate two pairs of models that differ in their priors on short-run and dynamic elasticities of oil supply and demand, with priors summarized in Table 6. These four models then have identical priors or calibration for the remaining parameters, allowing us to isolate the role of priors about horizon-dependent elasticities in identifying the sources and macroeconomic consequences of oil price fluctuations.

The first pair is based on priors for the short-run elasticities of oil supply and demand motivated by KM14, while the second is based on priors motivated by BH19. In the cases inspired by KM14, the short-run elasticity of oil supply is bounded above by 0.026 using a rescaled Beta distribution defined on the interval $[0, 0.026]$, and the prior for the short-run elasticity of oil demand is centered around 0.26 (corresponding to the estimated mode in KM14). In the cases inspired by BH19, the priors are centered around 0.10 for both the short-run elasticities of demand and supply.

Table 6: The four models and their elasticity priors

| ***KM-benchmark*** | ***KM-informed*** | ***BH-benchmark*** | ***BH-informed*** |
|---|---|---|---|
| $\sigma_{\text{SR}} \in (0; 0.026)$ | $\sigma_{\text{SR}} \in (0; 0.026)$ | $\sigma_{\text{SR}} \sim G(0.10, 0.05)$ | $\sigma_{\text{SR}} \sim G(0.10, 0.05)$ |
| $\sigma_{\text{LR}} \sim G(0.52, 0.30)$ | $\sigma_{\text{LR}} \sim G(0.52, 0.05)$ | $\sigma_{\text{LR}} \sim G(0.52, 0.30)$ | $\sigma_{\text{LR}} \sim G(0.52, 0.05)$ |
| $\eta_{\text{SR}} \sim B(0.26, 0.10)$ | $\eta_{\text{SR}} \sim B(0.26, 0.10)$ | $\eta_{\text{SR}} \sim G(0.10, 0.05)$ | $\eta_{\text{SR}} \sim G(0.10, 0.05)$ |
| $\eta_{\text{LR}} \sim G(0.45, 0.30)$ | $\eta_{\text{LR}} \sim G(0.45, 0.05)$ | $\eta_{\text{LR}} \sim G(0.45, 0.30)$ | $\eta_{\text{LR}} \sim G(0.45, 0.05)$ |

*Note: G (B) = Gamma (Beta) distribution. First and second parameters are the means and stds.*

Within each pair, the benchmark specification combines these short-run priors with diffuse

[26] Our starting date excludes the 1973/74 oil crisis. As argued by Baumeister and Kilian (2016), there are two conflicting views regarding the drivers of the oil price increase in that period. The conventional view relies on an oil supply cut in response to the war between Israel and a coalition of Arab countries. But another likely explanation for the rise in oil price is an endogenous adjustment to a strong demand for oil combined with a devaluation of the dollar. At that time, the price of oil produced by Middle Eastern countries had been fixed for a duration of five years. It is thus possible that the increase in oil prices was the reflection of demand/supply imbalances that predated the war. Exploring this question would, however, best be answered with a model capturing a structural break in the pricing of oil. By applying our simple model to this period, we might wrongly fully associate the oil price increase in 73/74 with an oil supply shock, because our model does not account for fixed prices. Avoiding this issue is an extra motivation for starting our estimation in 1975.

priors on the dynamic elasticities of oil supply and demand, whereas the alternative specification combines them with priors informed by the empirical literature (see Section 2.1). The prior means for the long-run elasticities of oil supply and demand are set to 0.52 and 0.45, respectively.[27] The prior mean of the oil well decay rate ($\delta_\Lambda$) is set to 0.038 based on the actual production profile of oil wells, and the depreciation rate of the oil-saving capital ($\delta_z$) is set to 0.033.

To obtain diffuse priors on dynamic elasticities, we keep the benchmark prior means unchanged while substantially increasing the standard deviations of the prior distributions of the long-run elasticities. This greater uncertainty about long-run elasticities allows dynamic elasticities to take a wide range of shapes, provided the elasticities do not decline over time.[28] We examine how these priors shape the estimated dynamic elasticities (Section 5.4) and how, in turn, those elasticities affect the relative importance of supply and demand shocks (Section 5.5).

It should be noted that the priors are specified directly on the short-run and long-run elasticities rather than on the underlying structural parameters. Some candidate draws in our estimation process may imply long-run elasticities that are smaller than their short-run counterparts (in absolute value). Such draws are inconsistent with the structure of the model. In particular, Eqs. (6) and (14) imply that the long-run elasticities must be at least as large as the short-run elasticities, since both are obtained by augmenting the short-run response with additional adjustment margins. Violations of this condition would imply inadmissible values of the underlying CES parameters. We therefore impose the theoretical restriction $\sigma_{\text{LR}} \geq \sigma_{\text{SR}}$ and $\eta_{\text{LR}} \geq \eta_{\text{SR}}$ by replacing any offending long-run elasticity draw with the value of its short-run counterpart. Results are virtually unchanged when these draws are discarded instead.

The remaining parameters can be organized in two groups. For the first group ($\beta$, $\delta_k$, $\alpha$, $\psi$, $\sigma_c$, $\sigma_h$, $\omega$, $V$, $\gamma$, $\lambda$), we simply use the calibration described in Section 4.1. For the second group ($b$, $\chi$, $\nu$, $\tau$), we set our prior means to the calibrated values reported in that section. For more details on the priors and posteriors, also see Appendix D.1.

[27] The literature suggests that demand is 2.5 times more elastic in the long-run: a prior mean of 0.45 for the long-run elasticity represents a good compromise considering the prior means of 0.26 and 0.10 for the short-run elasticities in the KM and BH cases ($\frac{0.1+0.26}{2} \times 2.5 = 0.45$). Using Hamilton (2009)'s rule-of-thumb to evaluate the crude oil elasticity from gasoline studies, a value of 0.45 lies near the upper end of the range of the values presented in Table 2.

[28] For a visual inspection of our priors for dynamic elasticities, see Figure D.9 in Appendix D.1.

## 5.3 Sign predictions implied by the model

We now discuss the sign restrictions implied by the model, calibration, and our priors. We use the KM- and BH-benchmark models, as their diffuse priors about dynamic elasticities ensure that we span the full range of possible outcomes. We generate admissible IRFs implied by 1000 random draws from these priors. Figure D.10 in Appendix D.2 reports results based on 20 of these draws.[29] We interpret a sign restriction as being imposed a priori when all draws have the same sign on impact. We then compare the model's sign predictions with the standard sign restrictions used in the SVAR literature, summarized in Table 7.

Table 7: Sign restrictions in SVARs and in our RBC model

| | Oil supply | Global activity | Oil-consumption | Oil-inventory |
|---|---|---|---|---|
| Oil production | - | + | + | + |
| Industrial prod | - | + | - | - |
| Oil price | + | + | + | + |
| Inventories | - | | - | + |

Note: sign restrictions are imposed a priori in KM14 (note there is no oil-consumption demand in KM14, but the signs are also consistent with KM12). In BH19, the priors imply a high probability that these restrictions are satisfied. Black: restrictions common in SVARs and in our model. Green: restrictions in our model that are not imposed a priori in KM14 and BH19.

The model's predictions are consistent with the restrictions in KM14 and BH19, which have been widely used in the literature (e.g., Lippi and Nobili, 2012; Baumeister et al., 2010; Baumeister and Peersman, 2013b,a; Peersman and van Robays, 2009; Lütkepohl and Netšunajev, 2014).[30] Our framework therefore reproduces the standard SVAR sign restrictions while offering the additional advantage of permitting restrictions on dynamic elasticities.

The model also supports additional impact restrictions. In particular, whereas standard SVARs leave the sign of inventories unrestricted following oil supply and oil-consumption demand shocks, the model predicts, for all a priori plausible parameter values, that inventories fall after either an adverse oil supply shock or a positive oil-consumption demand shock. Lippi and Nobili (2012) and Baumeister and Peersman (2013a) developed structural models to rationalize sign restrictions that have been widely used in the literature. These models, however, do not incorporate oil inventories.

[29] Results are qualitatively similar with a larger number of draws.

[30] Moreover, the impact of oil-specific consumption (and inventory) demand shock on global industrial production is most likely quite small, which echoes the magnitude restriction of KM12. Indeed, an unexpected increase in oil prices of 10% caused by an oil-specific demand shock is unlikely to cause a fall in industrial production that is larger than 0.5%, on impact.

## 5.4 Estimated dynamic elasticities

Figure 7 reports the posterior medians and credible intervals of the dynamic elasticities of oil supply and demand. The posterior mean, mode, and credible intervals of all estimated parameters are reported in Appendix D.1.[31] Under the KM and BH benchmark specifications, diffuse priors yield posterior elasticities that are constant across horizons. Such profiles are difficult to reconcile with the evidence reviewed in Section 2.1, which points to elasticities that rise with the horizon rather than remaining constant. The implied long-run oil supply elasticities are also implausibly low, at 0.06 in the KM benchmark and 0.10 in the BH benchmark.

By contrast, informative priors generate dynamic elasticities that increase with the horizon, and imply posterior modes for medium- and long-run oil supply elasticities closely aligned with the available empirical evidence (see Section 2.1). The difference relative to the benchmark models is particularly pronounced for the long-run supply elasticity, whose posterior modes rise to 0.46 in the KM-informed model and 0.47 in the BH-informed model.[32]

On the demand side, the posterior mode of the long-run oil demand elasticity is about 0.42 in the KM benchmark and 0.23 in the BH benchmark. In the BH-informed model, the dynamic elasticity of oil demand also rises with the horizon, increasing from 0.22 in the short run to 0.43 in the long run. By contrast, the demand elasticity remains constant across horizons in both the KM benchmark and the KM-informed model, reflecting the relatively high short-run demand elasticity estimated in those specifications.

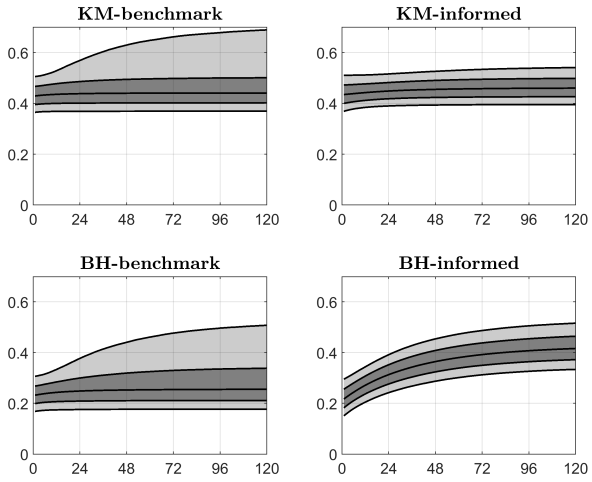
Overall, these results show that uninformative priors generate constant dynamic elasticities similar to SVAR-based elasticity proxies discussed in Section 2.2. This finding suggests that the estimation dataset contains limited information for identifying elasticities that increase with horizon. Imposing informative priors shifts the posterior toward dynamic elasticity profiles that are more consistent with the evidence. Section 6 further shows that augmenting the information set with drilling activity data also helps recover rising dynamic oil supply elasticities.

[31] Our estimated short-run elasticities are broadly in line with those of KM14 and BH19. The posterior mode of our SRES in the BH-benchmark model (0.10) is slightly lower than that of BH19 (0.15). The small difference may be explained by differences in the sample period and in the approximation of the oil consumption growth rate (see Rubaszek and Szafranek, 2025).

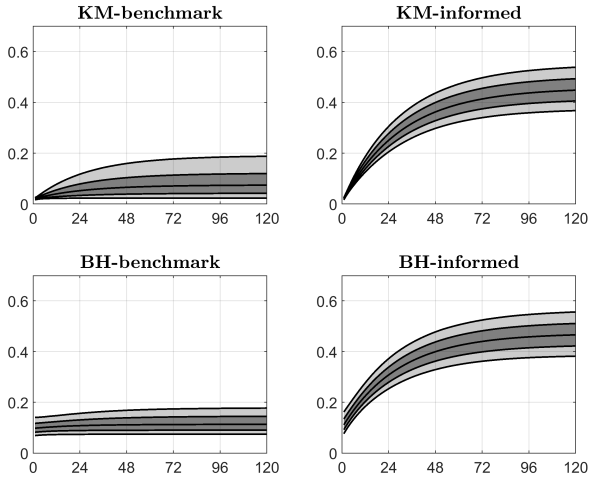
[32] At the 12-month horizon, the posterior median of supply elasticity is 0.15 in the KM variant and 0.22 in the BH variant. The average elasticities over months 1 to 12 stand at 0.09 and 0.17, close to the estimates in Bornstein et al. (2023) and Bogmans et al. (2024).

Figure 7: Estimated elasticities at different horizons

(a) Demand elasticities




(b) Supply elasticities




*This figure displays the posterior medians together with the 68% and 95% credible intervals of our demand and supply elasticities at different horizons, computed with equations (15) and (7). We vary the prior for the short and long-run elasticities in the four panels, while all other calibrated parameters and priors remain unchanged and are described in Section 5.2.*

## 5.5 The role of supply and demand shocks

### 5.5.1 Variance decomposition

Table 8 reports the forecast error variance decomposition (FEVD) across the four models for the four variables, attributed to the four structural shocks: oil supply, aggregate demand, oil-consumption demand, and oil-inventory demand. The results are discussed in turn.

Table 8: Variance decomposition across the four models

| | **Oil Supply** | **Aggregate Demand** | **Oil-consump Demand** | **Oil-invent Demand** |
|---|---|---|---|---|
| **KM-benchmark** | | | | |
| Oil prod | 86.71 | 2.45 | 9.88 | 0 |
| Ind prod | 0.32 | 86.48 | 13.02 | 0 |
| Oil price | 5.58 | 17.4 | 76.14 | 0.01 |
| *(10%-90%)* | (3.33 ; 9.41) | (10.61 ; 28.99) | (64.1 ; 84.39) | (0.01 ; 0.03) |
| Oil stock | 5.01 | 10.13 | 52.35 | 29.69 |
| **KM-informed** | | | | |
| Oil prod | 65.92 | 9.68 | 22.06 | 0 |
| Ind prod | 1.06 | 91.97 | 6.71 | 0 |
| Oil price | 16.43 | 16.39 | 66.14 | 0.02 |
| *(10%-90%)* | (11.68 ; 24.34) | (11.62 ; 23.82) | (57.06 ; 72.8) | (0.01 ; 0.05) |
| Oil stock | 8 | 8.08 | 42.44 | 39.71 |
| **BH-benchmark** | | | | |
| Oil prod | 58.23 | 8.55 | 31.06 | 0.01 |
| Ind prod | 0.87 | 90.18 | 8.55 | 0 |
| Oil price | 17.46 | 17.05 | 62.63 | 0.03 |
| *(10%-90%)* | (9.92 ; 30.25) | (10.4 ; 28.38) | (48.58 ; 75.28) | (0.01 ; 0.07) |
| Oil stock | 13.24 | 9.33 | 39.06 | 34.11 |
| **BH-informed** | | | | |
| Oil prod | 54.8 | 9.11 | 33.82 | 0.01 |
| Ind prod | 1.68 | 93.3 | 4.7 | 0 |
| Oil price | 37.7 | 11.38 | 50.01 | 0.05 |
| *(10%-90%)* | (27.33 ; 50.47) | (7.47 ; 16.41) | (39.47 ; 59.75) | (0.02 ; 0.11) |
| Oil stock | 17.94 | 5.37 | 28.52 | 46.15 |

*Note: Median variance decomposition at the infinite horizon. Units are percentages. Entries may not sum to 100% due to rounding and the use of the median. Variables are expressed in levels. For oil prices, we also report the first and last deciles of the credible interval.*

The first panel of Table 8 shows that supply shocks play a quantitatively negligible role in oil price fluctuations in the KM-benchmark model. Even at the 90th percentile of the posterior FEVD, they explain only about 9% of oil price fluctuations. Oil-consumption demand shocks instead dominate oil price fluctuations, accounting for 76% of the FEVD.

Because oil enters final-goods production, these shocks also affect real activity, explaining about 13% of the FEVD of industrial production. They also account for about 52% of fluctuations in oil inventories. This large contribution to oil inventories reflects the role of inventories in absorbing the imbalance between strong demand and weak oil production. Taken together, these results confirm the KM14 view within our framework: supply shocks do not matter when the short-run elasticity of oil supply is low and diffuse priors imply flat, low dynamic supply elasticities.

The third panel of Table 8 turns to the BH benchmark. The results confirm that priors on short-run elasticities matter quantitatively in the SVAR debate: the contribution of oil supply shocks to oil price fluctuations rises from 6% in the KM benchmark to 17% in the BH benchmark. At the same time this comparison is not driven by the short-run elasticity alone, since the two benchmark models also differ in their long-run elasticities. In the BH benchmark, the posterior mode of the long-run supply (demand) elasticity is 0.10 (0.23), compared with 0.06 (0.42) in the KM benchmark. These differences also help explain the larger role assigned to supply shocks in the BH benchmark, with a corresponding decline in the contribution of oil-consumption demand shocks for oil prices, oil inventories, and industrial production. In contrast, their contribution to oil production rises substantially, from about 10% to about 31%.[33]

We now turn to the quantitative role of informative priors on dynamic elasticities. The second panel of Table 8 shows that, within the KM specification, imposing informative priors on long-run elasticities raises the contribution of oil supply shocks from 6% in the benchmark model to 16% in the informed model. Appendix D.8 shows that this contribution could rise further—to about 27%—under a stronger long-run supply response, for instance, if the long-run supply elasticity were equal to 1 in the KM specification. This finding contrasts with the

[33] Surprisingly, the contribution of aggregate demand shocks to oil prices is similar in the KM benchmark and BH benchmark models, at 17.40 and 17.05%, respectively. To understand this result, we compute IRFs to an aggregate demand shock under combinations of demand and supply elasticities consistent with the priors in the two benchmark models (see Figure C.8 in Appendix C.4). While the higher supply elasticity in the BH benchmark dampens the effect of the shock, the lower demand elasticity amplifies it. These offsetting forces imply that the KM priors do not necessarily assign a larger role to aggregate demand shocks than the BH priors. The main quantitative difference between the two benchmark models instead concerns the relative importance of oil supply and oil-consumption demand shocks. A similar result emerges with SVAR models, as illustrated by the IRFs reported in Figure A.4 of Appendix A.3. Using the original BH19 model with alternative priors, as described in Section 2, we likewise find that differences in the IRFs are much more pronounced for oil supply and oil demand shocks—consumption and inventory demand—and are broadly similar for aggregate demand shocks. These findings suggest that the main issue in accounting for oil price fluctuations concerns the relative contribution of oil supply and oil-specific demand shocks, rather than aggregate demand shocks.

SVAR literature, which has typically assigned only a marginal role to supply shocks, when low values are imposed on the short-run price elasticity of oil supply. Correspondingly, the contribution of oil-consumption demand shocks declines substantially, from 76% to 66% for oil prices and from 13% to 7% for economic activity.

An important implication of our framework is that, once informative priors are imposed on dynamic elasticities in the KM specification, the KM informed and BH benchmark models imply much closer quantitative roles for supply shocks in oil price fluctuations—16% versus 17%—despite maintaining very different short-run supply elasticities. This finding suggests that disagreement in the SVAR literature reflects not only differences in impact elasticities, but also differences in the horizon profiles of oil market elasticities.

Finally, the fourth panel of Table 8 shows that informative priors on dynamic elasticities also matter quantitatively in the BH specifications. The contribution of oil supply shocks to oil price fluctuations rises from 17% in the BH benchmark to 38% in the BH-informed model, the largest share among the four specifications considered.[34] This large relative contribution of supply shocks reflects the combination of a strong supply response to demand shocks and a relatively low short-run oil demand elasticity. Although the long-run demand elasticity is also higher than in the BH benchmark, that effect is more than offset by the stronger supply response in the determination of oil prices. Correspondingly, the role of supply in industrial production also increases, while that of oil-consumption demand declines. For oil production, by contrast, the contribution of oil supply shocks falls slightly from about 58% to 55%, in the BH-informed model, while that of oil-consumption demand rises only modestly from 31% to 34%, suggesting that the stronger demand response is more important for that variable.

Overall, our framework shows that disciplining dynamic elasticities not only shifts the relative importance of structural shocks in global oil markets, but also helps reconcile competing views in the SVAR literature on the role of supply shocks in oil price fluctuations. While the four specifications differ in the role they assign to oil supply shocks, they share two features in common. Oil-consumption demand shocks remain central across the models, whereas oil-inventory demand shocks play a marginal role for oil prices, oil production and industrial production. The latter result reflects the fact that our variance decomposition is evaluated at the infinite horizon, while inventory demand shocks affect oil prices only

[34] Appendix D.8 shows that this contribution could rise further—to about 51%—under a stronger long-run supply response, for instance, if the long-run supply elasticity were equal to 1.

temporarily (see Figure D.13 and Appendix D.5). Moreover, a large fraction of fluctuations in inventory data are absorbed by a measurement error, which further limits the contribution of inventory-demand shocks.

### 5.5.2 When did supply shocks matter for global oil prices?

Figure 8 reports the historical decomposition of oil prices attributable to oil supply shocks across the four models.[35] Three points emerge. First, the interpretation of key episodes – notably the run-up in oil prices before the 2007-2008 global financial crisis (GFC) – depends on the priors imposed on the contemporaneous and dynamic elasticities of oil supply and demand. Second, for other episodes such as the Iranian Revolution and the Iran-Iraq war in the late 1970s and early 1980s, the four models deliver broadly similar narratives, although they differ in the relative contribution assigned to demand and supply shocks. Third, informative priors on dynamic elasticities generally assign a larger historical role to supply shocks.[36]

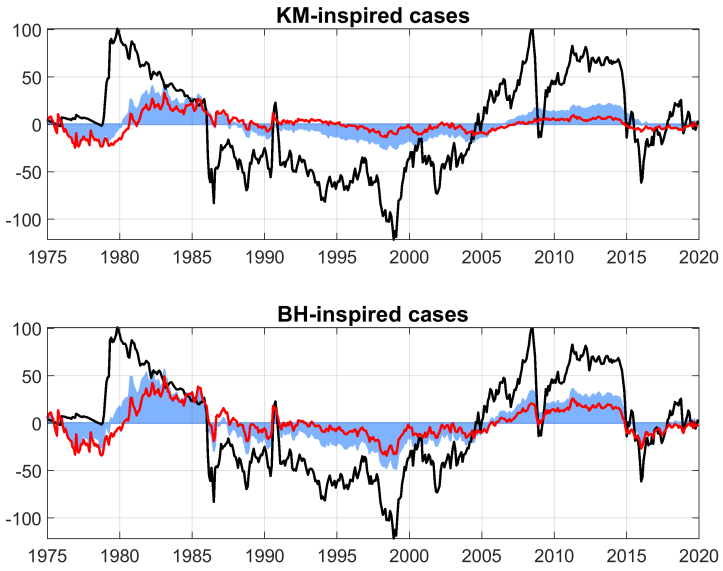
The four models agree that the 1979 oil-price spike during the Iranian Revolution cannot be attributed primarily to an oil supply shock.[37] The results also indicate that a sequence of adverse supply shocks exerted strong upward pressure on oil prices in the early 1980s, although with varying intensities across specifications. The Iranian Revolution in 1979 was followed by the Iran-Iraq war, which began in September 1980 and lasted for eight years. During this period, OPEC also attempted to counter the decline in oil prices from their 1979 peak. Our results suggest that, taken together, these supply shocks delayed the return of oil prices toward equilibrium, which would otherwise have occurred much sooner. The 1986 oil price collapse, by contrast, is explained by a combination of weak demand and abundant supply, partly associated with Saudi Arabia's reversal of its earlier policy of cutting production in response to falling prices. Among the four models, the contribution of oil supply shocks in the early 1980s is largest in the BH-informed model. Through the lens of the model with higher short-run and long-run supply elasticities, the combination of

[35] Appendix D.3 presents the results for economic activity and oil-consumption demand shocks.

[36] Historical decomposition for oil prices reported in Appendix D.3 also shows that, in several episodes, informative priors amplify the contribution of aggregate-demand and oil-consumption demand shocks.

[37] Instead, they point to a combination of global economic activity and oil-consumption demand shocks, consistent with Barsky and Kilian (2002) and KM14. The contribution of global economic activity shocks turns negative in the early 1980s as economic activity weakens following the tightening of US monetary policy under Volcker. By the mid-1980s, the contribution of oil-consumption demand shocks also turns negative, plausibly reflecting efforts to reduce oil use after the two major oil crises of the 1970s.

Figure 8: Historical contribution of supply shocks to oil-price fluctuations




*Note: Black: actual oil price fluctuations.*
*Blue: KM- and BH-informed models.*
*Red: KM- and BH-benchmark models.*

relatively high prices and falling oil supply can only be reconciled with larger adverse supply shocks.

By contrast, the sharpest disagreement across the four models concerns the oil price boom preceding the GFC. In the KM benchmark, supply shocks play essentially no role, in line with K09, KM12, and KM14. In the BH-informed model, they account for roughly half of the increase in oil prices, consistent with a view in which strong demand confronted unexpectedly stagnating supply. The two models therefore offer fundamentally different interpretations of a period marked by high oil prices and stagnating supply. In the KM benchmark, the weak supply response to higher prices is a normal implication of low supply elasticities, whereas in the BH-informed model, the same pattern reflects a sequence of adverse oil supply shocks that materially contributed to the oil price boom.[38]

Finally, oil supply shocks also contributed to the rise in oil prices observed after the GFC, although their role remains very limited in the KM benchmark. Plausible sources of these shocks include the Libyan uprising in 2011 and the sanctions imposed on Iran in 2012. Oil

[38] Despite this disagreement, the four models assign a central role to global economic activity shocks during the GFC and the subsequent recovery, see Appendix D.3.

supply shocks are also visible during the subsequent commodity-price slump–again except in the KM benchmark–coinciding with the period of rapid expansion of US shale production and Iran's return to the market.

## 5.6 Robustness

We assess the robustness of our results along three dimensions. First, we use the Index of Global Real Economic Activity (IGREA) proposed by K09 and used in KM12 and KM14, as an alternative measure of global demand for industrial commodities, in place of industrial production; see details in Appendix D.7.1. Our results are robust to replacing industrial production with IGREA. Diffuse priors continue to generate posterior dynamic elasticities that are essentially flat across horizons, while informative priors lead to posterior elasticities that increase with the horizon. As in the baseline, informative priors therefore increase the importance of supply shocks for oil price fluctuations. With IGREA, the FEVD for oil prices attributed to supply shocks rises from about 5% in the KM-benchmark to 15% in the KM-informed model.

Second, we re-estimate the models on the 1995M1-2019M12 subsample, rather than the 1975M1-2019M12 baseline sample; see details in Appendix D.7.2. The main conclusions remain qualitatively unchanged: informative priors on dynamic elasticities continue to play an important role in oil-market dynamics. At the same time, subsample results indicate that the short-run elasticities may have changed over time. For example, the posterior mode of the SRED and SRES in the BH benchmark falls from 0.23 and 0.10 in the full sample to 0.10 and 0.05 in the 1995-2019 sample. At the same time, uncertainty about very small elasticities magnifies uncertainty about the sources of oil price fluctuations. In the BH-benchmark model, the 10%-90% credible interval for the contribution of oil supply shocks to oil prices ranges from 14% to 51% in the recent period. In addition, the contribution of supply shocks increases in the KM-benchmark, owing to the decline in the posterior mode of the SRED and LRED.

Nevertheless, dynamic elasticities remain quantitatively important in the FEVD: supply shocks account for about 9% of price fluctuations in the KM benchmark, compared with about 17% in the KM informed model. Informative priors thus continue to amplify the role of supply shocks, although the effect is somewhat smaller than in the full sample. In the most recent sample, the SRED is lower, and the elasticity of demand can thus increase with

the horizon in the informed models. Finally, aggregate demand shocks play a larger role in the later sample across the four models, reflecting the lower oil-market elasticities estimated for the recent period.

Third, we assess robustness by relaxing prior discipline on short-run elasticities imposed in BH and KM benchmark specifications, replacing these priors with diffuse priors. This leads us to define an HM benchmark, in which both the short-run and dynamic elasticities are assigned diffuse priors. We compare this specification with an HM-informed model, which maintains diffuse priors on short-run elasticities but imposes informative priors on dynamic elasticities. This design allows us to isolate more clearly the role of dynamic elasticities in shock propagation, separately from their role in shock identification; see Appendix D.7.3 for details.

Our main qualitative conclusions remain unchanged. Informative dynamic priors continue to increase the role of supply shocks. At the same time, the HM benchmark reveals considerable uncertainty about the relative importance of supply and demand shocks. The 10th-90th percentile credible interval for the contribution of oil supply shocks to the FEVD of oil price fluctuations ranges from 7% to 24%, with a median of about 13%. We show that this uncertainty reflects the joint dependence among oil-market elasticities, which amplifies uncertainty in the FEVD. Informative priors help reduce this uncertainty and raise the median contribution of supply shocks to about 32%, confirming the baseline result that dynamic elasticities matter quantitatively. We further show that informative priors on dynamic elasticities have only a limited effect on shock identification. Therefore, we conclude that dynamic elasticities matter primarily for the propagation of oil-market shocks.

# 6 Discussion, model validation, and simulation

## 6.1 Discussion

Our framework introduces prior information on dynamic elasticities and shows that these priors matter for identifying the sources of oil-price fluctuations. The main advantage of our approach is that it combines different sources of prior information in a single structurally

coherent framework. It builds on the efforts of the SVAR literature[39], which has successfully exploited sign, magnitude, and short-run elasticity restrictions, and extends it by incorporating prior knowledge about dynamic elasticities. Since information for disciplining dynamic elasticities is available and materially affects the propagation of oil-market shocks, it should not be left unused.

The main drawback of introducing priors on dynamic elasticities is that they lead to a deterioration in marginal data density (MDD).[40] When the model is estimated using the traditional four oil-market variables—oil production, oil prices, oil inventories, and a measure of global economic activity—the likelihood tends to favor flat elasticity profiles and relatively small long-run elasticities, especially on the supply side. This result is not entirely surprising, since the IRF-based elasticity proxies constructed from SVAR using similar datasets tend to imply flat dynamic elasticity profiles where long-run elasticities are no larger than their short-run counterparts (see Section 2.2).

The lower marginal data density highlights an empirical tension between the standard four-variable likelihood and external evidence on the dynamics of oil supply. While the likelihood favors relatively flat supply-elasticity profiles, this result may reflect the limited information contained in the conventional information set about slow structural adjustment rather than evidence against the external restrictions themselves. These restrictions are informed by drilling activity, engineering sciences, and long-run elasticity estimates. Bayesian estimation is valuable precisely because it allows economically meaningful information outside the likelihood to be incorporated in a transparent way. In addition, Section 6.2 shows that augmenting the information set with drilling activity shifts the posterior toward a rising supply-elasticity profile.[41]

We also assess the models' ability to reproduce the correlations among the main variables used in the empirical analysis. Appendix D.6 reports the correlation coefficients in the data and in each of the four models. The results are mixed, depending on the pair of variables considered. Informative priors improve the correlation between oil production and industrial production in both KM and BH cases, bringing the model-implied moments closer to the

[39] For example, KM12 demonstrated the benefits of combining signs and magnitude restrictions, while BH19 developed a new method to introduce priors on short-run elasticities.

[40] The MDDs are -4052.24, -4062.24, -4041.96, and -4048.19 in the KM-benchmark, KM-informed, BH-benchmark, and BH-informed models, respectively.

[41] By the same logic, the fact that the MDD may also disfavor the KM12-KM14 prior bound on the short-run elasticity of oil supply is not, by itself, grounds for rejecting that restriction, provided the underlying evidence is interpreted as in Kilian (2022).

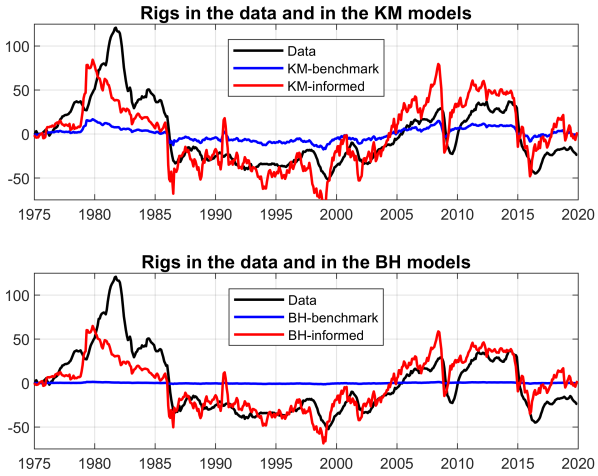
data. They also modestly improve some correlations involving inventories. By contrast, the BH benchmark matches the correlation between oil production and oil prices most closely, while the other three specifications move further away from the data. Finally, the KM-informed model improves the correlation between oil price and industrial production, whereas the BH-informed specification does not.

## 6.2 Model validation

To validate the framework, we bring data external to the baseline estimation, which relies on oil production, oil prices, oil inventories, and a measure of global economic activity. On the supply side, we use drilling activity, measured by oil rig counts, as an indicator of oil producers' investment aimed at raising production over the medium and long horizons. On the demand side, comparable long-run data on firms' investment in oil-use efficiency are not readily available. We therefore use US vehicle fuel efficiency as a proxy for oil-saving investment. This is a useful benchmark because road transportation accounts for a large share of crude oil consumption. We implement two exercises. First, we compare the model-implied path of rig counts and vehicle fuel efficiency with their observed counterparts across benchmark and informed specifications. This allows us to assess whether the mechanisms that generate dynamic elasticities in the model are consistent with observed adjustment patterns. Second, we augment the estimation dataset with rig counts as an additional observable variable and examine how this affects the dynamic supply elasticity.

Figures 9 and 10 report the results for the model-implied paths exercise for rig counts and vehicle fuel efficiency, respectively. One argument in favor of informative priors on dynamic elasticities of oil supply and demand is that they help the model better reproduce the dynamics of these observables. The results show that the KM and BH informed specifications track these external variables more closely than the corresponding benchmark models. By contrast, the benchmark specifications capture their dynamics only poorly. On the supply side, for instance, the short and long-run elasticities of oil supply are very close in the benchmark specifications. To generate such profiles, the model requires a perfect complementarity between capital (i.e., rigs) and land in the production of new wells (i.e., $\theta = 0$). This implies that oil drilling activity remains essentially constant and does not respond to oil price fluctuations, which is at odds with the evidence discussed in Section 2.1. A similar logic applies

Figure 9: Oil rigs in activity: models vs the data



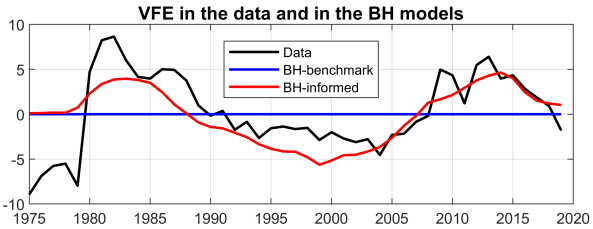

*Notes. RBC: dynamics of the unobserved drilling activity, as measured by $I_t(o)$ in percentage deviation from its steady-state, implied by the Kalman smoother, at the estimated modes in each model. Data: Baker Hughes international rig count in percentage deviation from its historical mean.*

on the demand side in the vehicle fuel efficiency exercise (Figure 10).[42]

Finally, we turn to our second model-validation exercise. We show that incorporating information from oil rig activity supports dynamic oil supply elasticities that rise with the horizon and implies a long-run elasticity consistent with the evidence reviewed in Section 2.1. In this exercise, we re-estimate the HM benchmark model, continuing to impose diffuse priors on contemporaneous and dynamic supply elasticities while adding in oil rig activity as a fifth observed variable. Specifically, we implement two minimal modifications to the model by introducing investment adjustment costs and a drilling-specific investment shock. Additional details are provided in Appendix E. Figure 11 reports the estimated dynamic oil supply elasticities and compares them with those obtained from the benchmark specifications.

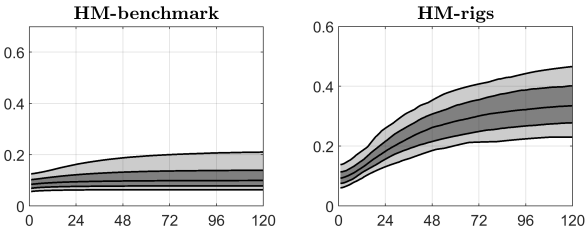
[42] In Figure 10, we only display the results from the BH-inspired models. In the KM-inspired models, the short and long-run elasticities of oil demand are almost equal, resulting in an almost constant level of fuel efficiency. This result is explained by the fact that the estimated short-run elasticity is already high in the KM-inspired model. This result depends more on the time-span of the data than on the short-run priors. For example, estimating the KM models starting after the Great Moderation produces lower short-run elasticities. In that case, the short and long-run elasticities differ in the KM-informed model, which then becomes better at matching the observed VFE data. It is also important to note that we de-trend the level of VFE to allow for a comparison with our RBC model concept of fuel efficiency. Specifically, we use a band-pass filter to remove periodicities longer than 30 years corresponding to the duration of a commodity super-cycle. Also note that the VFE data are only available at an annual frequency, so we compute the yearly average for our model-implied measure of fuel efficiency.

Figure 10: Vehicle fuel efficiency: models vs the data




*Notes. RBC: dynamics of the unobserved fuel efficiency, as measured by $Z_t$ in percentage deviation from its steady state, implied by the Kalman smoother, at the estimated modes in each model. Data: U.S. Environmental Protection Agency (miles per gallon for new light-duty vehicles in the United States) in percentage deviation from its historical mean. Data detrended with a band-pass filter to remove periodicities longer than 30 years (corresponding to the duration of a commodity super-cycle).*

Figure 11: Dynamic supply elasticities with rigs as an observed variable




*Notes: Supply elasticity in the HM-rigs model is approximated with the impulse response of oil production to an exogenous and permanent 1% increase in the oil price. We compare the HM-rigs model with the HM-baseline model, which is estimated using only four observables and excludes rig adjustment costs. Incorporating rig adjustment costs into the latter would have a negligible effect on the results, as rig investment remains virtually unchanged. Hence, the differences between the two models are primarily driven by the inclusion of rigs as a fifth observable.*

The results show that, once oil rig activity is added to the information set, the estimated supply elasticity rises with the horizon. In turn, this provides additional validation for the mechanisms capturing the dynamic adjustment of oil producers introduced in our model, and the use of informative priors in the baseline estimation.

## 6.3 Dynamic Elasticities in SVARs: Evidence from an RBC Model

In this section, we assess the ability of SVARs to recover dynamic elasticities using data simulated from a calibrated version of our RBC model. We focus on the supply elasticity, while the impact and dynamic elasticities of demand are held constant at 0.1. We set the

impact supply elasticity to zero, the long-run supply elasticity to 0.52, and the oil-well decay rate to 0.05. The corresponding structural dynamic oil-supply elasticities, $\sigma(h)$, are obtained with Eq. (7).

We proxy the supply elasticity at horizon $h$, $\hat{\sigma}^{\text{SVAR}}(h)$, by the ratio of IRFs of oil production to that of the real oil price following an economic activity shock. We construct an analogous supply-elasticity proxy directly from the RBC model, $\tilde{\sigma}^{\text{RBC}}(h)$, using the corresponding RBC impulse responses. This allows us to first examine the conditions under which the IRF-ratio proxy tracks the underlying true structural elasticities by comparing $\tilde{\sigma}^{\text{RBC}}(h)$ with $\sigma(h)$. Conditional on this first comparison, we then assess how closely the SVAR-based proxy, $\hat{\sigma}^{\text{SVAR}}(h)$, tracks the true structural elasticity.

The simulation exercise focuses on oil prices and quantities. Because we restrict attention to these two variables, we abstract from storage in the simulated RBC model. We simulate data from the calibrated RBC model driven by oil supply shocks and economic activity shocks.[43] We consider three degrees of persistence for these shocks: 0.8, 0.9 and 0.95. All other parameters are calibrated as in Section 4.1.

We perform two simulation exercises. First, we simulate a large sample of 500,000 monthly observations from the RBC model. Second, we conduct Monte Carlo simulations using 500 samples of 700 monthly observations, which is close to the size of the largest dataset used in BH19. This second exercise allows us to assess the role of sampling uncertainty. In both exercises, we do not combine simulated data with actual observations, since our objective is to evaluate whether SVARs can reproduce the impulse responses and dynamic elasticities generated by the RBC model. Successful recovery of the true structural dynamic elasticities in these exercises would provide a basis for combining RBC-based prior information with actual data in an SVAR framework, along the lines of the DSGE-VAR approach of Del Negro and Schorfheide (2004).

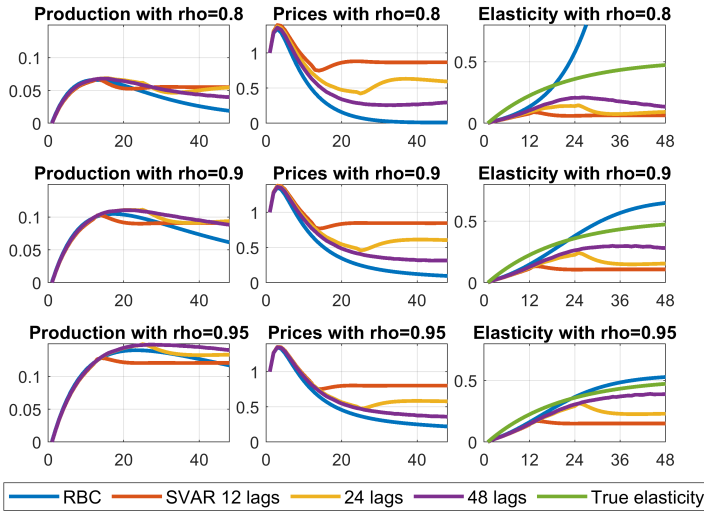
We estimate a two-variable SVAR model in first differences[44] by OLS using the simulated data and consider three lag specifications: 12, 24 and 48 lags. Structural shocks are identified through a Cholesky decomposition, with oil production ordered first so that its impact response to an economic activity shock is zero, consistent with the zero-impact supply elasticity

[43] The results are qualitatively similar when the simulated economy is driven by oil-specific consumption demand shocks instead of economic activity shocks.

[44] Because the SVAR is estimated in first differences, we use cumulated impulse responses to construct $\hat{\sigma}^{\text{SVAR}}(h)$.

imposed in the simulated RBC model.

Figure 12: IRFs, structural supply elasticities, and SVAR elasticity proxies




*Notes: The first and second columns show the IRFs of oil production and prices to an economic activity shock, respectively. These IRFs are computed from the RBC model used to simulate data (blue line) and from our SVAR models estimated on these data using 12, 24, or 48 lags (in red, yellow, purple). The third column shows supply elasticities in the RBC and SVAR models that are approximated with the ratio of these IRFs. These values are compared with the true structural value (in green) given by Eq. (7) with* $\sigma_{SR} = 0$, $\sigma_{LR} = 0.52$, *and* $\delta_{\Lambda} = 0.05$.

Figure 12 reports the IRFs of oil production and prices following an economic activity shock, together with the corresponding impact and dynamic supply-elasticity proxies constructed from IRF ratios in the SVARs and the RBC model using the large simulated sample. Figure 13 reports the medians across the 500 Monte Carlo replications based on samples of 700 observations, together with the corresponding 16th–84th percentile ranges. Both figures also report the true structural impact and dynamic supply elasticities implied by the RBC model.

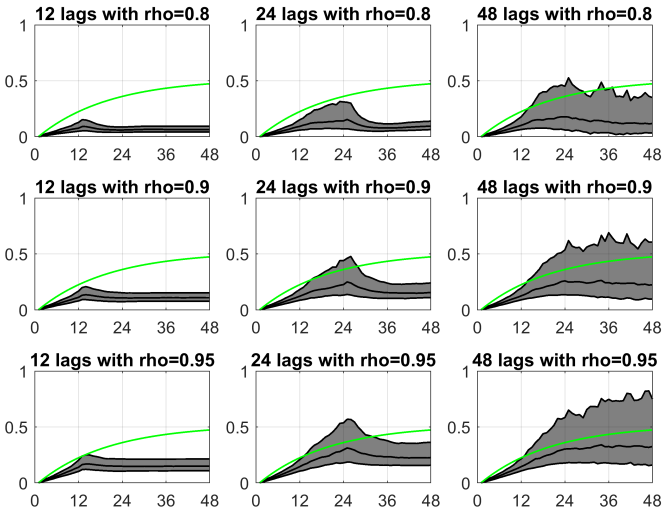
Three results emerge. First, Figure 12 shows that when shocks are less persistent ($\rho = 0.8$), the response of the real oil price decays faster than that of oil production. As a result, supply-elasticity proxies constructed from IRF ratios deviate more substantially from the true structural elasticity. By contrast, when shocks are more persistent ($\rho = 0.95$), prices adjust more gradually, and the *IRF-ratio proxies* track the true structural elasticities more closely. Notice, however, that the impact and very short-run dynamic elasticities, up to about three months, are consistently well recovered. The recovery problem therefore arises mainly at medium and longer horizons.

Second, Figure 12 shows that the ability of the SVAR to reproduce the RBC IRFs and

elasticity proxies, and hence the true structural elasticity, depends crucially on the lag specification. For $\rho = 0.95$, the 12-lag specification captures the initial increase in the dynamic elasticity but then begins to flatten around the 13-month horizon. As the lag length increases to 24 and 48 lags, the SVAR-based elasticity proxies move closer to both the RBC IRF-based proxies and the true structural elasticities. Intuitively, the lag specification should be sufficiently rich to capture the relevant horizon over which oil supply adjusts. In the RBC model, the speed of this adjustment is governed by the oil-well decay rate. With a decay rate set to 0.05 as in the simulation, oil-supply adjustment is largely completed within 48 months.[45] In this case, an SVAR with 48 lags is therefore substantially better able to capture the gradual dynamics generated by the RBC model.

These results also support the notion that the IRF-based elasticity proxies introduced in Section 2.2 provide a useful approximation of the underlying dynamic elasticities, at least over horizons covered by the SVAR lag structure, since the identified shocks generate persistent movements in oil prices.

Figure 13: Dynamic supply elasticities in short samples (700 observations)




*Notes: Supply elasticities in SVAR models are approximated with the ratio of these IRFs at the OLS estimates of SVAR parameters. The solid black line reports the median across 500 Monte Carlo replications and the shaded region reports the 16th–84th percentile range. Each replication uses 700 monthly observations simulated from the RBC model. The green line reports the structural value of the dynamic supply elasticity implied by the RBC model.*

Third, Figure 13 shows that, in small samples, there is a trade-off between bias in recovering

[45] Using Eq.(7) we obtain $\sigma(48) = 0.47$ and $\sigma(\infty) = 0.52$, implying that about 90% of the long-run adjustment has already been achieved by month 48.

the true structural dynamic elasticities and the precision of the estimated SVAR-based elasticity proxies across lag specifications. Under the 12-lag specification, the Monte Carlo bands are relatively narrow, but the true structural elasticities lie above the bands at medium and longer horizons, indicating a substantial downward bias in the SVAR-based dynamic elasticity proxies. This downward bias decreases somewhat as shock persistence increases, holding the lag specification fixed, but remains substantial at medium and longer horizons. As the lag length increases to 24 and 48 lags, the bias declines but the Monte Carlo bands widen substantially, reflecting lower precision of the estimates.

# 7 Conclusion

This paper develops a dynamic general equilibrium model to study the sources of crude-oil price fluctuations and their macroeconomic consequences. The framework delivers horizon-dependent elasticities of oil demand and supply through the gradual adjustment of producers and consumers over time. We distinguish between impact (short-run) elasticities, which govern within-month responses of supply and demand to oil price changes, and their longer-horizon counterparts, which we label dynamic elasticities. We derive closed-form expressions for the elasticities, allowing us to discipline empirical analysis with priors on short-run and dynamic elasticities within a simple RBC model. This is a key advantage relative to SVAR models, where dynamic elasticities are typically complex functions of many reduced-form parameters. More generally, our framework provides a tractable way to incorporate prior information on horizon-dependent elasticities into models of storable commodity markets, and provides a foundation for introducing RBC-based priors on dynamic elasticities in SVAR models. While we leave this issue for future research, it may also help discipline the calibration of models of the green transition, where long-run commodity demand and supply elasticities are central determinants of estimated transition costs.

Our theoretical results show that while short-run elasticities are primarily relevant for identifying structural shocks and their impact response, dynamic elasticities are central to their propagation. Accordingly, varying only the short-run elasticity of oil supply, while holding the longer-horizon elasticities fixed, mainly affects the contemporaneous responses of oil prices and real activity, with little effect on their subsequent dynamics. By contrast, varying the dynamic elasticities of oil supply and demand has a much stronger effect on oil prices and real activity at all horizons.

Our empirical analysis shows that diffuse priors on dynamic elasticities imply elasticity profiles that are essentially flat across horizons. This finding helps explain the SVAR debate, in which small differences in short-run supply elasticity can lead to large quantitative differences in the role assigned to supply shocks. By contrast, informative priors yield dynamic elasticities that rise with the horizon, increase the contribution of supply shocks, and reduce the importance of oil-consumption demand shocks. For instance, we find that oil supply shocks account for about 16% of oil price fluctuations when informative priors are imposed on dynamic elasticities, although the short-run supply elasticity is constrained to be no greater than 0.026. Under diffuse priors this share falls to 6%. A key contribution of our paper is thus to show that supply shocks can play a non-negligible role even when the short-run elasticity of oil supply is tightly constrained to a very low value, in contrast with the existing SVAR literature.

Robustness exercises leave our main results qualitatively unchanged. At the same time, the specification with diffuse priors on short-run and dynamic elasticities reveals substantial uncertainty about the relative importance of oil supply and demand disturbances. In particular, uncertainty about oil-market elasticities translates into substantial uncertainty in oil price dynamics. This uncertainty has two main sources. First, small changes in key elasticities can have large effects on oil price dynamics. Second, the joint posterior distribution of these elasticities displays substantial cross-parameter dependence, which further amplifies uncertainty. In addition, we show that an expanded information set including drilling activity supports dynamic oil supply elasticities that rise with the horizon.

# A Details on SVAR models (see Section 2)

Section 2.2 discussed the role of priors on short-run elasticities of oil supply and demand in SVAR models, based on estimates obtained with the original codes and data from BH19. This Appendix provides additional details on that analysis. Appendix A.1 presents the priors, data, and replication sources. Appendix A.2 presents the estimated shocks. Appendix A.3 reports estimated impulse response functions and the SVAR-based elasticity proxies.

## A.1 Data and priors

We proceed in two steps. First, we replicate the BH19 results using their original prior specification for all parameters. For the short-run supply elasticity, the BH19 prior is a Student's $t$ distribution with mode 0.1, scale parameter 0.2, and 3 degrees of freedom. Second, we modify the prior on the short-run supply elasticity to make it consistent with the upper bound of 0.026 imposed in KM14. Specifically, the KM-inspired prior is a Student's $t$ distribution with mode 0.01, scale parameter 0.005, and 100 degrees of freedom.

Figure A.1: Priors (PDFs) on the short-run elasticity of oil supply

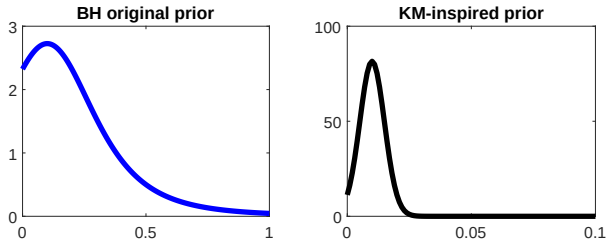


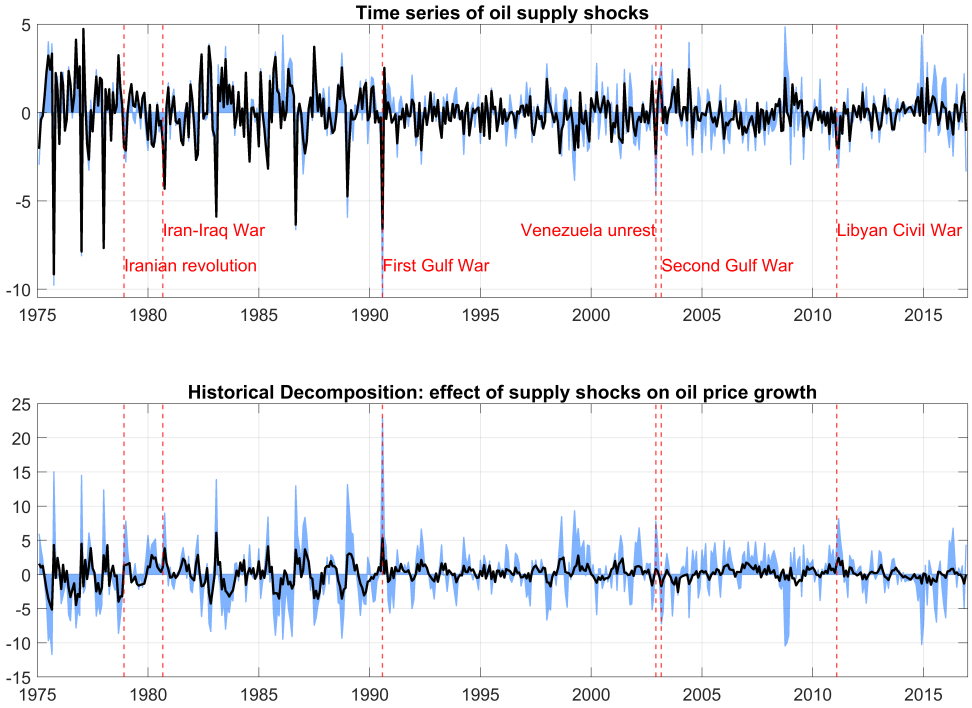

Figure A.1 reports the prior distributions for the short-run elasticity of oil supply. Under the KM-inspired prior, the probability that this elasticity exceeds 0.026 is essentially zero. By contrast, the original BH19 prior is much more diffuse and implies about 10% probability that the elasticity exceeds 0.5.

All other priors are kept identical in both cases as defined in BH19. For example, the prior on the short-run demand elasticity is a Student's $t$ distribution with mode 0.1, a scale parameter of 0.2, and 3 degrees of freedom. For additional detail see Baumeister and Hamilton (2019). The data and replication codes are available from https://sites.google.com/site/cjsbaumeister/research.

## A.2 Estimated structural shocks

**Oil supply shocks** Figure A.2 compares the structural supply shocks identified with the BH-original and KM-inspired models. Overall, we find that the time series of the identified structural supply shocks with these two models are broadly similar: the contemporaneous correlation coefficient between the two series is very high, at 0.87. In addition, the two different identification strategies are successful in identifying the major oil supply shocks described in Antolín-Díaz and Rubio-Ramírez (2018). These small differences in time series of the structural supply shocks are thus an unlikely explanation for the very different roles that these shocks play in the models of KM14 and BH19.

Figure A.2: Time series of structural oil supply shocks and their effect on oil prices: BH (blue) vs KM-inspired (black) models




We identified many periods in which the time series of the shocks are similar, yet the historical decomposition differs. This is the case for most well-known supply shocks such as the Iranian Revolution, the Iran-Iraq war, and the first Gulf War. In these periods, shocks of similar size translated into different impacts on oil prices, as displayed in the lower panel of Figure A.2. The implication is that the SVAR disagreement about the sources of oil-price fluctuations is

not only a matter of shock identification, but also a matter of how similar shocks can affect oil prices. Indeed, the IRFs in Appendix A confirm that a one-standard-deviation shock has similar impacts on oil production in the BH and KM-inspired models, but has different consequences for oil prices.

Nevertheless, there are also periods where the shocks differ across the BH-original and KM-inspired models. For instance, the 2004-2005 period is characterized by adverse oil supply shocks according to the BH-original model, but we do not find such shocks in the KM-inspired variant. These two models thus give a different interpretation of the stagnating supply observed during the oil price boom in 2004-2005. This behavior is expected according to the KM-model where oil supply is price-inelastic, while it is surprising (i.e. a shock) through the lens of the BH model. Another example is the commodity price slump in 2015, where the relatively abundant oil supply during a period of low prices is interpreted as a positive oil supply shock in the BH-original model, but not in the KM-inspired variant.

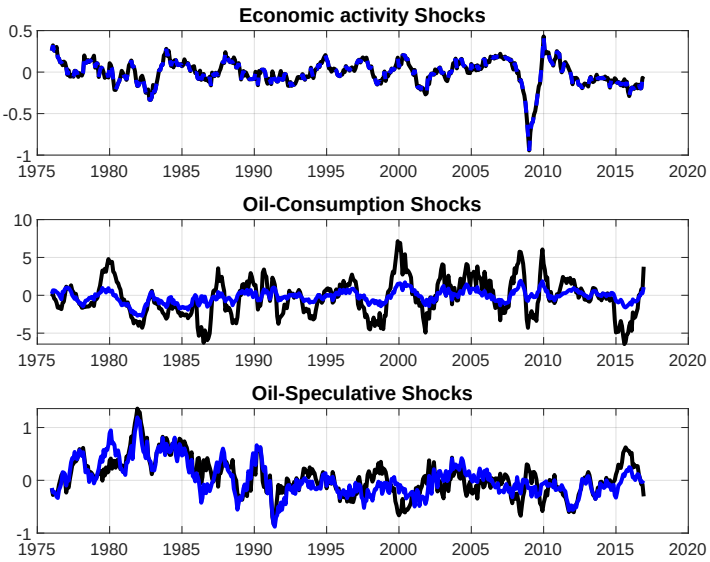
**Demand shocks** Figure A.3 compares the structural demand shocks identified with the BH-original and KM-inspired models. Overall, the time series of the identified structural demand shocks are broadly similar in these two models. The contemporaneous correlation coefficients between each pair of demand shocks are very high, at 0.99, 0.83, and 0.81 for aggregate demand, consumption demand, and inventory demand shocks, respectively. One difference stands out: the variance of oil consumption demand shocks is larger in the KM-inspired model. In the next subsection, we show that a one standard deviation oil consumption demand shock has a larger impact on oil prices in the KM-inspired model.

## A.3 IRFs and the implied elasticities

Figure A.4 shows the impact of one standard deviation shocks in the BH-original (blue) and KM-inspired models (grey). The dashed lines and shaded area show the 68% credible bands.

These IRFs show that the most important drivers of oil price fluctuations in the original model of BH19 are oil consumption demand and oil supply shocks. When using the KM-inspired prior on the short-run elasticity of oil supply (thus imposing a small value on this elasticity), the impact of a (one standard deviation) oil supply shock declines, while the impact of an oil consumption demand shock increases.

Figure A.3: Time series of structural demand shocks:
BH (blue) vs KM-inspired (black) models
(12-month moving averages)




The IRFs to an oil supply shock also show that the different impact of oil supply shocks in the two models cannot be explained by the size of the supply disturbance, thus ruling out this simple explanation. Since the responses of oil production and oil inventories are similar in both models, while the oil price responses differ across all horizons, a more likely explanation for the SVAR disagreement is a difference in the dynamic elasticity of oil demand.

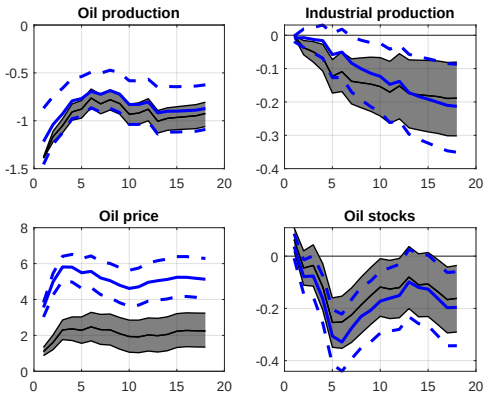
The IRFs to an oil consumption demand shock also show that the short and long-run elasticities of oil supply probably differ in the two models. Indeed, with the KM-inspired prior, the relatively stronger increase in oil prices only results in a small increase in oil production on impact. In the medium run, oil supply *declines*. In contrast, the relatively smaller increase in oil prices in the original BH model results in a persistent increase in oil production.

In Section 2.2, we compute the elasticity of oil supply using an oil consumption demand shock. The reason is that this shock is the most important driver of oil prices (on the demand side). Here, we also approximate this elasticity using the other demand shocks. The results are displayed in Figure A.5.

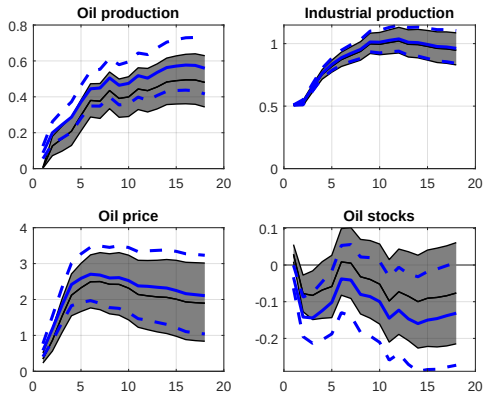
For a given model (i.e., KM or BH), the short-run elasticities of oil supply are identical for the three demand shocks. The reason is simple: in the short run, oil supply can only respond to a change in prices (or to an oil supply shock), as implied by equation (27) in the original

Figure A.4: IRFs in SVARs (68% credible bands, one-standard-deviation shocks)
BH-original prior (blue) vs KM-inspired prior (black)

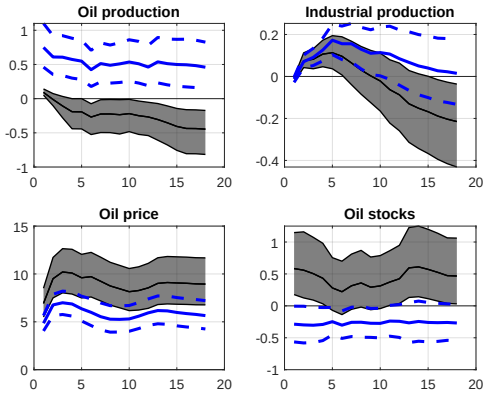
(a) Oil supply shock




(b) Economic activity shock




(c) Oil consumption demand shock




(d) Oil inventory demand shock

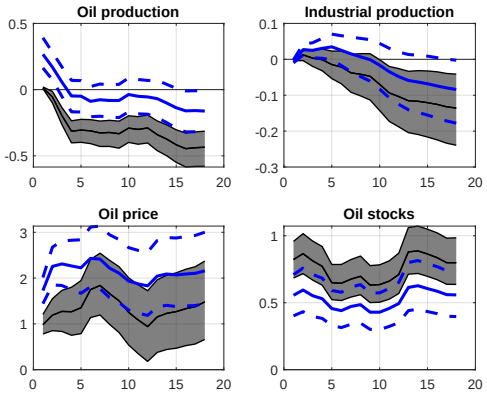
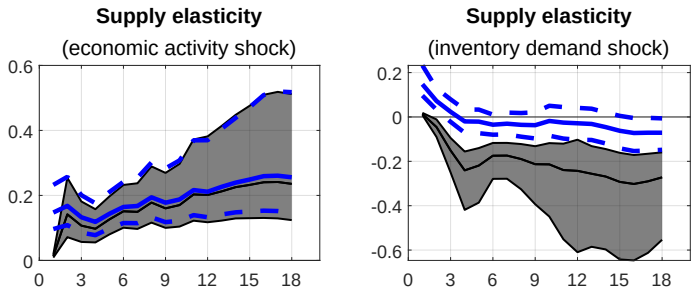


Figure A.5: Approximated supply elasticities with other demand shocks:
BH (blue) vs KM-inspired (grey) models




paper of BH19. The IRF ratio is thus simply given by the short-run elasticity of oil supply (denoted $\alpha_{qp}$ in their paper).

The dynamic elasticities approximated with IRF ratios are shock-dependent in SVAR models, as the auto-regressive coefficients ($b$) start playing a role. For example, in the original BH model, the approximated price elasticity of oil supply converges to about 0.25 with aggregate demand shocks, while it becomes negative with an inventory demand shock. In contrast, the dynamic elasticities are given by a few structural parameters in the RBC model.

Going back to a comparison between the BH-original and KM-inspired models, we find that the oil supply elasticities derived from an aggregate demand shock differ in the short run, but not in the medium run. In fact, the auto-regressive coefficients show that oil production loads on industrial production. Oil production thus catches up with industrial production progressively, as the shock has a relatively large impact on this variable. This is an additional motivation to use an oil-specific demand shock, which is closer to the ceteris paribus requirement often used when defining elasticities.

The oil supply elasticities derived from an oil-inventory demand shock in the two models differ in both the short and medium runs. In this case, the elasticity proxies turn negative, which can be interpreted as a motivation to use a structural model capable of ruling out these negative supply elasticities across all horizons.

# B Details on the RBC model of the crude oil market

This appendix is designed to be self-contained. Section B.1 studies the oil producers' problem and derives a closed-form expression for the short-run supply elasticity. Section B.2 shows how to impose a zero impact elasticity of oil supply, while leaving the elasticity unchanged at longer horizons, and Section B.3 derives the corresponding long-run supply elasticity. Section B.4 derives the dynamic elasticity of supply. Section B.5 studies the final-goods producers and derives a closed-form expression for the short-run demand price elasticity. Sections B.6 and B.7 derive the corresponding long-run and dynamic demand elasticities, respectively. Section B.9 characterizes the household problem. Section C.1 provides additional details on the calibration of standard parameters. Section D.2 reports the model's sign predictions.

## B.1 The short-run elasticity of oil supply

The short-run price elasticity of oil supply is defined as the ratio of the percentage change in oil supplied to the percentage change in the price of oil within one month. This section derives a closed-form expression for that elasticity.

Risk-neutral oil producers maximize the present value of profits

$$\mathrm{E}_0 \sum_{t=0}^{\infty} \beta^t \left[ p_t Y_t(o) - I_t(o) - w H_t(o) \right], \tag{A.1}$$

where $\beta$ is their discount factor and $p_t$ is the real price of oil, i.e. the nominal price divided by the final good price. We assume that $w$ is a constant unit labor cost and that investment goods are produced with one unit of the final good. The production technology is given by the following three equations.

Oil is produced by operating existing wells using labor

$$Y_t(o) = \varepsilon_t^{os} \left[ (1-\lambda)^{\frac{1}{\phi}} H_t(o)^{\frac{\phi-1}{\phi}} + (\lambda)^{\frac{1}{\phi}} \Lambda_t^{\frac{\phi-1}{\phi}} \right]^{\frac{\phi}{\phi-1}}, \tag{A.2}$$

where $\phi$ is the elasticity of substitution between labor, $H_t(o)$, and wells, $\Lambda_t$, in oil production,

$1-\lambda$ is the labor share, and $\varepsilon_t^{os}$ is an exogenous oil-supply shock. Linearizing this production function around the steady state gives*:

$$\hat{Y}_t(o) = (1-\lambda)\,\hat{H}_t(o) + \lambda\,\hat{\Lambda}_t(o) + \hat{\varepsilon}_t^{os}. \tag{A.3}$$

New wells, $\Lambda_t^{new}$, are drilled on available land using investment in physical capital

$$\Lambda_t^{new} = a(o)\left[(1-\gamma)^{\frac{1}{\theta}} I_t(o)^{\frac{\theta-1}{\theta}} + (\gamma)^{\frac{1}{\theta}} L^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}, \tag{A.4}$$

where $\theta$ is the elasticity of substitution between capital investment ($I_t(o)$) and land ($L$) in the production of new wells and $\gamma$ is the income share of land. The stock of new exploitable land ($L$) available in each period is fixed. The parameter $a(o)$ is a scaling constant. Log-linearizing this expression around the steady state, assuming a fixed stock of land, gives:

$$\hat{\Lambda}_t^{new} = (1-\gamma)\hat{I}_t(o). \tag{A.5}$$

These newly drilled wells are added to the stock of producing wells with a one-period lag.

$$\Lambda_t = (1-\delta_\Lambda)\Lambda_{t-1} + \Lambda_{t-1}^{new}, \tag{A.6}$$

where existing wells depreciate at a rate $\delta_\Lambda$, capturing the decline in productive capacity of existing wells as reservoir pressure gradually declines over time (see e.g. Chapter 3 of Dake, 1978). Log-linearizing around the steady state yields

$$\hat{\Lambda}_t = (1-\delta_\Lambda)\hat{\Lambda}_{t-1} + \delta_\Lambda \hat{\Lambda}_{t-1}^{new}. \tag{A.7}$$

The first-order condition of Eq. A.1 w.r.t. hours worked, $H_t(o)$, is $p_t \frac{\partial Y_t(o)}{\partial H_t(o)} = w$. Developing this expression and combining with Eq. A.2 gives:

$$w = p_t(1-\lambda)^{\frac{1}{\phi}} \left(\frac{H_t(o)}{Y_t(o)}\right)^{-\frac{1}{\phi}} (\varepsilon_t^{os})^{\frac{\phi-1}{\phi}}. \tag{A.8}$$

* Variables with hat denote percentage deviations from their steady-state values

Isolating $H_t(o)$ yields the labor demand equation:

$$H_t(o) = (1-\lambda)Y_t(o)\left(\frac{p_t}{w}\right)^{\phi}(\varepsilon_t^{os})^{(\phi-1)}. \tag{A.9}$$

Linearizing this expression gives:

$$\hat{H}_t(o) = \hat{Y}_t(o) + \phi\hat{p}_t - (1-\phi)\hat{\varepsilon}_t^{os}. \tag{A.10}$$

To find a closed-form expression for the short-run elasticity of oil supply, we impose two restrictions. First, the stock of wells is fixed at its steady state since investment in new wells is assumed to take one month to become productive, so $\hat{\Lambda}_t(o) = 0$, in the short run. Second, there are no supply shocks, $\hat{\varepsilon}_t^{os} = 0$. Substituting the linearized labor demand, Eq. A.10, into the linearized-production function, Eq. A.3, yields:

$$\hat{Y}_t(o) = \frac{\phi(1-\lambda)}{\lambda}\hat{p}_t, \tag{A.11}$$

$$\hat{Y}_t(o) = \sigma_{\text{SR}}\,\hat{p}_t. \tag{A.12}$$

## B.2 Imposing a zero elasticity of oil supply on impact

We show how we can impose a zero elasticity of oil supply on impact, while leaving the elasticity unchanged at all subsequent horizons. To do so, we assume that hours worked in period $t$ are chosen one period in advance (in $t-1$). Under this assumption, all production inputs are fixed within the month, so the impact elasticity of oil supply is zero. From the second month onward, however, the elasticity is identical to that in the baseline model. Specifically, the production function becomes:

$$Y_t(o) = \varepsilon_t^{os}\left[(1-\lambda)^{\frac{1}{\phi}}H_{t|t-1}(o)^{\frac{\phi-1}{\phi}} + (\lambda)^{\frac{1}{\phi}}\Lambda_t^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}. \tag{A.13}$$

The first-order condition of Eq. A.1 w.r.t. hours worked in the next period, $H_{t+1|t}(o)$, is $\mathrm{E}_t p_{t+1}\frac{\partial Y_{t+1}(o)}{\partial H_{t+1|t}(o)} = w$. Under the timing assumption, the impact elasticity is zero because both hours and new wells are predetermined: on impact, production cannot be adjusted to an unexpected change in oil prices. The dynamic elasticities are unchanged, and from the second month onward, we can show that this elasticity is numerically equivalent to that of

our baseline model.

## B.3 The long-run elasticity of oil supply

The long-run price elasticity of oil supply is defined as the ratio of the percentage change in oil supplied to the percentage change in the price of oil after a permanent oil-price change, once the economy has converged to its new steady state. This section derives a closed-form expression for that elasticity. Specifically, we combine the linearized production function with oil producers' labor and investment decisions, while imposing the long-run equilibrium condition $\hat{x}_t = \hat{x}_{t+s}\ \forall x$. For example, assuming the long-run equilibrium condition, $\hat{\Lambda}_t = \hat{\Lambda}_{t-1}$, Eq. A.7 yields:

$$\hat{\Lambda}_t = \hat{\Lambda}_t^{new}. \tag{A.14}$$

It is useful to decompose the oil producer's problem into two margins: $(i)$ the current-period utilization of existing wells, which can be represented as a rental decision for existing productive capacity; and $(ii)$ the investment decision for new wells, which governs the accumulation of future capacity. This decomposition is adopted purely for expositional convenience. Because the rental rate of a well equals its marginal product, the investment choice is independent of whether the producer ultimately uses the well in its own operations or rents it out to another producer.

We begin with the rental decision for existing wells. At the rental rate $r_t^{\Lambda}$, the first order condition of Eq. A.1 w.r.t. wells, $\Lambda_t$, is: $p_t \frac{\partial Y_t(o)}{\partial \Lambda_t} = r_t^{\Lambda}$. Expanding this expression and combining with Eq. A.2 yields:

$$r_t^{\Lambda} = p_t(\lambda)^{\frac{1}{\phi}} \left( \frac{\Lambda_t}{Y_t(o)} \right)^{-\frac{1}{\phi}} (\varepsilon_t^{os})^{\frac{\phi-1}{\phi}}. \tag{A.15}$$

Linearizing the resulting expression around the steady state yields the following demand function for wells:

$$\hat{\Lambda}_t = \hat{Y}_t(o) + \phi \left( \hat{p}_t - \hat{r}_t^{\Lambda} \right) - (1-\phi)\hat{\varepsilon}_t^{os}. \tag{A.16}$$

We now turn to the investment decision for new wells. Oil producers maximize

$$\mathrm{E}_0 \sum_{s=0}^{\infty} (1-\delta_\Lambda)^s \beta^{1+s} r^\Lambda_{t+1+s} \Lambda^{new}_t - I_t(o), \tag{A.17}$$

where the first terms represent the discounted values (starting in the next period) of the future income associated with a new well that depreciates at the rate $\delta_\Lambda$, and the second term is the investment cost. The first order condition of A.17 w.r.t $I_t(o)$ yields the well-investment function

$$\sum_{s=0}^{\infty} (1-\delta_\Lambda)^s \beta^s r^\Lambda_{t+1+s} \frac{\partial \Lambda^{new}_t}{\partial I_t(o)} = \frac{1}{\beta}, \tag{A.18}$$

where using Eq A.4 we define

$$\frac{\partial \Lambda^{new}_t}{\partial I_t(o)} = a(o)^{\frac{\theta-1}{\theta}} (1-\gamma)^{\frac{1}{\theta}} \left( \frac{I_t(o)}{\Lambda^{new}_t} \right)^{-\frac{1}{\theta}}. \tag{A.19}$$

Log-linearizing the well-investment function around the steady state yields:

$$\sum_{s=0}^{\infty} (1-\delta_\Lambda)^s \beta^s \left[ \hat{r}^\Lambda_{t+1+s} - \frac{1}{\theta} \left( \hat{I}_t(o) - \hat{\Lambda}^{new}_t \right) \right] = 0. \tag{A.20}$$

In the long run, when $\hat{x}_t = \hat{x}_{t+s}\ \forall x$, this expression simplifies to:

$$\hat{r}^\Lambda_t = \frac{1}{\theta} \left( \hat{I}_t(o) - \hat{\Lambda}^{new}_t \right). \tag{A.21}$$

Finally, using $\varepsilon^{os}_t = 0$, we obtain the following system of six equations:

$$\hat{Y}_t(o) = (1-\lambda)\hat{H}_t(o) + \lambda \hat{\Lambda}_t, \qquad \text{(oil production, Eq. (A.3))} \tag{A.22a}$$

$$\hat{H}_t(o) = \hat{Y}_t(o) + \phi \hat{p}_t, \qquad \text{(labor demand, Eq. (A.10))} \tag{A.22b}$$

$$\hat{\Lambda}_t = \hat{Y}_t(o) + \phi \left( \hat{p}_t - \hat{r}^\Lambda_t \right), \qquad \text{(oil-well demand, Eq. (A.16))} \tag{A.22c}$$

$$\hat{\Lambda}^{new}_t = (1-\gamma)\hat{I}_t(o), \qquad \text{(new oil wells, Eq. (A.5))} \tag{A.22d}$$

$$\hat{I}_t(o) = \hat{\Lambda}^{new}_t + \theta \hat{r}^\Lambda_t, \qquad \text{(oil-well investment, Eq. (A.20))} \tag{A.22e}$$

$$\hat{\Lambda}_t = \hat{\Lambda}^{new}_t, \qquad \text{(oil-well stock, Eq. (A.14)).} \tag{A.22f}$$

Solving this system for $\hat{Y}_t(o)$ yields:

$$\hat{Y}_t(o) = \left[\frac{\phi(1-\lambda)}{\lambda} + \frac{\theta(1-\gamma)}{\lambda\gamma}\right]\hat{p}_t, \tag{A.23}$$

$$\hat{Y}_t(o) = \sigma_{\text{LR}}\,\hat{p}_t. \tag{A.24}$$

## B.4 Dynamic elasticity of oil supply

We now derive the price elasticity of oil supply at an arbitrary horizon $h$. The derivation proceeds in three steps. First, we show that, in the absence of drilling adjustment costs, investment in new wells adjusts immediately to its new long-run level following an unexpected and permanent increase in the oil price. Second, we decompose the response of oil production into an immediate intensive-margin response and a gradual response through the stock of producing wells. Third, we use the law of motion for producing wells to characterize this gradual adjustment and derive the closed-form expression for the dynamic elasticity of oil supply.

First, we show the immediate adjustment of investment in new wells. Combining the log-linearized oil-production function, Eq. A.22a, with the log-linearized labor-demand equation, Eq. A.22b, gives:

$$\hat{H}_t(o) - \hat{\Lambda}_t = \frac{\phi}{\lambda}\hat{p}_t. \tag{A.25}$$

This expression shows that the optimal ratio of hours worked to the stock of producing wells is a static function of the oil price. As a result, this ratio adjusts immediately to its new long-run value following a permanent increase in the oil price.

Combining the log-linearized demand for existing wells, Eq. A.22c, with the labor-demand equation, Eq. A.22b gives:

$$\hat{H}_t(o) - \hat{\Lambda}_t = \phi\hat{r}_t^{\Lambda}. \tag{A.26}$$

Combining Eqs. A.25 and A.26 therefore yields:

$$\hat{r}_t^{\Lambda} = \frac{1}{\lambda}\hat{p}_t. \tag{A.27}$$

Consequently, the rental rate of producing wells is also a static function of the oil price and

adjusts immediately to its new long-run value following a permanent increase in the oil price.

Combining the log-linearized first-order condition for investment in new wells, Eq. A.20, with the log-linearized technology for producing new wells, Eq. A.5, gives

$$\sum_{s=0}^{\infty}(1-\delta_{\Lambda})^{s}\beta^{s}\left[\hat{r}^{\Lambda}_{t+1+s}-\frac{\gamma}{\theta}\hat{I}_{t}(o)\right]=0. \tag{A.28}$$

Consider an unexpected permanent change in the oil price at date $t$, so that $\hat{p}_{t+s}=\hat{p}_{t}$ for all $s\geq 0$. Using Eq. (A.27) implies that $\hat{r}^{\Lambda}_{t+1+s}=\hat{r}^{\Lambda}_{t}$ for all $s\geq 0$. Hence, Eq. (A.28) reduces to:

$$\left[\hat{r}^{\Lambda}_{t}-\frac{\gamma}{\theta}\hat{I}_{t}(o)\right]\sum_{s=0}^{\infty}(1-\delta_{\Lambda})^{s}\beta^{s}=0. \tag{A.29}$$

Since the geometric sum is strictly positive and finite, combining Eqs. (A.29) and (A.27) yields:

$$\hat{I}_{t}(o)=\frac{\theta}{\lambda\gamma}\hat{p}_{t}. \tag{A.30}$$

This equation shows that, in the absence of drilling adjustment costs, investment in new wells jumps immediately to its new long-run level following a permanent change in the oil price.

Second, we decompose the response of oil production. Combining the log-linearized oil-production function, Eq. (A.22a), with the log-linearized labor-demand equation, Eq. (A.22b) yields:

$$\hat{Y}_{t}(o)=\frac{\phi(1-\lambda)}{\lambda}\hat{p}_{t}+\hat{\Lambda}_{t}. \tag{A.31}$$

Using the definition of the short-run supply elasticity,

$$\sigma_{\text{SR}}=\frac{\phi(1-\lambda)}{\lambda},$$

Eq. (A.31) can be written as

$$\hat{Y}_t(o) = \sigma_{\text{SR}}\, \hat{p}_t + \hat{\Lambda}_t. \tag{A.32}$$

Eq. (A.32) decomposes the response of oil production, $\hat{Y}_t(o)$, into an immediate intensive-margin response, governed by $\sigma_{\text{SR}}$, and a gradual response through the stock of producing wells, $\hat{\Lambda}_t$.

Consider an unexpected permanent increase in the real price of oil at date $t$. Normalizing the permanent price change to one, so that $\hat{p}_{t+h} = 1$ for all $h \geq 0$, Eq. (A.32) implies that the price elasticity of oil supply at horizon $h$ is:

$$\sigma(h) = \sigma_{\text{SR}} + \hat{\Lambda}_{t+h}. \tag{A.33}$$

Since the stock of producing wells is predetermined on impact and newly drilled wells become productive only with a one-period lag, $\hat{\Lambda}_t = 0$. Eq. (A.33) therefore implies:

$$\sigma(0) = \sigma_{\text{SR}}.$$

Taking the limit of Eq. (A.33) as $h \to \infty$ gives

$$\sigma_{\text{LR}} = \sigma_{\text{SR}} + \hat{\Lambda}_{\infty}, \tag{A.34}$$

and hence

$$\hat{\Lambda}_{\infty} = \sigma_{\text{LR}} - \sigma_{\text{SR}}. \tag{A.35}$$

Third, we characterize the gradual adjustment of the stock of producing wells. As shown above, investment in new wells immediately adjusts to its new long-run level, following a permanent increase in the oil price. Moreover, since $\Lambda^{new} = \delta_{\Lambda}\Lambda$ in steady state using Eq. (A.6), it follows that:

$$\hat{\Lambda}^{new}_{t+h} = \hat{\Lambda}_{\infty}, \qquad h \geq 0. \tag{A.36}$$

Substituting this result into the one-period-ahead version of the log-linearized law of motion for the stock of producing wells, Eq. (A.7), gives:

$$\hat{\Lambda}_{t+1} = (1 - \delta_\Lambda)\hat{\Lambda}_t + \delta_\Lambda \hat{\Lambda}_\infty. \tag{A.37}$$

Subtracting $\hat{\Lambda}_\infty$ from both sides gives:

$$\hat{\Lambda}_{t+1} - \hat{\Lambda}_\infty = (1 - \delta_\Lambda)\left(\hat{\Lambda}_t - \hat{\Lambda}_\infty\right). \tag{A.38}$$

Iterating Eq. (A.38) to horizon $h$ and using $\hat{\Lambda}_t = 0$ gives

$$\hat{\Lambda}_{t+h} = \left[1 - (1 - \delta_\Lambda)^h\right]\hat{\Lambda}_\infty. \tag{A.39}$$

Substituting Eq. (A.35) into Eq. (A.39) yields:

$$\hat{\Lambda}_{t+h} = \left[1 - (1 - \delta_\Lambda)^h\right](\sigma_{\text{LR}} - \sigma_{\text{SR}}). \tag{A.40}$$

Finally, substituting Eq. (A.40) into Eq. (A.33) gives:

$$\begin{aligned}\sigma(h) &= \sigma_{\text{SR}} + \left[1 - (1 - \delta_\Lambda)^h\right](\sigma_{\text{LR}} - \sigma_{\text{SR}}) \\ &= (1 - \delta_\Lambda)^h \sigma_{\text{SR}} + \left[1 - (1 - \delta_\Lambda)^h\right]\sigma_{\text{LR}}.\end{aligned} \tag{A.41}$$

Thus, the dynamic supply elasticity converges geometrically from $\sigma_{\text{SR}}$ on impact to $\sigma_{\text{LR}}$ in the long run, with the speed of convergence governed by the well-decay parameter $\delta_\Lambda$:

$$\sigma(h+1) - \sigma_{\text{LR}} = (1 - \delta_\Lambda)\left[\sigma(h) - \sigma_{\text{LR}}\right]. \tag{A.42}$$

## B.5 Short-run elasticities of oil demand

To simplify the exposition, we assume that final-goods producers can trade oil services, $S_t$, among themselves. This assumption leaves the model dynamics unchanged.

Oil services, $S_t$, are given by

$$S_t = O_t + Z_t - \bar{Z}, \tag{A.43}$$

where $O_t$ is oil consumption; $Z_t$ is the stock of oil-saving capital that turns one unit of oil into two units of oil services[†]; and $\bar{Z}$ is either a fixed oil-input cost (when $\bar{Z} > 0$) or an exogenously given endowment (when $\bar{Z} < 0$).

The final good serves as a numeraire, so that all prices are expressed in real terms, and $p_t(s)$ denotes the real price of oil services. As already noted in Section 3.2.2, Eq. (A.43) implies that $p_t(s) = p_t$. Indeed, if final-goods producers can also purchase oil inputs directly, the first order condition w.r.t. oil inputs is $p_t(s)\frac{\partial S_t}{\partial O_t} = p_t$, so that $p_t(s) = p_t$ holds.

Log-linearizing Eq. (A.43) yields:

$$\hat{S}_t = \frac{O}{S}\hat{O}_t + \frac{Z}{S}\hat{Z}_t. \tag{A.44}$$

Oil-saving capital evolves according to the following law of motion

$$Z_t = (1 - \delta_z)Z_{t-1} + I_{t-1}(z), \tag{A.45}$$

where $I_t(z)$ is an irreversible investment and $\delta_z$ is the depreciation rate of oil-saving capital. Log-linearizing this expression and imposing the restriction that $\hat{Z}_t = \hat{Z}_{t+s}$ yields:

$$\hat{Z}_t = \hat{I}_t(z). \tag{A.46}$$

Final-goods producers maximize expected profits given by

$$\mathrm{E}_t \sum_{j=0}^{\infty} \beta^j \{Y_{t+j}(f) - w^f_{t+j} H_{t+j}(f) - r^k_{t+j} K_{t+j} - p_{t+j} O_{t+j} - a(z) \left( \frac{I_{t+j}(z)}{I(z)} \right)^{\frac{1}{\varphi}} I_{t+j}(z)\}, \tag{A.47}$$

[†] This assumption implies that $Z$ units of physical oil are combined with oil-saving capital to deliver $2 \times Z_t$ units of productive oil services: $S_t = O_t - Z_t + 2 \times Z_t - \bar{Z}$. In that sense, oil services reflect the effective oil input entering the final-goods production.

where $w^f_{t+j}$ and $r^k_{t+j}$ denote the wage rate and the rental rate of capital, respectively. The term

$$a(z)\left(\frac{I_t(z)}{I(z)}\right)^{\frac{1}{\varphi}} I_t(z),$$

captures the cost of investing in oil-saving capital. The parameter $\varphi \geq 0$ governs the curvature of this cost function. It implies that the marginal cost of investment is increasing in $I_t(z)$.

The first order condition of Eq. (A.47) w.r.t. oil services, $S_t$, is $\frac{\partial Y_t(f)}{\partial S_t} = p_t$. Expanding this expression gives:

$$p_t = (\omega)^{\frac{1}{\xi}} (\varepsilon^{od}_t)^{\frac{\xi-1}{\xi}} \left(\frac{S_t}{Y_t(f)}\right)^{-\frac{1}{\xi}}. \tag{A.48}$$

Isolating $S_t$ yields the oil services demand curve:

$$S_t = \omega Y_t(f) p_t^{-\xi} (\varepsilon^{od}_t)^{\xi-1}. \tag{A.49}$$

Log-linearization yields:

$$\hat{S}_t = \hat{Y}_t(f) - \xi \hat{p}_t - (1-\xi)\hat{\varepsilon}^{od}_t. \tag{A.50}$$

Let $\chi = \frac{S}{O}$ and assume that $\frac{Z}{S} = 1$. We calibrate $a(z)$ so that this restriction holds in the steady state, which allows $\omega$ to be interpreted as the share of oil in industrial production when $\chi = 1$.

In the short run, $Z_t$ is predetermined, so that $\hat{Z}_t = 0$. Abstracting from oil demand shocks, combining Eqs. (A.50) and (A.44) yields

$$\hat{O}_t = \frac{S}{O}\left(\hat{Y}_t(f) - \xi \hat{p}_t\right), \tag{A.51}$$

$$\hat{O}_t = \chi \hat{Y}_t(f) - \eta_{\text{SR}} \hat{p}_t, \tag{A.52}$$

where $\chi = \frac{S}{O}$ is the output elasticity of oil demand and $\eta_{\text{SR}} = \frac{S}{O}\xi$ is the price elasticity of oil demand.

## B.6 Long-run elasticity of oil demand

Final-goods firms choose $I_t(z)$ to maximize the expected discounted flow of future profits associated with that investment:

$$\sum_{j=0}^{\infty} \beta^{1+j}(1-\delta_z)^j p_{t+1+j} I_t(z) - a(z)\left(\frac{I_t(z)}{I(z)}\right)^{\frac{1}{\varphi}} I_t(z). \tag{A.53}$$

Note that since we work with a permanent change in prices, we can ignore the expectation operator. The first-order condition of Eq. (A.53) w.r.t. $I_t(z)$ is

$$\sum_{j=0}^{\infty} \beta^{1+j}(1-\delta_z)^j p_{t+1+j} = a(z)\frac{(1+\varphi)}{\varphi}\left(\frac{I_t(z)}{I(z)}\right)^{\frac{1}{\varphi}}, \tag{A.54}$$

where $a(z)$ is calibrated such that $\sum_{j=0}^{\infty} \beta^{1+j}(1-\delta_z)^j = a(z)\frac{(1+\varphi)}{\varphi}$ holds in steady state. Under the long-run equilibrium condition $X_{t+j} = X_{t+j+k}$, the linearized FOC becomes:

$$\hat{p}_t = \frac{1}{\varphi}\hat{I}_t(z). \tag{A.55}$$

Combining Eqs. (A.46) and (A.55) yields:

$$\hat{Z}_t = \varphi \hat{p}_t. \tag{A.56}$$

Abstracting from the shock term, we obtain a system of three equations given by (A.50), (A.44), and (A.56):

$$\hat{S}_t = \hat{Y}_t(f) - \xi \hat{p}_t \tag{A.57}$$

$$\hat{S}_t = \frac{O}{S}\hat{O}_t + \hat{Z}_t \tag{A.58}$$

$$\hat{Z}_t = \varphi \hat{p}_t. \tag{A.59}$$

Solving this system for $\hat{O}_t$ yields:

$$\hat{O}_t = \frac{S}{O}\left(\hat{Y}_t(f) - (\xi+\varphi)\,\hat{p}_t\right), \tag{A.60}$$

$$\hat{O}_t = \chi\hat{Y}_t(f) - \eta_{\text{LR}}\hat{p}_t, \tag{A.61}$$

where $\chi = \frac{S}{O}$ is the long-run output elasticity and $\eta_{\text{LR}} = \frac{S}{O}(\xi+\varphi)$ is the long-run price elasticity of demand. The framework therefore assumes identical output elasticity in the short run and the long run.

## B.7 Dynamic elasticity of oil demand

The dynamic elasticity of oil demand can be derived using a strategy analogous to that used for oil supply. Consider an unexpected permanent change in the oil price at date $t$, so that

$$\hat{p}_{t+s} = \hat{p}_t, \qquad s \geq 0.$$

We proceed in three steps. First, we show that investment in oil-saving capital jumps immediately to its new long-run level. Second, we decompose the response of oil-consumption demand into an immediate response and a gradual component operating through the stock of oil-saving capital. Third, we combine this decomposition with the law of motion for oil-saving capital to derive the dynamic elasticity of oil demand.

First, log-linearizing the first-order condition for investment in oil-saving capital in Eq. (A.54) gives

$$\frac{\sum_{j=0}^{\infty}\beta^{1+j}(1-\delta_z)^j\hat{p}_{t+1+j}}{\sum_{j=0}^{\infty}\beta^{1+j}(1-\delta_z)^j} = \frac{1}{\varphi}\hat{I}_t(z).$$

Since the change in the oil price is permanent, $\hat{p}_{t+1+j} = \hat{p}_t$ for all $j \geq 0$, and this equation simplifies to:

$$\hat{I}_t(z) = \varphi\hat{p}_t.$$

Hence, investment in oil-saving capital immediately jumps to its new long-run level following a permanent change in the oil price.

Second, combining Eqs.(A.50) and (A.44), using $Z/S = 1$, and abstracting from oil-demand

shocks, $\hat{\varepsilon}_t^{od}$, gives:

$$\hat{O}_t = \frac{S}{O}\hat{Y}_t(f) - \frac{S}{O}\xi\hat{p}_t - \frac{S}{O}\hat{Z}_t.$$

Using the following two definitions,

$$\chi = \frac{S}{O} \qquad \text{and} \qquad \eta_{\text{SR}} = \frac{S}{O}\xi,$$

this expression becomes

$$\hat{O}_t = \chi\hat{Y}_t(f) - \eta_{\text{SR}}\hat{p}_t - \chi\hat{Z}_t.$$

Holding output constant and normalizing the permanent oil-price change to one, the price elasticity of oil demand at horizon $h$ is therefore

$$\eta(h) = \eta_{\text{SR}} + \chi\hat{Z}_{t+h}.$$

Since oil-saving capital is predetermined on impact, $\hat{Z}_t = 0$, implying $\eta(0) = \eta_{\text{SR}}$.

Third, we characterize the gradual adjustment of oil-saving capital. The one-period-ahead log-linearized version of Eq. (A.45) is

$$\hat{Z}_{t+1} = (1-\delta_z)\hat{Z}_t + \delta_z\hat{I}_t(z).$$

Since investment immediately adjusts to its new long-run level following the permanent oil-price change, and

$$\hat{I}_{t+h}(z) = \varphi, \qquad h \geq 0,$$

the law of motion becomes

$$\hat{Z}_{t+h+1} = (1-\delta_z)\hat{Z}_{t+h} + \delta_z\varphi.$$

Iterating this equation forward from $\hat{Z}_t = 0$ gives

$$\hat{Z}_{t+h} = \left[1 - (1-\delta_z)^h\right]\varphi.$$

Substituting into the expression for $\eta(h)$ yields

$$\eta(h) = \eta_{\text{SR}} + \chi\varphi\left[1 - (1-\delta_z)^h\right].$$

From Eq. (A.61) ,

$$\eta_{\text{LR}} = \frac{S}{O}(\xi + \varphi) = \eta_{\text{SR}} + \chi\varphi,$$

so that

$$\chi\varphi = \eta_{\text{LR}} - \eta_{\text{SR}}.$$

Therefore,

$$\begin{aligned}\eta(h) &= \eta_{\text{SR}} + \left[1 - (1-\delta_z)^h\right](\eta_{\text{LR}} - \eta_{\text{SR}}) \\ &= (1-\delta_z)^h \eta_{\text{SR}} + \left[1 - (1-\delta_z)^h\right]\eta_{\text{LR}}. \end{aligned} \tag{A.62}$$

Hence, the dynamic elasticity of oil demand is

$$\eta(h) = (1-\delta_z)^h \eta_{\text{SR}} + \left[1 - (1-\delta_z)^h\right]\eta_{\text{LR}}$$

The elasticity therefore converges geometrically from $\eta_{\text{SR}}$ on impact to $\eta_{\text{LR}}$ in the long run, with the speed of convergence governed by $\delta_z$.

## B.8 The storage demand with aggregate inventory-dependent costs

Let $V_{j,t} \geq 0$ be inventories held by firm $j$ in a unit-mass continuum of firms, and let

$$V_t = \int_0^1 V_{j,t}\, dj$$

be aggregate inventories. Let $\bar{V} > 0$ and $\bar{p} > 0$ denote the deterministic steady-state values of aggregate inventories and the real oil price. Each firm treats $V_t$, $p_t$, and $E_t[p_{t+1}]$ as given. The positive storage-demand shock $\varepsilon_t^v$ is common to firms, is observed at date $t$, and is normalized to one in steady state.

The individual firm's objective is

$$\max_{V_{j,t} \geq 0} \left\{\varepsilon_t^v E_t[p_{t+1}] V_{j,t} - p_t V_{j,t} \Phi(V_t, p_t)\right\}. \tag{16}$$

where the quantity multiplying the unit cost is firm-specific.

The FOC with respect to $V_{j,t}$ is

$$\varepsilon_t^v E_t[p_{t+1}] = p_t \Phi(V_t, p_t).$$

where the inventory holding cost is $\Phi(V_t, p_t) = \left(\frac{V_t}{V}\right)^{\frac{1}{\nu(1-\tau)}} \left(\frac{p_t}{p}\right)^{\frac{\tau}{1-\tau}}$.

Log-linearizing yields the first order condition described in Section 3.3:

$$\hat{V}_t = \nu\Big\{\mathrm{E}_t\Delta\hat{p}_{t+1} - \tau\mathrm{E}_t\hat{p}_{t+1}\Big\} + \hat{\varepsilon}_t^v \tag{A.63}$$

where the shock has been rescaled by a factor $\nu(1-\tau)$.

## B.9 The household's problem

Households derive utility from consumption, $C_t$, and disutility from labor, $H_t(f)$, in the final good sector. They maximize their utility given by

$$\mathrm{E}_0^j \sum_{t=0}^{\infty} \beta^t \left[ \frac{(C_{j,t} - \mathbf{b}C_{t-1})^{1-\sigma_c}}{1-\sigma_c} - A_h \frac{(H(f)_{j,t})^{1+\sigma_h}}{1+\sigma_h} \right], \tag{A.64}$$

where $\mathbf{b}$ is an external habit parameter, $\sigma_c$ is the inverse of the inter-temporal elasticity of substitution (IES) for consumption, and $\sigma_h$ is the inverse Frisch elasticity of labor supply. Their budget constraint is

$$C_t + I_t(f) + B_{t+1} = R_{t-1}B_t + w_t H_t(f) + wH_t(o) + r_t^k K_t + \Pi_t + SC_t, \tag{A.65}$$

where $R_t$ is the real gross rate of interest paid on bonds $B_t$. The term $\Pi_t$ represents the sum of profits transferred from oil producers, final good producers, and oil-inventory firms. We assume that part of the storage costs, $SC_t = p_t V_t(1 - \Phi(V_t, p_t))$, are rebated to households and therefore do not constitute a net loss of resources.

Productive capital, $K_t$, is accumulated with investment, $I_t(f)$

$$K_{t+1} = \left[1 - \frac{\psi}{2}\left(\frac{I_t(f)}{I_{t-1}(f)} - 1\right)^2\right] I_t(f) + (1-\delta_k)K_t, \tag{A.66}$$

where $\psi$ is the investment adjustment cost in the final good sector and $\delta_k$ is the depreciation

rate of capital.

The first order conditions of Eq. (A.64) w.r.t. $C_t$, $H_t(f)$, $B_t$, $K_t(f)$ and $I_t(f)$, subject to the constraints in Eqs. (20) and (21) are:

$$(C_t - \mathbf{b}C_{t-1})^{-\sigma_c} = \lambda_t \tag{A.67}$$

$$A_h H_t^{\sigma_h} = \lambda_t w_t \tag{A.68}$$

$$\lambda_t = \beta R_t \mathrm{E}_t \lambda_{t+1} \tag{A.69}$$

$$\mu_t = \beta \mathrm{E}_t \left(\lambda_{t+1} r^k_{t+1} + (1-\delta_k)\mu_{t+1}\right) \tag{A.70}$$

$$\lambda_t = \mu_t \left(1 - \tfrac{\psi}{2}\left(\tfrac{I_t}{I_{t-1}} - 1\right)^2 - \psi\left(\tfrac{I_t}{I_{t-1}} - 1\right)\tfrac{I_t}{I_{t-1}}\right) + \beta \mathrm{E}_t \mu_{t+1} \psi \left(\tfrac{I_{t+1}}{I_t} - 1\right)\left(\tfrac{I_{t+1}}{I_t}\right)^2 \tag{A.71}$$

where $\lambda$ and $\mu$ are the shadow values associated with constraints Eqs. (A.65) and (A.66). Define $P^k_t = \frac{\mu_t}{\lambda_t}$. Log-linearizing the expressions yields:

$$\hat{w}_t = \sigma_h \hat{H}_t + \tfrac{\sigma_c}{1-b}\left(\hat{C}_t - b\,\hat{C}_{t-1}\right) \tag{A.72}$$

$$\hat{C}_t = \tfrac{1}{1+b}\,\mathrm{E}_t \hat{C}_{t+1} + \tfrac{b}{1+b}\,\hat{C}_{t-1} - \tfrac{1-b}{\sigma_c\,(1+b)}\,\hat{R}_t \tag{A.73}$$

$$\hat{p}^k_t = (1 - \beta(1-\delta_k))\,\mathrm{E}_t \hat{r}^k_{t+1} + \beta(1-\delta_k)\mathrm{E}_t \hat{p}^k_{t+1} - \hat{R}_t \tag{A.74}$$

$$\hat{I}_t = \tfrac{1}{1+\beta}\hat{I}_{t-1} + \tfrac{\beta}{1+\beta}\mathrm{E}_t \hat{I}_{t+1} + \tfrac{1}{(1+\beta)\psi}\hat{p}^k_t \tag{A.75}$$

# C More on dynamic elasticities and shock propagation

## C.1 Calibration of standard parameters

**Factor shares in oil production** We calibrate the land share in oil well production, $\gamma$, to 0.74, to target a ratio of oil rents (from the World Development Indicators of the World Bank: https://data.worldbank.org/indicator/NY.GDP.PETR.RT.ZS) to oil production (using production data from the EIA: https://www.eia.gov/international/data/world with the average price of crude oil from the World Bank Pink Sheet: https://www.worldbank.org/en/research/commodity-markets) at the world level of 2/3 ($\gamma\lambda = 2/3$). Oil rents capture the importance of natural resources in the production of oil.

Table C.1: Calibration, priors & posteriors

| Calibrated parameters | Value | |
|---|---|---|
| Depreciation rate of capital | 0.025/3 | |
| Capital income share (final good) | 0.32 | |
| Discount factor | $0.99^{1/3}$ | |
| Inverse IES of consumption | 1 | |
| Labour supply elasticity | 2 | |
| Oil share in industrial production | 0.05 | |
| Oil inventories to production ratio | 1.00 | |
| Land share in oil production | 0.66 | |
| Labor share in oil production | 0.10 | |
| Investment adjust. cost (final good) | 12 | |
| **Estimated parameters** | **Prior mean** | **Prior std** |
| Habits in consumption | 0.85 | 0.05 |
| Storage demand elast. to $\mathrm{E}_t\Delta\hat{p}_{t+1}$ | 0.46 | 0.1 |
| Storage demand: weight penalty for $\mathrm{E}_t\hat{p}_{t+1}$ | 0.13 | 0.05 |
| Income elasticity of oil demand | 1 | 0.25 |

We calibrate the income share of labor to 0.10, based on the ratio of lifting costs to prices per barrel of major oil producers. The lifting costs come from the EIA (https://www.eia.gov/finance/performanceprofiles/oil_gas.php) and capture the costs to operate and maintain oil wells. We can thus interpret the labor share more broadly, as the share of all flexible production factors.

It is important to note that our qualitative results are robust to the use of other values for the factor shares, because the factor substitutability can adjust to fit any desired pair of short and long-run elasticities.

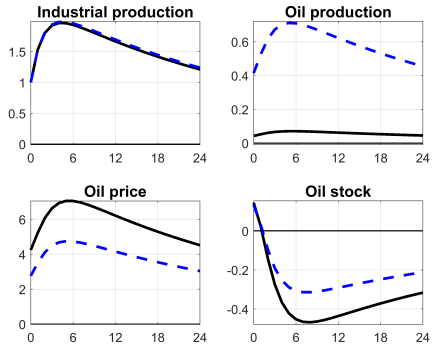
**Standard parameters** We set the discount factor $\beta$ to $0.99^{(1/3)}$ and the depreciation rate of capital $\delta$ to 0.025/3. The inverse of the inter-temporal elasticity of substitution for consumption $\sigma_c$ is set to 1 while the inverse Frisch elasticity of labor supply $\sigma_h$ is set to 2. For the investment adjustment cost parameter, we use a value of 3*4, consistent with the prior of Smets and Wouters (2007) (SW07) used for quarterly data.

The share of oil in the production basket $\omega$ is calibrated to 0.05 to match the total oil market value to the world industrial production. Our calibration also ensures that the ratio of inventories to oil production equals 1 as observed in the data.

## C.2 Varying the short and long-run price elasticity of oil supply

A joint disagreement over the short and long-run price elasticities of oil supply – such as the one we described in Section 2 in SVAR models – has the potential to strongly affect the dynamics of oil prices. To illustrate this point, we simulate the effects of an aggregate demand shock under two calibrations. The first calibration, inspired by the results of BH19, uses a value of 0.15 for both the short and long-run elasticities of oil supply. The second, inspired by KM14, has a value of 0.01 for both the short and long-run elasticities of oil supply. Note that neither KM14 nor BH19 impose a value on this elasticity in the long run. However, it turns out that their IRF-implied elasticities are consistent with this calibration.

Figure C.6: Economic activity shock and the all-horizon price elasticity of oil supply




*Blue: BH19 case:* $\sigma_{SR} = \sigma_{LR} = 0.15$
*Black: KM14 case:* $\sigma_{SR} = \sigma_{LR} = 0.01$

A more inelastic oil supply in the short- and long-run amplifies the response of oil prices to a global economic activity shock. When oil supply is more inelastic (in black), all the

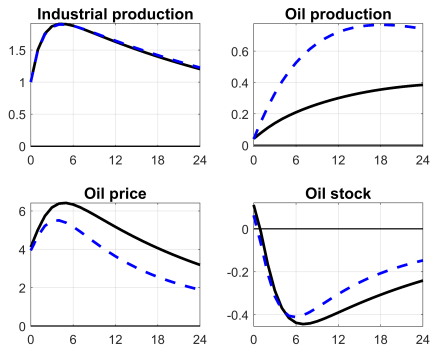
adjustment goes through the demand for oil, and it takes a larger increase in oil prices to convince final good producers to substitute enough oil inputs with other production factors.

Similarly, a joint disagreement over the short and long-run price elasticities of oil demand strongly affects the dynamics of oil prices following an oil supply shock (results available upon request).

## C.3 Adjustment speed of oil supply

We now describe the impact of increasing the oil well decay rate, which effectively increases the adjustment speed of oil supply. We compare the effect of an aggregate demand shock when the production half-life of oil wells is set to either three years or one year. This experiment illustrates the importance of this parameter for the dynamics of oil prices, but may also shed some light on the possible future consequences of the shale oil revolution in the US, where production from unconventional wells decays at a faster rate.

Figure C.7: Global economic activity shocks and the adjustment speed of oil supply




*Black:* $\sigma_{SR} = 0.01$ *;* $\sigma_{LR} = 0.52$ *; Production half-life of 36 months;*
*Blue:* $\sigma_{SR} = 0.01$ *;* $\sigma_{LR} = 0.52$ *; Production half-life of 12 months*

Figure C.7 shows that a faster supply adjustment (in blue) strongly alters the dynamics of oil prices: the increase in oil prices is more muted in the medium run. Overall, we can also see that the effect of an increase in the adjustment speed on the dynamics of oil prices is similar to that of an increase in the long-run elasticity.

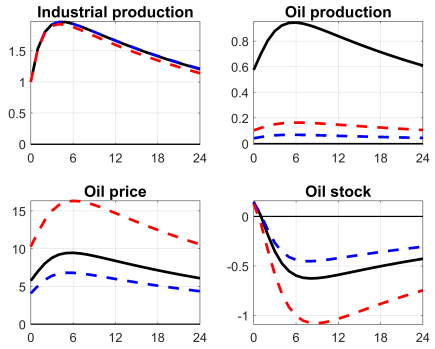
Similarly, a change in the adjustment speed of oil demand can affect the dynamics of oil prices following an oil supply shock (results available upon request).

## C.4 Aggregate demand shocks

This section shows that while models with higher supply and lower demand elasticities favor oil supply shocks over oil-specific demand shocks, they do not necessarily reduce the relative importance of global economic activity shocks. The intuition is simple: a higher supply elasticity dampens the effects of global economic activity shocks; but a lower demand elasticity magnifies their effects.

The figure below shows the IRFs to an aggregate demand shock for different combinations of demand and supply elasticities. Starting from values of the short and long-run elasticities of oil supply and demand that are all set to 0.1 (thus consistent with the BH-benchmark prior described in section 5.2), we show that lowering the supply elasticities to 0.01 amplifies the oil price response, but raising the demand elasticities to 0.27 mitigates it. Overall, it shows that elasticities that are consistent with the KM-benchmark prior do not necessarily favor aggregate demand shocks compared to the BH-case. The overall conclusion is that these prior choices matter the most for the relative contributions of oil demand and oil supply shocks.

Figure C.8: Global economic activity shocks and demand and supply elasticities



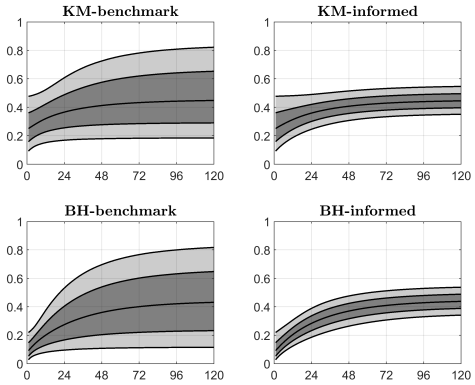

*Black:* $\sigma_{SR} = \sigma_{LR} = \eta_{SR} = \eta_{LR} = 0.10$*;*
*Red:* $\sigma_{SR} = \sigma_{LR} = 0.01$*;* $\eta_{SR} = \eta_{LR} = 0.10$
*Blue:* $\sigma_{SR} = \sigma_{LR} = 0.01$*;* $\eta_{SR} = \eta_{LR} = 0.27$

# D More on the sources of oil price fluctuations

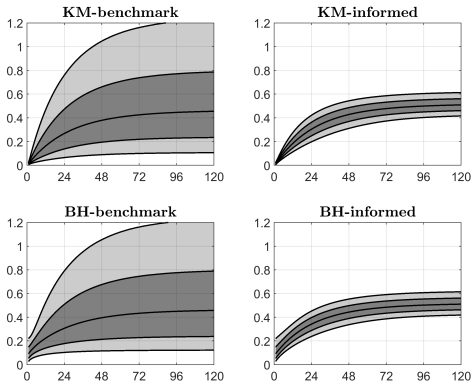
## D.1 Priors on dynamic elasticities and estimated parameters

Figure D.9: Prior distributions of elasticities at different horizons

(a) Demand elasticities




(b) Supply elasticities




*This figure displays the prior distribution of our demand and supply elasticities at different horizons, computed with equations (15) and (7), based on the prior draws from the short and long-run elasticities, and the adjustment speeds. Mode, 68 and 95% prior bands.*

Table D.2: Estimated parameters in KM-benchmark

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.84 | 0.83 | 0.77 | 0.92 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.35 | 1.34 | 1.28 | 1.42 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.56 | 2.49 | 2.16 | 3.03 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.33 | 0.27 | 0.19 | 0.53 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.83 | 0.95 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.88 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.88 | 0.87 | 0.83 | 0.94 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.94 | 0.95 | 0.91 | 0.97 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.85 | 0.6 | 0.96 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.91 | 1.89 | 1.66 | 2.17 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.26 | 0.1 | 0.43 | 0.42 | 0.37 | 0.49 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.3 | 0.46 | 0.42 | 0.38 | 0.62 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.01 | 0.005 | 0.02 | 0.02 | 0.02 | 0.02 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.3 | 0.08 | 0.06 | 0.03 | 0.16 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.04 | 0.03 | 0.03 | 0.05 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.31 | 0.3 | 0.22 | 0.42 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.09 | 0.09 | 0.05 | 0.14 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.6 | 0.6 | 0.54 | 0.67 |

Table D.3: Estimated parameters in KM-informed

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.83 | 0.82 | 0.76 | 0.91 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.36 | 1.36 | 1.3 | 1.43 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.64 | 2.58 | 2.22 | 3.13 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.34 | 0.27 | 0.19 | 0.55 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.82 | 0.95 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.88 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.95 | 0.95 | 0.92 | 0.98 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.89 | 0.95 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.85 | 0.61 | 0.96 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.89 | 1.88 | 1.64 | 2.16 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.26 | 0.1 | 0.44 | 0.43 | 0.38 | 0.5 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.05 | 0.46 | 0.43 | 0.41 | 0.53 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.01 | 0.005 | 0.02 | 0.02 | 0.02 | 0.02 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.05 | 0.46 | 0.46 | 0.39 | 0.53 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.03 | 0.03 | 0.03 | 0.04 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.29 | 0.29 | 0.21 | 0.4 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.09 | 0.08 | 0.05 | 0.13 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.61 | 0.6 | 0.54 | 0.67 |

Table D.4: Estimated parameters in BH-benchmark

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.82 | 0.81 | 0.75 | 0.89 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.46 | 1.45 | 1.36 | 1.58 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.2 | 2.16 | 1.85 | 2.61 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.36 | 0.3 | 0.2 | 0.58 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.83 | 0.95 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.88 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.89 | 0.88 | 0.84 | 0.94 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.94 | 0.94 | 0.91 | 0.97 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.85 | 0.6 | 0.97 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.32 | 1.31 | 1.06 | 1.61 |
| $\eta_{\text{SR}}$ | SRED | Gamma | 0.1 | 0.05 | 0.23 | 0.23 | 0.18 | 0.29 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.3 | 0.28 | 0.23 | 0.19 | 0.46 |
| $\sigma_{\text{SR}}$ | SRES | Gamma | 0.1 | 0.05 | 0.1 | 0.1 | 0.07 | 0.13 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.3 | 0.12 | 0.1 | 0.08 | 0.17 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.04 | 0.03 | 0.03 | 0.05 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.3 | 0.29 | 0.21 | 0.41 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.1 | 0.1 | 0.06 | 0.15 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.59 | 0.59 | 0.52 | 0.66 |

Table D.5: Estimated parameters in BH-informed

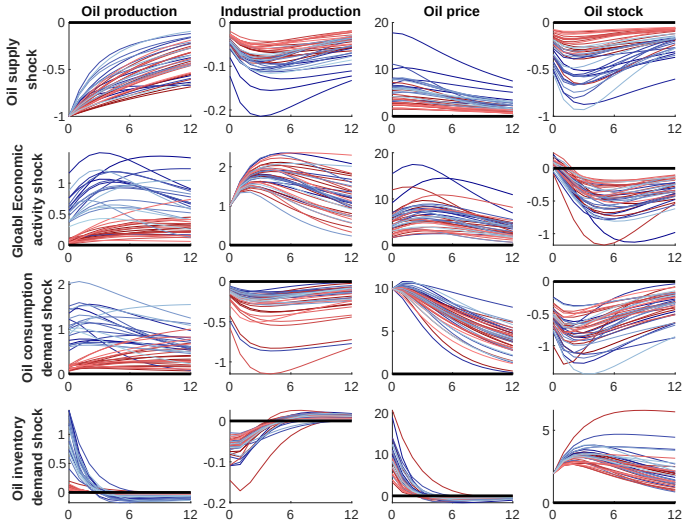
| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.81 | 0.8 | 0.74 | 0.88 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.52 | 1.49 | 1.4 | 1.65 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.27 | 2.23 | 1.9 | 2.7 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.38 | 0.31 | 0.21 | 0.59 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.82 | 0.95 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.88 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.95 | 0.95 | 0.92 | 0.98 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.94 | 0.94 | 0.91 | 0.97 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.86 | 0.59 | 0.97 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.24 | 1.25 | 0.97 | 1.53 |
| $\eta_{\text{SR}}$ | SRED | Gamma | 0.1 | 0.05 | 0.22 | 0.22 | 0.16 | 0.28 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.05 | 0.43 | 0.43 | 0.36 | 0.52 |
| $\sigma_{\text{SR}}$ | SRES | Gamma | 0.1 | 0.05 | 0.11 | 0.11 | 0.08 | 0.15 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.05 | 0.47 | 0.47 | 0.4 | 0.55 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.02 | 0.01 | 0.04 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.03 | 0.03 | 0.03 | 0.04 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.29 | 0.29 | 0.2 | 0.4 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.09 | 0.09 | 0.05 | 0.14 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.58 | 0.58 | 0.52 | 0.65 |

## D.2 Sign predictions of the model

Figure D.10 reports results based on 20 draws (results are qualitatively similar with a larger number of draws). The logic of the model can be illustrated by considering each of the four structural shocks in turn. For instance, an adverse oil supply disturbance reduces oil production (Eq. 3) and raises oil prices. As a result, industrial production declines due to both oil scarcity and price effects through the cost push channel. In turn, higher oil prices encourage storage firms to draw down their inventories.

Figure D.10: Set of admissible IRFs

*Note: Variables expressed in percentage deviation from steady state. Horizon in months. All lines correspond to a particular draw from our priors, from the BH (blue) or KM cases (red).*




The global economic activity shock raises the productivity of labor and capital in the production of intermediate goods, Eq. (8). The increase in intermediate goods raises the demand for oil that is used to turn them into final goods, Eq. (9). The price of oil thus increases, and higher prices stimulate oil production. The impact on inventories is ambiguous, which shows that imposing restrictions on this variable could be controversial. On the one hand, the immediate increase in oil prices encourages storage firms to sell their inventories. On the other hand, the increase in prices is hump-shaped and persistent, which encourages storage firms to accumulate more stocks to profit from higher expected future prices. The first effect dominates when the parameter $\tau$ in Eq. (18) is large, while the second dominates when it is low. Thus, we cannot impose a sign a priori as can be seen in Figure D.10.

The oil-consumption demand shock causes a fall in oil-services productivity, Eq. 9. It implies

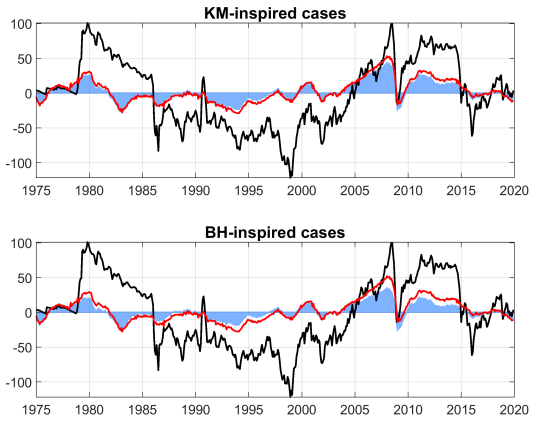
that more oil is required to maintain production at its original level (owing, for example, to a particularly harsh winter). The increase in oil demand causes an increase in oil prices, which, together with the decline in oil-services productivity, causes a fall in industrial production. The temporary increase in oil prices encourages storage firms to sell their inventories.

An oil-inventory demand shock that causes a fall in net storage costs encourages storage firms to accumulate inventories. Higher demand for inventories raises the price of oil and causes a fall in industrial production. Higher oil prices encourage oil production. The increase in prices is not very persistent, even when the increase in inventories is. Indeed, a persistent increase in inventories creates an imbalance between oil production and consumption demand on impact only (as one can note from the market-clearing condition in section 3.3).

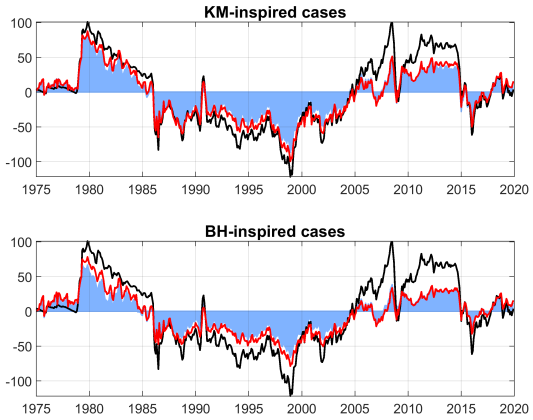
## D.3 Historical Decomposition: demand shocks

Figure D.11: Historical contribution of demand shocks to oil-price fluctuations

(a) Economic activity shock




(b) Oil demand shock

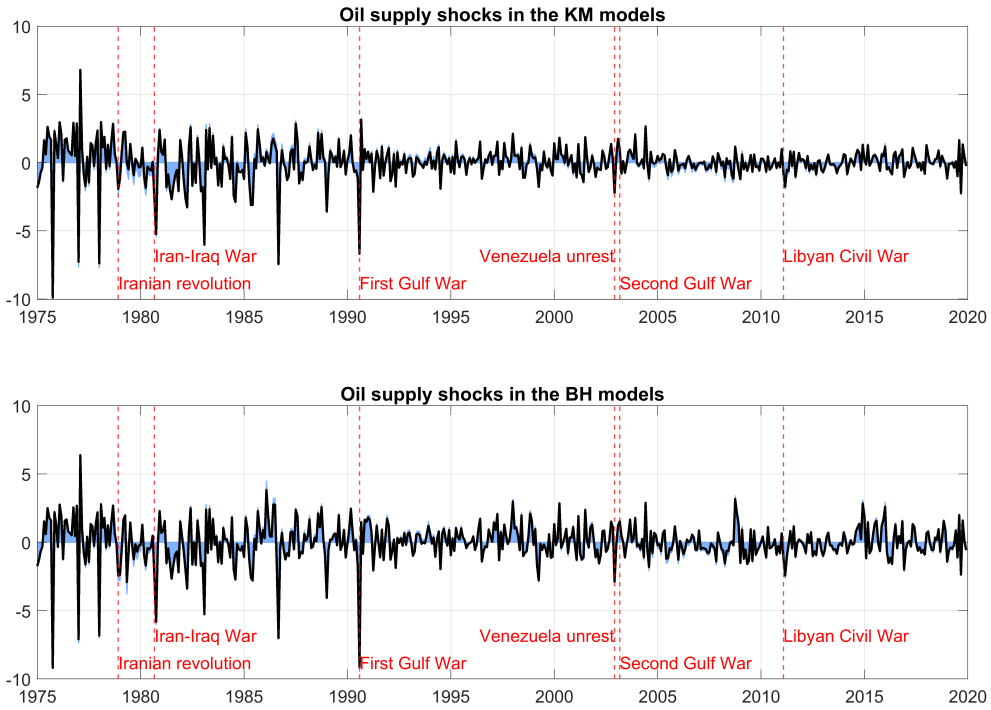



*Note: Black: actual oil price fluctuations.*
*Blue: KM- and BH-informed models.*
*Red: KM- and BH-benchmark models.*

## D.4 Estimated supply shocks and key historical events

Figure D.12 reports estimated median oil supply shocks. The shocks capture the main historical supply disturbances discussed in the literature (e.g., Kilian, 2009; Hamilton, 2009; Antolín-Díaz and Rubio-Ramírez, 2018; Kilian and Lee, 2014). In particular, they are broadly consistent with the narrative restrictions used in Antolín-Díaz and Rubio-Ramírez (2018), with one exception. For the Iraq war in 2003, we identify a negative supply shock in April rather than in March. This timing is plausible since the US invasion began on March 20, Baghdad was captured in April, and President George W. Bush declared the "end of major combat operations" on May 1.

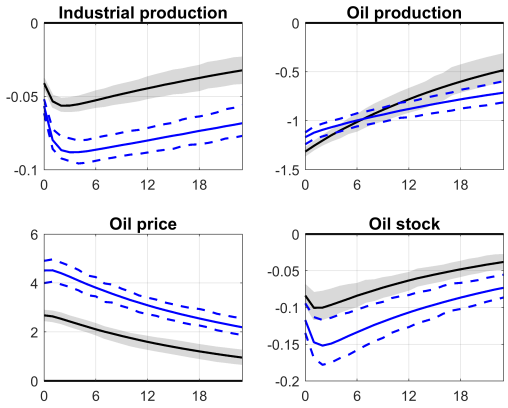
Figure D.12: Time series of structural oil supply shocks in the RBC model: BH (blue) vs KM-inspired (black) models



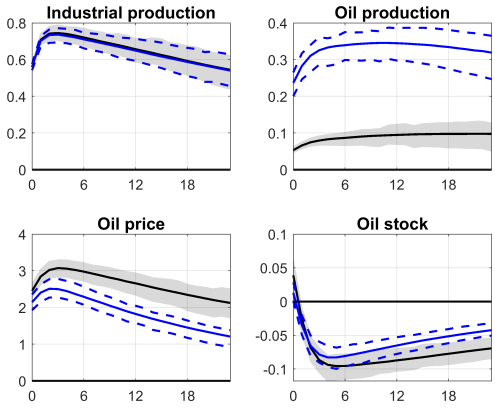
## D.5 IRFs from estimated RBC model

Figure D.13: IRFs in RBC models (80% credible bands, one-standard-deviation shocks)
BH-informed (blue) vs KM-benchmark (black)

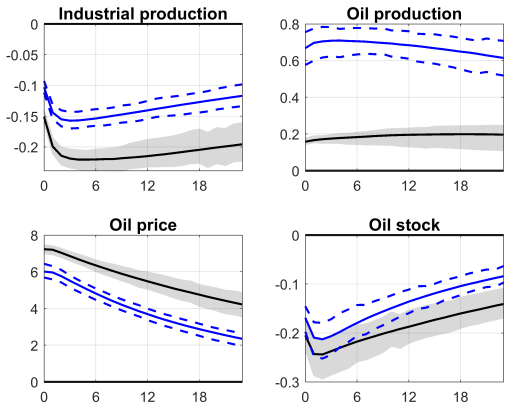
(a) Oil supply shock



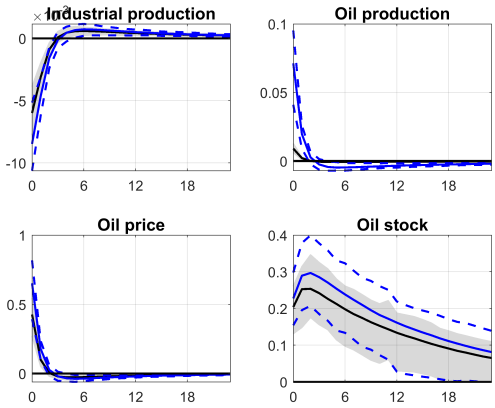

(b) Economic activity shock




(c) Oil consumption demand shock




(d) Oil inventory demand shock



## D.6 Data and model-implied correlations

This section discusses the correlation coefficients in the data and in each of the four models used in Section 5.5, together with HM benchmark and informed models used in Section 5.6. The results are mixed, depending on the pair of variables considered. For instance, informative priors improve the real-side co-movement of the oil market: in both BH and KM cases, the correlation between oil production and industrial production moves closer to the data.

Figure D.14: Correlations: data vs the models

| DATA | Oil prod | Ind prod | Oil price | Oil stock |
|---|---|---|---|---|
| Oil prod | 1 | 0.52 | 0.26 | -0.68 |
| Ind prod | 0.52 | 1 | 0.28 | -0.13 |
| Oil price | 0.26 | 0.28 | 1 | -0.41 |
| Oil stock | -0.68 | -0.13 | -0.41 | 1 |
| **KM-benchmark** | Oil prod | Ind prod | Oil price | Oil stock |
| Oil prod | 1 | 0.08 | 0.05 | 0 |
| Ind prod | 0.08 | 1 | 0.11 | -0.05 |
| Oil price | 0.05 | 0.11 | 1 | -0.83 |
| Oil stock | 0 | -0.05 | -0.83 | 1 |
| **KM-informed** | Oil prod | Ind prod | Oil price | Oil stock |
| Oil prod | 1 | 0.2 | 0.08 | -0.08 |
| Ind prod | 0.2 | 1 | 0.16 | -0.09 |
| Oil price | 0.08 | 0.16 | 1 | -0.77 |
| Oil stock | -0.08 | -0.09 | -0.77 | 1 |
| **BH-benchmark** | Oil prod | Ind prod | Oil price | Oil stock |
| Oil prod | 1 | 0.19 | 0.25 | -0.17 |
| Ind prod | 0.19 | 1 | 0.16 | -0.1 |
| Oil price | 0.25 | 0.16 | 1 | -0.8 |
| Oil stock | -0.17 | -0.1 | -0.8 | 1 |
| **BH-informed** | Oil prod | Ind prod | Oil price | Oil stock |
| Oil prod | 1 | 0.22 | 0.04 | -0.05 |
| Ind prod | 0.22 | 1 | 0.1 | -0.07 |
| Oil price | 0.04 | 0.1 | 1 | -0.74 |
| Oil stock | -0.05 | -0.07 | -0.74 | 1 |
| **HM-benchmark** | Oil prod | Ind prod | Oil price | Oil stock |
| Oil prod | 1 | 0.22 | 0.23 | -0.15 |
| Ind prod | 0.22 | 1 | 0.15 | -0.09 |
| Oil price | 0.23 | 0.15 | 1 | -0.81 |
| Oil stock | -0.15 | -0.09 | -0.81 | 1 |
| **HM-informed** | Oil prod | Ind prod | Oil price | Oil stock |
| Oil prod | 1 | 0.27 | 0.03 | -0.05 |
| Ind prod | 0.27 | 1 | 0.14 | -0.09 |
| Oil price | 0.03 | 0.14 | 1 | -0.73 |
| Oil stock | -0.05 | -0.09 | -0.73 | 1 |

*Data : variables in percentage deviation from a linear trend. Models : variables in percentage deviation from their steady-state, simulated at the posterior mode of the estimated parameters. Standard estimation with the 4 variables described in section 5.1.*

## D.7 Details on robustness

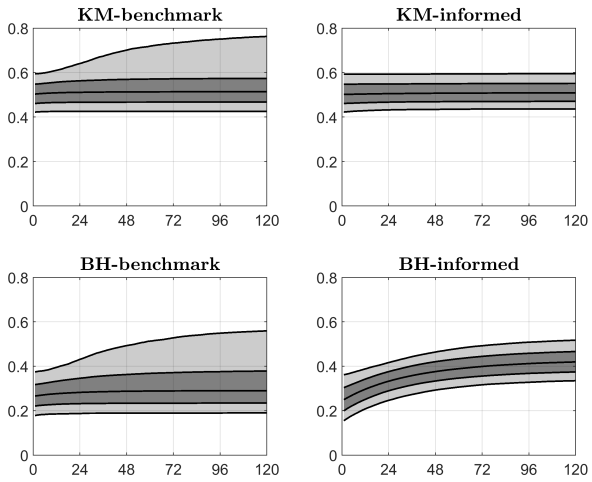
### D.7.1 IGREA as an alternative measure of global economic activity

We use the Index of Global Real Economic Activity (IGREA) proposed by K09 and used in KM12 and KM14, as an alternative measure of global demand for industrial commodities, in place of industrial production. We rescale the first difference in the IGREA index, so that its variance matches that of the industrial production concept, $Y_t(f)$, used in our framework. This rescaling is necessary to interpret $\chi$ as the income elasticity of demand (see Eq. A.51). Table D.6 and Figure D.15 report the variance decomposition and posterior of dynamic elasticities across the four models, respectively.

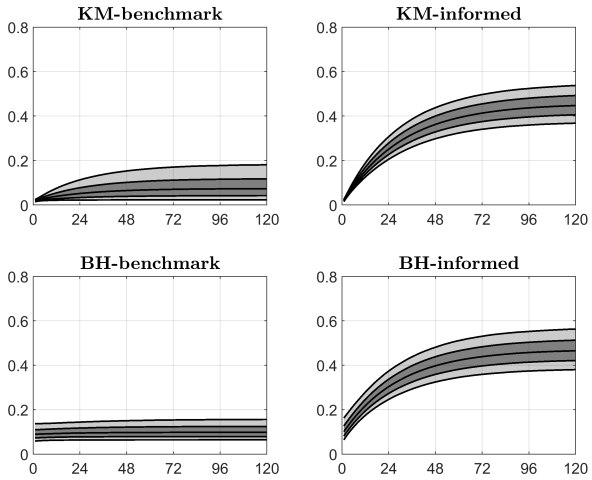
The results in Sections 5.4 and 5.5.1 are robust to replacing industrial production with IGREA. Diffuse priors continue to generate posterior dynamic elasticities that are essentially flat across horizons, while informative priors lead to posterior elasticities that increase with the horizon. As in the baseline, informative priors therefore increase the importance of supply shocks for oil price fluctuations. The main quantitative difference is that supply shocks play a somewhat smaller role (in all specifications) for oil price fluctuations under IGREA than in Table 8.

Figure D.15: Estimated elasticities at different horizons (IGREA)

(a) Demand elasticities




(b) Supply elasticities




*This figure displays the posterior distribution of our demand and supply elasticities at different horizons, computed with equations (15) and (7). We vary the prior for the short and long-run elasticities in the four panels, while all other calibrated parameters and priors remain unchanged and are described in section 5.2.*

Table D.6: Variance decomposition (with IGREA)

| | **Oil Supply** | **Aggregate Demand** | **Oil-consump Demand** | **Oil-invent Demand** |
|---|---|---|---|---|
| **KM-benchmark** | | | | |
| Oil prod | 88.48 | 0.82 | 10.24 | 0 |
| Ind prod | 0.3 | 78.89 | 20.72 | 0 |
| Oil price | 4.81 | 10.4 | 84.11 | 0.01 |
| *(10%-90%)* | (2.72 ; 8.26) | (6.42 ; 15.74) | (76.93 ; 89.99) | (0 ; 0.03) |
| Oil stock | 3.76 | 7.23 | 54.08 | 33.82 |
| **KM-informed** | | | | |
| Oil prod | 71.02 | 2.78 | 25.24 | 0 |
| Ind prod | 1.02 | 86.12 | 12.61 | 0 |
| Oil price | 14.81 | 11.52 | 72.71 | 0.02 |
| *(10%-90%)* | (9.97 ; 22.86) | (8.43 ; 15.93) | (65.29 ; 78.95) | (0.01 ; 0.04) |
| Oil stock | 6.46 | 6.73 | 41.83 | 44.08 |
| **BH-benchmark** | | | | |
| Oil prod | 65.27 | 3.32 | 30.71 | 0.01 |
| Ind prod | 0.82 | 81.79 | 17.14 | 0 |
| Oil price | 15.09 | 8.53 | 75.07 | 0.03 |
| *(10%-90%)* | (7.84 ; 27.93) | (5.11 ; 13.6) | (62.23 ; 85.05) | (0.01 ; 0.06) |
| Oil stock | 11.01 | 5.82 | 45.68 | 33.42 |
| **BH-informed** | | | | |
| Oil prod | 59.87 | 3.12 | 36.09 | 0.01 |
| Ind prod | 1.89 | 86.96 | 10.64 | 0 |
| Oil price | 36.16 | 7.41 | 56.07 | 0.04 |
| *(10%-90%)* | (24.53 ; 51.44) | (4.65 ; 11.06) | (42.78 ; 66.54) | (0.02 ; 0.1) |
| Oil stock | 17.16 | 4.57 | 31.96 | 42.97 |

### D.7.2 Subsample analysis

We re-estimate the models on the period 1995M1-2019M12, rather than the 1975M1-2019M12 baseline sample. Table D.7 and Figure D.16 report the variance decomposition and posterior of dynamic elasticities across the four models, respectively. The baseline conclusions remain qualitatively unchanged: informative priors on dynamic elasticities continue to play an important role in oil-market dynamics. At the same time, three quantitative differences stand out.

First, Figure D.16 shows that the estimated short-run elasticities of oil demand and supply are lower in the 1995-2019 subsample than in the baseline 1975-2019 sample reported in Figure 7. This result is consistent with the time-varying SVAR evidence in Baumeister and Peersman (2013b,a), which likewise suggests that these elasticities have declined over time. As a result, the estimated short-run elasticities are less different across the two benchmark specifications. However, the implied differences in the FEVD in the two benchmark specifications remain quantitatively important: supply shocks account for about 9% in the KM benchmark, compared with about 29% in the BH benchmark (see Tables D.7 and 8). When all elasticities are low, even small differences in their values can have large quantitative effects on the FEVD, especially through the lower demand elasticity in the BH benchmark. More generally, the subsample analysis points to a larger role for supply shocks in both benchmark models, because the decline in the estimated demand elasticity more than offsets the lower variance of supply shocks in the recent period.

Second, the difference in the contribution of oil supply shocks across the two BH cases is quantitatively smaller in the subsample than in the full sample period. The reason is that, in the 1995-2019 period, introducing prior information on the long-run elasticity of demand plays a larger role. In particular, both the short-run and long-run demand elasticities are substantially lower in the BH benchmark estimated on the subsample. Informative priors therefore raise the demand elasticity by more in this case, which mitigates the effect of oil supply shocks on oil prices.

Third, the relative importance of aggregate demand shocks increases in the later sample across the four models. The joint decline in demand and supply elasticities over 1995-2019, relative to the full sample, implies that neither side of the oil market adjusts easily to the demand shift induced by an aggregate demand shock. As a result, market clearing requires a larger price movement, raising the contribution of aggregate demand shocks to fluctuations

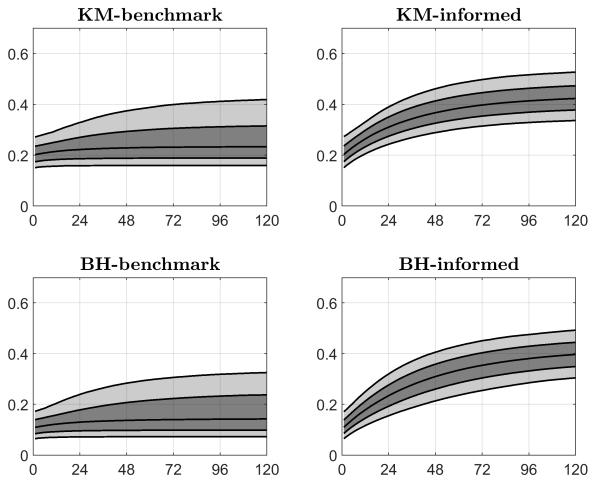
in oil prices, oil production and industrial production.

Table D.7: Variance decomposition (1995-2019)

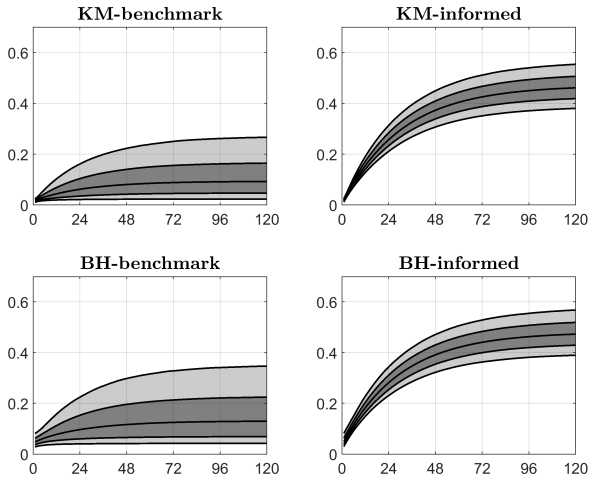
| | **Oil Supply** | **Aggregate Demand** | **Oil-consump Demand** | **Oil-invent Demand** |
|---|---|---|---|---|
| **KM-benchmark** | | | | |
| Oil prod | 74.98 | 13.5 | 8.64 | 0.01 |
| Ind prod | 0.31 | 96.85 | 2.71 | 0 |
| Oil price | 9.12 | 37.34 | 50.9 | 0.25 |
| *(10%-90%)* | (4.79 ; 16.93) | (24.85 ; 54.25) | (35.24 ; 65.61) | (0.07 ; 0.52) |
| Oil stock | 3.73 | 11.42 | 21.29 | 61.75 |
| **KM-informed** | | | | |
| Oil prod | 60.92 | 20.62 | 15.02 | 0.01 |
| Ind prod | 0.54 | 97.4 | 1.95 | 0 |
| Oil price | 16.69 | 27.8 | 53.8 | 0.45 |
| *(10%-90%)* | (11.82 ; 23.12) | (21.12 ; 36.04) | (45.91 ; 61.95) | (0.17 ; 0.78) |
| Oil stock | 3.75 | 6.43 | 17.39 | 71.89 |
| **BH-benchmark** | | | | |
| Oil prod | 60.67 | 22.53 | 13.95 | 0.14 |
| Ind prod | 0.87 | 97.45 | 1.32 | 0 |
| Oil price | 28.7 | 32.14 | 34.57 | 0.54 |
| *(10%-90%)* | (14.36 ; 50.64) | (19.59 ; 50.02) | (20.68 ; 50.77) | (0.25 ; 0.94) |
| Oil stock | 9.89 | 9.46 | 14.41 | 62.57 |
| **BH-informed** | | | | |
| Oil prod | 55.13 | 22 | 20.04 | 0.1 |
| Ind prod | 0.76 | 97.92 | 1.21 | 0.01 |
| Oil price | 34.98 | 22.33 | 40.83 | 0.8 |
| *(10%-90%)* | (23.49 ; 49.28) | (15.36 ; 30.2) | (29.77 ; 50.79) | (0.46 ; 1.27) |
| Oil stock | 9.19 | 5.62 | 13.64 | 70.61 |

Figure D.16: Estimated dynamic elasticities (1995-2019)

(a) Demand elasticities




(b) Supply elasticities




*This figure displays the posterior distribution of our demand and supply elasticities at different horizons, computed with equations (15) and (7). We vary the prior for the short and long-run elasticities in the four panels, while all other calibrated parameters and priors remain unchanged and are described in Section 5.2.*

Table D.8: Estimated parameters in KM-benchmark (1995-2019)

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.88 | 0.86 | 0.78 | 0.99 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 0.7 | 0.7 | 0.65 | 0.75 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 1.72 | 1.62 | 1.38 | 2.15 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.6 | 0.62 | 0.3 | 0.87 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.71 | 0.7 | 0.61 | 0.81 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.91 | 0.91 | 0.86 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.88 | 0.87 | 0.79 | 0.95 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.88 | 0.87 | 0.81 | 0.94 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.76 | 0.82 | 0.54 | 0.93 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.25 | 1.21 | 0.99 | 1.55 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.26 | 0.1 | 0.2 | 0.19 | 0.16 | 0.26 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.3 | 0.25 | 0.19 | 0.17 | 0.4 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.01 | 0.005 | 0.02 | 0.02 | 0.01 | 0.02 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.3 | 0.11 | 0.08 | 0.03 | 0.23 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.04 | 0.03 | 0.03 | 0.05 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.24 | 0.22 | 0.16 | 0.34 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.12 | 0.12 | 0.06 | 0.19 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.67 | 0.66 | 0.59 | 0.74 |

Table D.9: Estimated parameters in KM-informed (1995-2019)

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.88 | 0.86 | 0.78 | 0.99 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 0.71 | 0.71 | 0.66 | 0.76 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 1.73 | 1.63 | 1.38 | 2.14 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.65 | 0.65 | 0.36 | 0.89 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.69 | 0.69 | 0.59 | 0.79 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.89 | 0.9 | 0.84 | 0.94 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.95 | 0.95 | 0.91 | 0.98 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.87 | 0.88 | 0.81 | 0.93 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.76 | 0.82 | 0.53 | 0.93 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.26 | 1.22 | 1 | 1.54 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.26 | 0.1 | 0.21 | 0.19 | 0.16 | 0.26 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.05 | 0.44 | 0.43 | 0.36 | 0.53 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.01 | 0.005 | 0.02 | 0.02 | 0.01 | 0.02 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.05 | 0.47 | 0.48 | 0.4 | 0.55 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.02 | 0.02 | 0.04 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.03 | 0.03 | 0.03 | 0.04 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.23 | 0.22 | 0.15 | 0.32 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.12 | 0.12 | 0.06 | 0.19 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.68 | 0.67 | 0.6 | 0.75 |

Table D.10: Estimated parameters in BH-benchmark (1995-2019)

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.87 | 0.86 | 0.78 | 0.98 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 0.78 | 0.79 | 0.7 | 0.89 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 1.52 | 1.45 | 1.22 | 1.89 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.67 | 0.67 | 0.43 | 0.9 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.71 | 0.71 | 0.64 | 0.79 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.91 | 0.91 | 0.85 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.9 | 0.91 | 0.83 | 0.96 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.85 | 0.82 | 0.75 | 0.93 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.75 | 0.81 | 0.53 | 0.93 |
| $\chi$ | OED | Normal | 1 | 0.25 | 0.86 | 0.8 | 0.61 | 1.14 |
| $\eta_{\text{SR}}$ | SRED | Gamma | 0.1 | 0.05 | 0.11 | 0.1 | 0.07 | 0.16 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.3 | 0.16 | 0.1 | 0.08 | 0.31 |
| $\sigma_{\text{SR}}$ | SRES | Gamma | 0.1 | 0.05 | 0.05 | 0.05 | 0.03 | 0.07 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.3 | 0.15 | 0.13 | 0.05 | 0.31 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.04 | 0.03 | 0.03 | 0.05 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.24 | 0.23 | 0.16 | 0.35 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.13 | 0.14 | 0.07 | 0.21 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.66 | 0.66 | 0.59 | 0.74 |

Table D.11: Estimated parameters in BH-informed (1995-2019)

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.86 | 0.85 | 0.77 | 0.97 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 0.79 | 0.78 | 0.71 | 0.9 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 1.53 | 1.47 | 1.22 | 1.91 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.69 | 0.68 | 0.47 | 0.91 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.71 | 0.7 | 0.63 | 0.78 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.9 | 0.9 | 0.85 | 0.95 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.94 | 0.94 | 0.9 | 0.97 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.88 | 0.88 | 0.81 | 0.94 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.75 | 0.81 | 0.52 | 0.93 |
| $\chi$ | OED | Normal | 1 | 0.25 | 0.86 | 0.83 | 0.61 | 1.13 |
| $\eta_{\text{SR}}$ | SRED | Gamma | 0.1 | 0.05 | 0.11 | 0.11 | 0.07 | 0.16 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.05 | 0.43 | 0.43 | 0.35 | 0.51 |
| $\sigma_{\text{SR}}$ | SRES | Gamma | 0.1 | 0.05 | 0.05 | 0.05 | 0.03 | 0.07 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.05 | 0.48 | 0.48 | 0.41 | 0.56 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.02 | 0.02 | 0.01 | 0.04 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.03 | 0.03 | 0.03 | 0.04 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.24 | 0.23 | 0.16 | 0.34 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.13 | 0.13 | 0.07 | 0.2 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.67 | 0.67 | 0.59 | 0.74 |

### D.7.3 Diffuse priors on short-run elasticities

In this section, we assess robustness by relaxing prior discipline on short-run elasticities imposed in the BH and KM specifications. Specifically, we replace these priors with diffuse priors. This leads us to define a new benchmark specification, which we label the HM benchmark, in which both the short-run and dynamic elasticities are assigned diffuse priors. We compare this specification with an HM-informed model, which maintains diffuse priors on short-run elasticities but imposes informative priors on dynamic elasticities. Specifically, we use a Beta distribution with mean and standard deviation set to 0.5 and 0.288675, which implies that the priors are almost perfectly flat in the [0,1] interval. We proceed in three steps. First, we examine the estimated elasticities. Second, we study the implied FEVD for the different variables. Third, we compare the time series of identified shocks. This design allows us to isolate more clearly the role of dynamic elasticities in shock propagation, separately from their role in shock identification.

Tables D.13 and D.14 report the posterior distributions of the various elasticities, together with the adjustment speeds. In the HM benchmark, the posterior modes of the short-run supply and demand elasticities are about 0.09 and 0.27, respectively, placing them between the KM and the BH benchmark estimates. The implied dynamic elasticities are fairly flat. In the HM-informed model, by contrast, both demand and supply dynamic elasticities rise with the horizon, reaching long-run posterior modes of about 0.43 and 0.47. As a result, Table D.12 shows that the contribution of oil supply shocks to oil-price fluctuations increases from 13% in the HM benchmark to 32% in the HM-informed model, confirming our baseline result that informative priors on dynamic elasticities matter quantitatively.

Table D.12 also reveals a considerable uncertainty about the relative importance of supply and demand shocks in the HM benchmark. The 10th-90th percentile credible interval for the contribution of oil supply shocks to the FEVD of oil price fluctuations ranges from 7% to 24%. This suggests that, under diffuse priors for both the short-run and dynamic elasticities, the data do not pin down precisely whether supply shocks are quantitatively important drivers of oil prices. At the same time a similarly wide interval in the BH benchmark—about 10%–30%—suggests that this uncertainty is not driven solely by diffuse priors on short-run elasticities. We examine this issue in more detail below. This uncertainty has two main sources. First, small changes in key elasticities can have large effects on oil price dynamics. Second, the joint posterior distribution of these elasticities displays substantial cross-parameter dependence, which further widens the FEVD credible intervals.

Table D.12: Variance decomposition with diffuse short-run priors

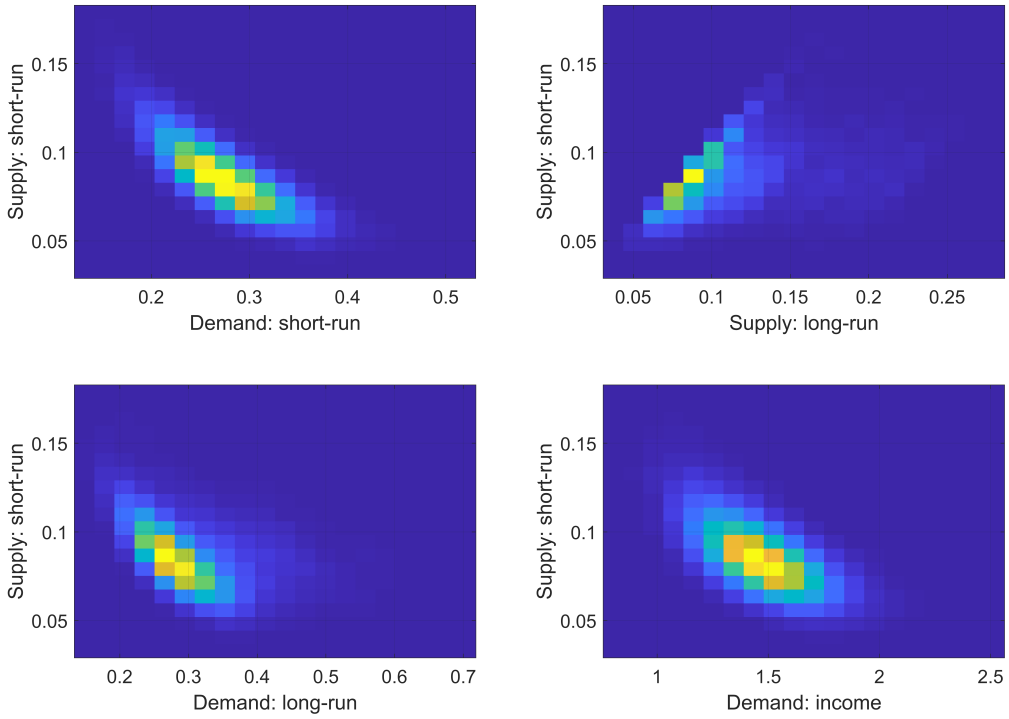
| | Oil Supply | Aggregate Demand | Oil-consump Demand | Oil-invent Demand |
|---|---|---|---|---|
| **HM-benchmark** | | | | |
| Oil prod | 63.71 | 7.62 | 27.33 | 0.01 |
| Ind prod | 0.7 | 89.65 | 9.44 | 0 |
| Oil price | 13.31 | 17.97 | 66.18 | 0.02 |
| *(10%-90%)* | (7.26 ; 24.34) | (10.95 ; 29.14) | (52.78 ; 78.2) | (0.01 ; 0.06) |
| Oil stock | 10.52 | 9.95 | 42.18 | 33.57 |
| **HM-informed** | | | | |
| Oil prod | 56.96 | 9.28 | 31.06 | 0.01 |
| Ind prod | 1.55 | 93.17 | 4.99 | 0 |
| Oil price | 32.46 | 12.78 | 53.64 | 0.04 |
| *(10%-90%)* | (22.26 ; 44.14) | (8.69 ; 18.54) | (43.61 ; 63.17) | (0.02 ; 0.1) |
| Oil stock | 15.05 | 6.05 | 30.59 | 45.17 |

Figure D.17 presents pairwise scatter plots of 50,000 MCMC draws of the short-run supply elasticity against each of four other elasticities in the HM benchmark: the short-run demand elasticity, the long-run demand elasticity, the long-run supply elasticity, and income elasticity of demand. Two features stand out from these plots. First, the short-run and long-run supply elasticities are positively associated. Second, lower supply elasticities tend to be associated with higher short-run and long-run demand elasticities, and vice-versa. As a result, the posterior admits very different profiles of demand and supply elasticities, which in turn generate different contributions of supply shocks to the FEVD of oil prices. Some combinations of draws imply a large role for supply shocks, while others imply the opposite. The uncertainty surrounding the FEVD therefore reflects not only uncertainty about individual elasticities, but also the way this uncertainty is compounded in their joint dependence highlighted above.

This pattern echoes the SVAR literature (e.g. CCI19, BH19, and Herrera and Rangaraju, 2020), which documents an inverse relation between the short-run price elasticities of oil supply and demand. Unexpected changes in oil prices and quantities can therefore be rationalized by either low demand elasticity and high supply elasticities, or by the opposite configuration. Our analysis shows that prior discipline on short-run elasticities is essential for shock identification, while prior discipline on dynamic elasticities is equally important for understanding shock propagation. Dynamic elasticities therefore matter for understanding the sources and consequences of oil market fluctuations.

Figure D.18 shows that introducing prior information on dynamic elasticities leaves the

Figure D.17: Relation among oil market elasticities across horizons




*Note: Histogram representing the bivariate distribution of the short-run elasticity of supply with one other elasticity based on 50 000 MCMC draws.*

identified oil supply shocks largely unchanged. In particular, estimated shocks under the HM benchmark and the HM-informed model are highly correlated and similar in magnitude. This indicates that priors on dynamic elasticities matter mainly for the propagation of oil market shocks, not for their identification. Two factors explain this result: (1) dynamic elasticities have a limited effect on impact responses (see Section 4), and (2) informative priors on dynamic elasticities do not materially alter the estimated short-run elasticities (see Tables D.13 and D.14).

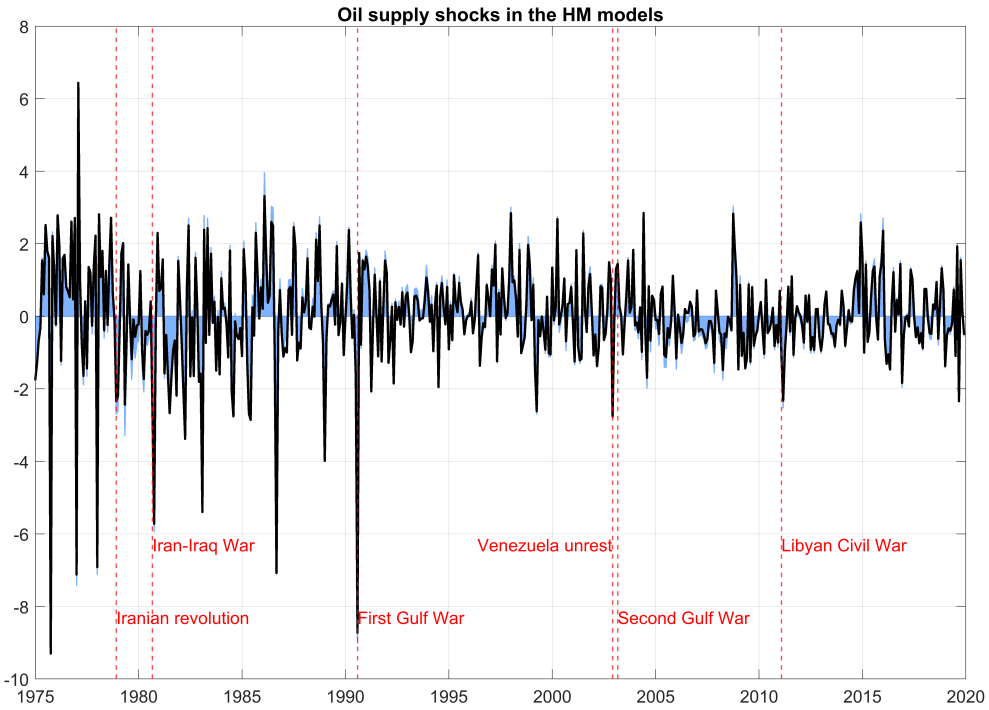
Table D.13: Estimated parameters in HM-benchmark

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.82 | 0.81 | 0.76 | 0.9 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.43 | 1.42 | 1.34 | 1.53 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.25 | 2.19 | 1.9 | 2.65 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.35 | 0.28 | 0.2 | 0.55 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.83 | 0.95 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.88 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.89 | 0.88 | 0.83 | 0.94 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.94 | 0.94 | 0.91 | 0.97 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.85 | 0.6 | 0.96 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.46 | 1.44 | 1.16 | 1.78 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.5 | 0.29 | 0.27 | 0.27 | 0.2 | 0.35 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.3 | 0.3 | 0.27 | 0.21 | 0.42 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.5 | 0.29 | 0.09 | 0.09 | 0.06 | 0.12 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.3 | 0.11 | 0.09 | 0.07 | 0.19 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.04 | 0.04 | 0.02 | 0.05 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.3 | 0.29 | 0.21 | 0.42 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.1 | 0.09 | 0.06 | 0.15 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.59 | 0.59 | 0.52 | 0.66 |

Table D.14: Estimated parameters in HM-informed

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.81 | 0.8 | 0.75 | 0.88 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.48 | 1.46 | 1.37 | 1.61 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.31 | 2.26 | 1.94 | 2.74 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.37 | 0.3 | 0.2 | 0.58 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.82 | 0.94 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.92 | 0.92 | 0.88 | 0.96 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.95 | 0.95 | 0.92 | 0.98 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.94 | 0.94 | 0.91 | 0.97 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.86 | 0.61 | 0.97 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.37 | 1.38 | 1.07 | 1.7 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.5 | 0.29 | 0.26 | 0.26 | 0.18 | 0.34 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.05 | 0.43 | 0.43 | 0.36 | 0.51 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.5 | 0.29 | 0.1 | 0.09 | 0.07 | 0.14 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.05 | 0.47 | 0.47 | 0.4 | 0.55 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.04 |
| $\delta_\lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.03 | 0.03 | 0.03 | 0.04 |
| $\nu$ | Storage demand elast. to $\Delta$price | Gamma | 0.46 | 0.1 | 0.29 | 0.29 | 0.2 | 0.4 |
| $\tau$ | Storage demand elast. to price | Gamma | 0.13 | 0.05 | 0.09 | 0.09 | 0.05 | 0.14 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.59 | 0.59 | 0.52 | 0.65 |

Figure D.18: Time series of structural oil supply shocks in the RBC model: HM-Informed (blue) vs HM benchmark (black) models



## D.8 What does it take for supply shocks to dominate?

In this section, we compute the contribution of supply shocks to oil-price fluctuations for different calibrated values of the long-run elasticities of oil demand and supply. The shock processes are estimated, while the other parameters – including the short-run elasticities and the adjustment speeds – are calibrated to their posterior modes. We work with two different calibrations of the short-run elasticities of supply and demand. The first case is calibrated to the KM-benchmark: the short-run elasticities of oil supply and demand are set to 0.02 and 0.43, respectively. The second case is calibrated to the BH-benchmark and these values are set to 0.10 and 0.23. The modes of the FEVD for each pair of models and each combination of long-run elasticities are reported in Table D.15.

Table D.15: Contribution of supply shocks to oil prices

| **KM-inspired** | $\sigma_{\text{LR}} = 0.02$ | $\sigma_{\text{LR}} = 0.1$ | $\sigma_{\text{LR}} = 0.25$ | $\sigma_{\text{LR}} = 0.50$ | $\sigma_{\text{LR}} = 1$ |
|---|---|---|---|---|---|
| $\eta_{\text{LR}} = 0.50$ | 4.66 | 6.26 | 10.95 | 18.22 | 27.33 |
| $\eta_{\text{LR}} = 1$ | 4.91 | 6.17 | 9.44 | 14.25 | 21.21 |
| $\eta_{\text{LR}} = 1.50$ | 5.49 | 6.49 | 8.98 | 12.50 | 18.10 |
| **BH-inspired** | $\sigma_{\text{LR}} = 0.02$ | $\sigma_{\text{LR}} = 0.1$ | $\sigma_{\text{LR}} = 0.25$ | $\sigma_{\text{LR}} = 0.50$ | $\sigma_{\text{LR}} = 1$ |
| $\eta_{\text{LR}} = 0.25$ | - | 16.46 | 28.38 | 40.70 | 50.88 |
| $\eta_{\text{LR}} = 0.50$ | - | 15.45 | 24.52 | 34.40 | 44.49 |
| $\eta_{\text{LR}} = 1$ | - | 16.48 | 22.29 | 28.88 | 37.23 |
| $\eta_{\text{LR}} = 1.50$ | - | 17.84 | 21.99 | 26.73 | 33.25 |

The upper panel of Table D.15 shows that in the KM-benchmark model with a small short-run elasticity of oil supply, one can find a relatively important role for supply shocks when the long-run elasticity of oil supply is high. Moreover, this contribution gets particularly high when the long-run elasticity of oil demand is low. This simple experiment demonstrates that one does not necessarily find a small role for supply shocks when supply is inelastic, as is usually the case in the SVAR literature.

Similarly, the lower panel of Table D.15 shows that in the BH-benchmark, one can also reach quantitatively different conclusions. For example, with long-run elasticities of demand and supply respectively at 0.25 and 1, one would reach the conclusion that oil supply shocks are the dominant source of oil-price fluctuations. It also highlights the importance of including land in the production function to produce realistic values of the long-run elasticity of oil supply, that would otherwise result in overestimating the role of supply shocks.

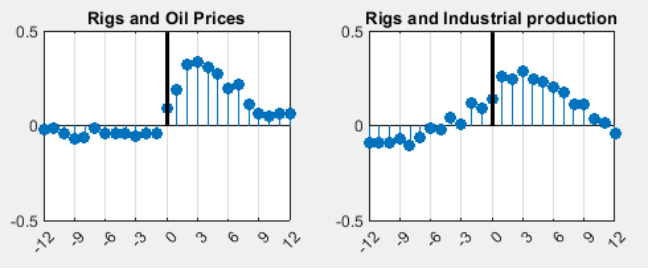
Surprisingly, we find that for very small values of the long-run elasticity of oil supply, a higher long-run elasticity of oil demand is not necessarily associated with a lower contribution of oil supply shocks. When supply is (almost) perfectly inelastic, firms' investment in efficiency is the only option available to mitigate the effects of a persistent oil-specific demand shock. In that case, a higher demand elasticity in the long-run strongly affects the persistence of the price effects of both oil supply and oil demand shocks. The net effect, in turn, depends on the degree of persistence of both shocks.

# E Details on model validation: Rig activity

We now estimate our model adding a fifth observed variable to the information set: oil rigs in activity. Our objective is to demonstrate that the information contained in this variable supports higher values of the long-run elasticity of oil supply that are coherent with the evidence reviewed in Section 2.1. Specifically, we start from the HM benchmark – in which we imposed diffuse priors on all oil market elasticities – and re-estimate the model with the growth rate of oil rigs in activity sourced from Baker Hughes.[‡]

In the data, oil drilling activity responds to oil price fluctuations with a short delay (which is noticeable from Figure 1 in the paper). More formally, the cross-correlation sequences in Figure E.19 show that the growth rates of oil prices (and industrial production) are leading the growth rate of oil drilling rigs. This implies that we have to introduce some form of real rigidities in our model – such as investment adjustment costs – to estimate our model with rigs as an observed variable.

Figure E.19: Cross-correlation coefficient sequences (leads and lags in months)




*Note: Left (right) : correlation between Rigs at time $t$ and oil prices (industrial production) at time $t-x$. Time horizon on the x-axis in months. Monthly growth rates.*

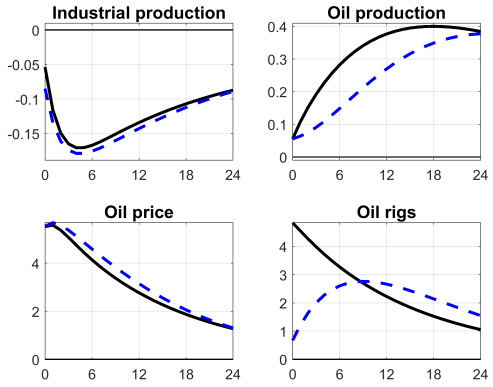
To capture these co-movements, we implement two minimal modifications to the model by introducing investment adjustment costs and a shock to oil investment (i.e., drilling). We assume that the cost of drilling investment at firm $j$ is given by

$$I_{j,t}(o) \times \left( \frac{I_t(o)}{I_{t-1}(o)} \right)^{\Phi(o)} \times \varepsilon_t^I, \tag{A.76}$$

where $\varepsilon_t^I$ is a drilling shock that can for example capture exogenous changes in the probability

[‡] Baker Hughes provides a monthly census of rotary rigs actively exploring for or developing oil and natural gas since 1975. We use the Active Rotary Rig Count at the world level. Details about this data are available at https://rigcount.bakerhughes.com/rig-count-faqs.

Figure E.20: Oil consumption demand shocks with investment adjustment costs




*Black: Baseline model:* $\sigma_{SR} = 0.01; \sigma_{LR} = 0.45$ *and* $\psi(o) = 0$
*Blue: with oil investment adjustment costs:* $\sigma_{SR} = 0.01; \sigma_{LR} = 0.45$ *and* $\psi(o) = 5$

of finding oil. When $\Phi(o) > 0$, the cost of drilling depends on past investment decisions, which generates a hump-shaped (and thus delayed) response of drilling activity to oil price fluctuations. Inside the parentheses, we do not index $I(o)$ with $j$ in order to prevent an internalization of this cost, which simplifies the FOC. Internalizing this cost could also lead to an overshooting response of oil production in response to some shocks. Also note that when $\Phi(o) = 0$ and $\varepsilon_t^I = 1$, we are back to our baseline model.

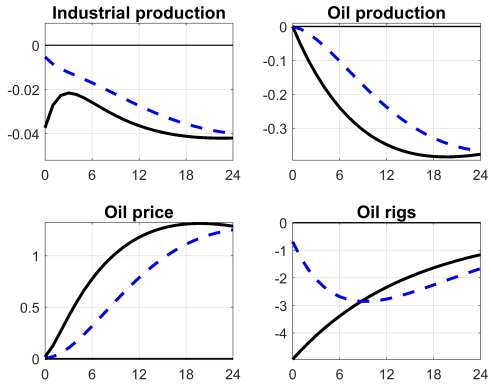
The linearized FOC capturing the investment decision becomes

$$\mathrm{E}_t \sum_{s=0}^{\infty} (1-\delta_\Lambda)^s \beta^s \left[ \hat{r}^{\Lambda}_{t+1+s} - \frac{1}{\theta} \left( (1+\psi(o)) \hat{I}_t(o) - \psi(o) \hat{I}_{t-1}(o) - \hat{\Lambda}_t^{new} \right) \right] = \hat{\varepsilon}_t^I, \qquad \text{(A.77)}$$

where $\psi(o) = \theta\Phi(o)$. Note that we estimate $\psi(o)$ and $\theta$ (instead of $\Phi(o)$ and $\theta$) to ease the identification of the investment adjustment cost and the CES parameter.

Before turning to the estimation of this extended model, we compare its dynamics to those of our baseline model without oil investment adjustment costs. Figure E.20 shows the effect of an oil consumption demand shock in the extended and baseline models. With adjustment costs, the response of oil rigs is hump-shaped, and peaks with a delay of a few months. The implication is that the adjustment in oil production is initially slower, and that the increase in oil prices is more pronounced in the medium run. The oil investment adjustment cost and the oil-well decay rate thus have similar effects on the dynamic adjustment of oil production and prices, as they both affect the adjustment speed of oil supply.

Figure E.21: Oil rig shocks with investment adjustment costs




*Black: Baseline model:* $\sigma_{SR} = 0.01; \sigma_{LR} = 0.52$ *and* $\psi(o) = 0$
*Blue: with oil investment adjustment costs:* $\sigma_{SR} = 0.01; \sigma_{LR} = 0.52$ *and* $\psi(o) = 5$

Figure E.21 shows the effect of an oil-rig shock with or without investment adjustment costs. A decline in oil rigs (i.e., in investment) gradually erodes the production capacities of oil producers, which gradually pushes up the price of oil. The decline in drilling investment, combined with the adverse effect of higher oil prices, results in a (modest) fall in industrial production.

We estimate the extended model with a relatively wide prior on the oil investment adjustment costs, reflecting a lack of prior studies about this parameter. All other priors are defined as in the HM-baseline experiment. We also introduce a measurement error on the observed oil-rig count, which, for example, captures the fact that some drilling activity occurs for exploration purposes that, if successful, would only imply an increase in production outside business cycle frequencies. This measurement error can also capture variations in productivity (per rig).

We obtain posterior modes for the short and long-run elasticities of oil supply of 0.09 and 0.34, respectively. These results indicate that the information contained in the rigs in activity supports higher values of the long-run elasticity of oil supply. The estimated posterior mode of the oil investment adjustment cost stands at 4.42, while the posterior modes of other parameters remain close to the HM-baseline estimation. For example, the estimated short and long-run elasticities of oil demand both stand at 0.26, thus close to the HM-baseline with four observed variables.

We could not obtain simple closed-form solutions for the dynamic elasticity of oil supply with oil investment adjustment costs (except for the short and long-run expressions that remain

unchanged). However, we can easily compute this dynamic elasticity numerically using the response of oil production following a permanent 1% increase in the oil price. Specifically, we replace the oil demand equation, (A.50), with an exogenous equation for prices: $\hat{p}_t = \hat{\varepsilon}_t^p$. We then simulate the effect of a permanent increase in oil prices of 1%.

The dynamic elasticities that we obtained are presented in Figure 11 in the paper. It should be noted that investment adjustment costs slow the dynamic adjustment of oil supply without altering the values of the short and long-run elasticities. The difference between these two cases is explained by the response of oil drilling activity to these shocks, which increases gradually with the investment adjustment costs but immediately jumps to a new equilibrium without (see Figures E.20 and E.21).

In this model, oil supply shocks account for 26% of the FEVD of oil prices (compared to 13% in the HM-benchmark model estimated with four variables). Shocks to oil rig activity only play a marginal role, accounting for 3% of the FEVD of oil production and 1% of the FEVD of oil prices. Oil demand shocks remain the most important drivers of oil prices, and they explain about 55% of the FEVD of oil prices, and 33% of oil-rig activity.

A larger supply elasticity helps the model to better replicate the correlations between oil prices, production, and drilling activity in the data (expressed in percentage deviation from a linear trend). Figure E.22 shows the correlation between our five observed variables in the data (first panel) and in the estimation discussed above (second panel). In this case, the moments generated by the model are relatively close to the data. In contrast, estimating a similar model with dynamic elasticities of oil supply constrained to be flat (with $\sigma_{\text{SR}} = \sigma_{\text{LR}}$, in the third panel) fails to reproduce some of the co-movements. The most striking examples are the correlation between oil prices and drilling activity and between oil prices and oil production.

Table E.16: Estimated parameters in HM-rigs

| | | Prior | | | Posterior | | | |
|---|---|---|---|---|---|---|---|---|
| Parameter | Description | Shape | Mean | Std | Mean | Mode | 5% | 95% |
| $Std(\epsilon^{ea})$ | Std economic activity | Inv Gamma | 0.5 | 0.5 | 0.81 | 0.8 | 0.75 | 0.88 |
| $Std(\epsilon^{os})$ | Std oil supply | Inv Gamma | 0.5 | 0.5 | 1.46 | 1.45 | 1.36 | 1.58 |
| $Std(\epsilon^{od})$ | Std oil consumption | Inv Gamma | 0.5 | 0.5 | 2.24 | 2.19 | 1.9 | 2.65 |
| $Std(\epsilon^{v})$ | Std oil inventory | Inv Gamma | 0.5 | 0.5 | 0.34 | 0.28 | 0.19 | 0.54 |
| $Std(\epsilon^{rigs})$ | Std oil rigs | Inv Gamma | 1 | 1 | 6.51 | 6.16 | 5.15 | 8.13 |
| $ME(V_t)$ | Measurement error (inventory) | Inv Gamma | 0.5 | 0.5 | 0.89 | 0.9 | 0.84 | 0.95 |
| $ME(RIGS_t)$ | Measurement error (rigs) | Inv Gamma | 0.5 | 0.5 | 1.48 | 1.49 | 1.33 | 1.63 |
| $\rho(\epsilon^{ea})$ | AR(1) economic activity | Beta | 0.8 | 0.1 | 0.93 | 0.94 | 0.89 | 0.97 |
| $\rho(\epsilon^{os})$ | AR(1) oil supply | Beta | 0.8 | 0.1 | 0.94 | 0.95 | 0.91 | 0.97 |
| $\rho(\epsilon^{od})$ | AR(1) oil consumption | Beta | 0.8 | 0.1 | 0.94 | 0.94 | 0.91 | 0.97 |
| $\rho(\epsilon^{v})$ | AR(1) oil inventory | Beta | 0.8 | 0.1 | 0.81 | 0.85 | 0.6 | 0.96 |
| $\rho(\epsilon^{rigs})$ | AR(1) oil rigs | Beta | 0.8 | 0.1 | 0.71 | 0.72 | 0.57 | 0.83 |
| $\chi$ | OED | Normal | 1 | 0.25 | 1.42 | 1.42 | 1.11 | 1.76 |
| $\eta_{\text{SR}}$ | SRED | Beta | 0.5 | 0.29 | 0.26 | 0.26 | 0.19 | 0.35 |
| $\eta_{\text{LR}}$ | LRED | Gamma | 0.45 | 0.3 | 0.32 | 0.26 | 0.21 | 0.54 |
| $\sigma_{\text{SR}}$ | SRES | Beta | 0.5 | 0.29 | 0.09 | 0.09 | 0.06 | 0.13 |
| $\sigma_{\text{LR}}$ | LRES | Gamma | 0.52 | 0.3 | 0.37 | 0.34 | 0.26 | 0.5 |
| $\delta_z$ | Oil-saving capital depreciation | Beta | 0.033 | 0.01 | 0.03 | 0.03 | 0.02 | 0.05 |
| $\delta_\Lambda$ | Oil well decay rate | Beta | 0.038 | 0.01 | 0.03 | 0.02 | 0.01 | 0.04 |
| $\nu$ | Storage demand elasticity to $\Delta$ price | Gamma | 0.46 | 0.1 | 0.3 | 0.29 | 0.21 | 0.41 |
| $\tau$ | Storage demand elasticity to price | Gamma | 0.13 | 0.05 | 0.09 | 0.09 | 0.05 | 0.14 |
| $b$ | Habits in consumption | Beta | 0.85 | 0.05 | 0.58 | 0.57 | 0.51 | 0.64 |
| $\psi(o)$ | Drilling adjustment costs | Gamma | 1 | 0.5 | 4.64 | 4.42 | 3.52 | 5.88 |

Figure E.22: Correlations: data vs the models with rigs

| DATA | Oil prod | Ind prod | Oil price | Oil stock | Oil Rigs |
|---|---|---|---|---|---|
| *Oil prod* | 1 | 0.52 | 0.26 | -0.68 | 0.22 |
| *Ind prod* | 0.52 | 1 | 0.28 | -0.13 | 0.27 |
| *Oil price* | 0.26 | 0.28 | 1 | -0.41 | 0.89 |
| *Oil stock* | -0.68 | -0.13 | -0.41 | 1 | -0.36 |
| *Oil Rigs* | 0.22 | 0.27 | 0.89 | -0.36 | 1 |
| ***HM-rigs*** | *Oil prod* | *Ind prod* | *Oil price* | *Oil stock* | *Oil Rigs* |
| *Oil prod* | 1 | 0.28 | 0.1 | -0.09 | 0.32 |
| *Ind prod* | 0.28 | 1 | 0.12 | -0.08 | 0.18 |
| *Oil price* | 0.1 | 0.12 | 1 | -0.81 | 0.67 |
| *Oil stock* | -0.09 | -0.08 | -0.81 | 1 | -0.58 |
| *Oil Rigs* | 0.32 | 0.18 | 0.67 | -0.58 | 1 |
| ***HM-flat*** | *Oil prod* | *Ind prod* | *Oil price* | *Oil stock* | *Oil Rigs* |
| *Oil prod* | 1 | 0.23 | -0.21 | 0.16 | 0.36 |
| *Ind prod* | 0.23 | 1 | 0.05 | -0.01 | 0.05 |
| *Oil price* | -0.21 | 0.05 | 1 | -0.82 | -0.22 |
| *Oil stock* | 0.16 | -0.01 | -0.82 | 1 | 0.1 |
| *Oil Rigs* | 0.36 | 0.05 | -0.22 | 0.1 | 1 |

*Data : variables in percentage deviation from a linear trend. Models : variables in percentage deviation from their steady-state, simulated at the posterior mode of the estimated parameters. Estimation with rigs as a fifth observed variable.*

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