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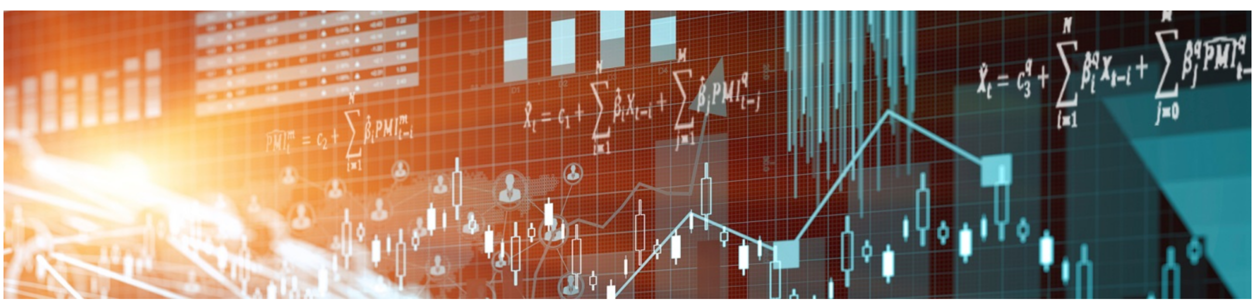
The Simple Economics of Global Fuel Consumption



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The Simple Economics of Global Fuel Consumption

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# Abstract

This paper presents a structural framework of the global oil market that relies on information on global fuel consumption to identify flow demand for oil. We show that under mild identifying assumptions, data on global fuel consumption help to provide comparatively sharp insights on elasticities and other key structural parameters of the global oil market. The estimated elasticity of global fuel demand in the short run with respect to crude oil prices is around -2 percent, which is considerably more inelastic than estimates of local fuel demand elasticities based on disaggregated data. Our framework is particularly suitable for understanding the evolution of quantities in the global oil market and provides new evidence on the magnitude of different types of oil price shocks and their macroeconomic and environmental impacts.

Bank topic: Economic models
JEL codes: C51, Q41, Q43, L71

Résumé

Dans la présente étude, nous proposons un cadre structurel du marché mondial du pétrole construit à partir de données sur la consommation mondiale de carburant pour déterminer la demande courante de pétrole. Nous montrons que, moyennant des hypothèses d'identification prudentes, les données de la consommation mondiale de carburant permettent de se faire une idée relativement précise des élasticités et d'autres grands paramètres structurels du marché mondial du pétrole. Selon notre modèle, l'élasticité estimée de la demande mondiale de carburant à court terme par rapport au prix du brut est d'environ -2 %, soit considérablement plus faible que les élasticités de demande locale estimées à partir de données détaillées. Notre cadre est particulièrement utile pour comprendre l'évolution des quantités de pétrole vendues sur le marché mondial. Entre autres, il apporte de nouveaux éléments de preuve étayant l'ampleur de différents types de chocs de prix du pétrole ainsi que leurs répercussions macroéconomiques et environnementales.

Sujet : Modèles économique
Codes JEL : C51, Q41, Q43, L71

Non-technical summary

A common view among practitioners and policy makers is that the demand for unrefined oil is ultimately determined by the demand for oil products (henceforth, fuels). Exploiting this link between fuel and crude oil markets, we propose a structural vector-autoregressive model of the global oil market that combines data on global fuel consumption with data on global oil production and real crude oil prices and identifies three types of structural shocks that form the basis of canonical models of markets for storable commodities: flow demand shocks that raise quantities and prices, flow supply shocks that raise quantities but decrease prices, and storage demand shocks that move production and consumption in opposite directions. We show that under mild identifying assumptions, the information on global fuel consumption helps to provide comparatively sharp insights on elasticities and other key quantitative features of the global oil market.

The results suggest that in the short run, both oil supply and fuel demand are very inelastic with respect to crude oil prices. The estimated short-run elasticity of global fuel demand with respect to crude oil prices is around -2%, which is considerably more inelastic than estimates of local fuel demand elasticities based on disaggregated data. We document that much of the apparent discrepancy between the global fuel demand elasticity and local fuel demand elasticities can be reconciled by an imperfect percent pass-through from global crude oil prices to local fuel prices. Based on data for gasoline and diesel prices in major oil consuming economies, we provide a rough estimate of this global percent pass-through that suggests that a 10% increase in crude oil prices is associated with only a 2% increase in the price of the average barrel of fuel. In contrast, existing studies often extrapolate the (much larger) US specific percent pass-through to the global oil market, and thus assume a much tighter relationship between global and local elasticities than suggested by our estimates.

These results are important for several reasons. First, the identified elasticity parameters govern the evolution of prices and quantities in the global oil market and are key to disentangling the various forces acting upon the oil market and to conducting counterfactual analysis. Second, they shed light on the effectiveness of global environmental or climate policies that act through the price of crude oil. Finally, our results also show that it is important to distinguish between global elasticities and local elasticities. Models of the global oil market often rely on micro- or cross-country estimates of the local elasticity to provide the bounds or priors for global elasticities that identify structural parameters. When global and local elasticities are very different, this practice can distort the estimation and inference in such models.

1 Introduction

Shifts in flow demand for oil are a key determinant of oil prices and their relationship with macroeconomic outcomes. To identify oil demand, standard structural vector autoregressive (SVAR) models of the global crude oil market infer global oil consumption by combining data on crude oil production with information on oil inventories (Kilian and Murphy 2014; Kilian and Lee 2014; Baumeister and Hamilton 2019). An alternative approach to measuring oil consumption is based on the insight that unrefined oil is only an intermediate input into the production of refined petroleum products, or "fuels," such as gasoline and diesel.[1] This implies that flow consumption of oil takes place in the form of fuels that are being consumed in the transportation or petrochemical sector and that global oil demand is ultimately governed by the global demand for refined products. While this view is common among policy makers and market participants, it has been left largely unexploited in quantitative models of the global oil market.[2]

This paper introduces information on fuel consumption into a simple structural framework of the global oil market. We combine data on global fuel consumption with data on global oil production and real crude oil prices in a SVAR model and use standard sign restrictions to identify three types of structural shocks that form the basis of canonical models of markets for storable commodities: flow demand shocks that raise quantities and prices, flow supply shocks that raise quantities but decrease prices, and storage demand shocks that move production and consumption in opposite directions.[3] We show that despite the parsimony of the identifying assumptions, the information on global fuel consumption helps to provide comparatively sharp insights on elasticities and other quantitative features of the global oil market.

The patterns observed in global fuel consumption data bear particularly clear-cut information on the magnitude of the price elasticity of global oil demand. The point estimates of the short-run fuel demand elasticity with respect to crude oil prices are around -2%. This is significantly lower (in absolute value) than recent estimates of the US gasoline demand elasticity, which are of the order of -30% or larger (Levin, Lewis, and Wolak 2017; Coglianese et al. 2017).[4] We document that much of the apparent discrepancy between the global fuel demand elasticity and "local" fuel demand elasticities can be reconciled by an imperfect

[1] Throughout the paper, we use the terms "fuels" and "oil products" interchangeably to refer to refined petroleum products.

[2] For policy institutions and other market participants that measure global oil consumption in the form of fuels, see, e.g., the global oil demand statistics in International Energy Agency's (IEA) *Oil Market Report* and *World Energy Outlook*, the Organization of the Petroleum Exporting Countries (OPEC) *World Oil Outlook*, or BP's *BP Statistical Review of World Energy*.

[3] These sign restrictions follow readily from economic theory for storable commodities (Roberts and Schlenker 2013; Kilian and Murphy 2014; Knittel and Pindyck 2016).

[4] Throughout the paper, "short-run" refers to the frequency of our data, which is quarterly.

percent pass-through from global crude oil prices to local fuel prices: based on data for gasoline and diesel prices in major oil-consuming economies, we provide a rough estimate of this global percent pass-through, which suggests that a 10% increase in crude oil prices is associated with only a 2% increase in price of the average barrel of fuel. In contrast, existing studies often extrapolate the (much larger) US-specific percent pass-through to the global oil market, and thus assume a much tighter relationship between global and local elasticities than suggested by our estimates.[5]

Although the model focuses on the global *fuel demand* elasticity, its estimates can also be used to provide bounds for the short-run elasticity of global *crude oil demand*. Under conservative assumptions, we find that this elasticity is likely to be in the -2% to -15% range, which is lower than median estimates of the crude oil demand elasticity in existing benchmark models (Kilian and Murphy 2014; Kilian and Lee 2014; Baumeister and Hamilton 2019). Our point estimate for the global oil supply elasticity is around 1.3%, consistent with existing evidence that oil supply is very inelastic in the short run (Kilian and Murphy 2014; Anderson, Kellogg, and Salant 2018; Newell and Prest 2019).

Our results have implications for the distributional effects of global energy and environmental policies that act through the price of oil (Davis and Kilian 2011). The evidence for a low fuel demand elasticity suggests that in the short run, a significant share of the tax incidence of such policies might accrue to oil consumers and distributors. It is also relevant for assessing the role of oil speculation in the global oil market: when both supply and demand are very inelastic, shifts in expectations can lead to large price swings that coincide with only small movements in quantities (Hamilton 2009). In fact, evidence that relies on more elastic gasoline demand has frequently been evoked to rule out important effects of speculation in the oil market (Fattouh, Kilian, and Mahadeva 2013; Knittel and Pindyck 2016). While our results show that most of the oil price fluctuations over the last decades can be attributed to shifts in the oil supply and oil demand curve, our historical decomposition of crude oil prices—which is associated with much smaller elasticity estimates—is not able to rule out significant price effects from shifts in speculative demand during selected periods such as the run-up of oil prices during the first half of 2008. Finally, our analysis also highlights the importance of distinguishing between crude oil demand elasticities and global and local fuel demand elasticities. The smooth evolution of global fuel consumption suggests that relatively strong consumption responses to local and fuel-specific price shocks add up to a much fainter pattern in the aggregate data, and thus cautions against the widespread use of local or cross-country fuel elasticity estimates to discipline models of the global crude oil market (Kilian and Murphy 2014; Caldara, Cavallo, and Iacoviello 2019; Baumeister and Hamilton 2019).

[5] See, e.g., Hamilton (2009) and Coglianese et al. (2017).

Despite important differences vis-á-vis existing elasticity estimates, the model-implied historical decompositions of oil price fluctuations into contributions from supply, (fuel) demand and storage demand shocks are largely consistent with established accounts of key oil market episodes. As in Kilian and Murphy (2014), for example, our model attributes the oil price spike in 1991 to a combination of oil supply and storage demand shocks. Likewise, our model attributes most of the run-up in oil prices during the mid-2000s and almost all of their decline in the wake of the financial crisis to fuel demand shocks. Given the importance of global economic activity for oil price fluctuations during this boom-and-bust cycle (see, e.g., Kilian 2009; Kilian and Hicks 2013), this seems to suggest that changes in aggregate demand manifest themselves in the oil market mainly through shifts in fuel demand. Analyzing the determinants of fuel consumption, historical decompositions show that shifts in the global demand curve explain most of the variation in global fuel consumptions in the short term and at business-cycle frequencies. Instead, oil supply shocks contributed importantly to some of the lower frequency movements in global oil consumption.

The implementation of our model relies on data on global fuel consumption provided by the International Energy Agency (IEA). The corresponding oil production series, also provided by the IEA, is based on a broad definition of total oil liquids production that covers not only crude oil but also other liquids that serve as refinery feedstock or blendstock in the production of fuels.[6] We introduce a stylized theoretical framework of the global oil market that highlights how data on fuel consumption and a broader measure of oil production changes the interpretation of structural shocks and elasticities vis-á-vis those of existing models that that focus on the narrower crude oil market. In our setting, oil supply shocks also take into account shifts in the supply of non-crude liquids that are substitutes to crude oil in the production of fuel. Moreover, in contrast to existing studies that model only crude oil inventories, our framework also separates oil demand for finished petroleum inventories from oil demand for flow consumption. This distinction clearly matters for understanding actual consumption flows and their consequences, such as global emissions from fuel consumption. It also matters for oil market dynamics, since storage—either in the form of unrefined oil or finished petroleum products—augments the availability of oil for future consumption. Our model takes into account that storage of oil takes place in the form of both unrefined oil and fuel inventories, and that both forms of storage are quantitatively important.

The use of actual fuel consumption data and a broader measure of oil production provides a new perspective on the relationship between oil markets and macroeconomic outcomes. The fact that our model and its identification rely purely on quantities and prices is particularly useful in this regard, as it implies that no prior restrictions on the relationship between oil price shocks and such outcomes are imposed. We document that during the last decades,

[6] For example, condensates, natural gas liquids (NGLs) and liquids from nonconventional production.

oil supply shocks had negative but small and statistically insignificant impacts on global industrial production growth, which was somewhat more pronounced in advanced economies than in emerging economies. In contrast, outward shifts in the fuel demand curve were strongly associated with increases in global industrial production growth in both advanced and emerging economies.

The link between fuel demand and unrefined oil demand is widely acknowledged in existing research.[7] It is therefore surprising that it has not been exploited more frequently in quantitative models of the global oil market. An exception is Kilian (2010), who investigates the relationship between the global crude oil market and US fuel consumption and documents important crude oil price effects from shifts in US gasoline consumption. Our analysis is complicated by the fact that no suitable global fuel price series exists. However, we show that the positive correlation between crude oil and fuel prices can be used to identify global fuel demand shocks even in the absence of corresponding fuel price data. The empirical results suggest that shifts in the *global* fuel demand did indeed account for the bulk of the fluctuations in crude oil prices over the last decades. Examining the link between crude oil prices and fuel demand from a different perspective, the Verleger hypothesis postulates that oil prices are determined in oil product markets. As a consequence, oil product prices should have predictive power for crude oil prices (Baumeister, Kilian, and Zhou 2018). Instead of focusing on a forecasting relationship, this paper provides a structural perspective on the role of fuel demand in the global oil market that relies on the idea that crude oil prices and fuel prices are simultaneously determined by oil supply and fuel demand.

The remainder of the paper is structured as follows: The next section presents a more detailed account of the underlying oil production and fuel consumption data; section 3 introduces a conceptual framework of the global oil market that motivates our empirical model; section 4 presents and discusses the results; and section 5 concludes.

2 Measuring global oil production, fuel consumption and the change in global oil inventories

2.1 Flow consumption and production

We measure quantities in the oil market as global oil flow production and oil products flow consumption.[8] The production and consumption series are drawn from the International

[7] See, for example, the stylized frameworks in Hamilton (2009) and Kilian and Murphy (2014).

[8] Although many existing studies rely on monthly data, the use of lower frequency has advantages, such as mitigating measurement problems that can arise from the timing of flow production and flow consumption. Given that longer-run elasticities tend to be larger than short-run elasticities (Kilian and Murphy 2014), the quarterly elasticity estimates presented in the paper can be interpreted as upper bounds for the monthly

Energy Agency's (IEA) Monthly Oil Data Service, a proprietary database that provides quarterly oil production and consumption data since the mid-1980s.[9]

The fuel consumption series tracks flow consumption of total oil products. The IEA defines consumption as all deliveries of oil to consumers, including bunker fuels and biofuel products. This definition includes products for all common uses of fuel, such as transportation and petrochemical feedstock. The data is collected from reporting by member countries for OECD countries, and from a combination of domestic sources, data from international organizations, and estimates based on other economic data for non-OECD countries.

The IEA does not provide a breakdown of the different components of oil consumption on a global level. However, we can use available data from OECD countries to gauge the relative importance of different fuels (figure 8 in Appendix A). In OECD countries, most fuel consumption takes place in the form of gasoline (constituting on average about 30% of OECD fuel consumption) and diesel (26%). The remaining consumption consists of "Other products" such as liquified petroleum gas and ethane, naphtha, jet fuel and kerosene (totalling 34% on average) and residual fuel (10%). The table also indicates that the relative composition of fuel consumption was fairly stable throughout the sample period, with the exception of a notable decline in residual fuel at the expense of diesel and "Other products."

The oil production series tracks the flow production of total oil liquids. Production includes crude oil as well as condensates, natural gas liquids (NGLs), nonconventional oils and biofuels that constitute refinery or blender inputs in the production of oil products.[10] The IEA's production measure also accounts for refining processing gains, thus ensuring a volumetric consistency between refinery inputs and outputs. Adjusting the oil production data for refinery gains thus ensures that the production and consumption series are directly comparable. The oil production series used in this study is hence given by

$$\begin{aligned} \text{Total Oil Production}_t \quad &= \quad \text{Crude Oil Production}_t + \text{Other Refinery Feedstock}_t + \\ &\quad\quad \text{Other Refinery Blendstock}_t + \text{Refinery Gains}_t. \end{aligned} \tag{1}$$

While crude oil is by far the largest component in total oil production (constituting on average about 87% of total oil production), the share of "Other Refinery Feedstock"—such as

elasticity.

[9]The relevant series are taken from the *Supply, Demand, Balances and Stocks* tables, distributed by IEA's Monthly Oil Data Service. The database contains data starting in 1986Q1. The first years of data were dismissed to avoid measurement problems at the outset of data publication. With *Total World Liquid Fuels Consumption* and *World Liquid Fuels Production*, the US Energy Information Administration (EIA) provides similar series. However, the historical coverage of the EIA series only goes back to 1997. In the periods where they coincide, the IEA and the EIA series track each other closely.

[10]Condensates are liquid hydrocarbons recovered from fractionation of gaseous flows. NGLs are components of natural gas that are separated from the gas state in the form of liquids. Nonconventional oils include synthetic crude oil from tar sands or oil shale and liquids from coal or gas liquefaction and refinery additives.

condensates, NGLs and nonconventional oils—in total oil production has increased considerably since the mid-2000s (figure 8 in Appendix A). In particular the US shale oil and gas revolution led to a strong increase in the production of very light condensates (hydrocarbons with gravities above 50 API) and NGLs (liquids that are extracted in the process of producing and processing natural gas). Despite these changes, variations in refinery gains remained very low, with refinery gains remaining between 2% and 2.5% of total oil production throughout the sample period.[11]

The IEA's definition of total oil production is broader than the one used in most existing structural models of the global oil market, which typically employ the narrower definition of oil production that relies on crude oil only.[12] The distinction between crude oil and other refinery feedstock and blendstock is not always clear cut, but it is typically made on the basis of the hydrocarbon's phase under normal surface temperatures and pressure, its physical characteristics, such as its density, and the form through which it is recovered.[13] How useful the aggregation of different types of oil into a single oil production number is depends on the degree of substitutability between crude oil and other non-crude liquids in the production of fuels.[14] To show that this substitution effect between crude oil and other refinery feedstock and blendstock is quantitatively important, figure 6 in Appendix A depicts US refiners' and blenders' crude oil input and total liquids input in comparison with their production of gasoline, diesel and jet fuel. While crude oil input rose in sync with the production of gasoline, diesel and jet fuel up to the mid-2000s, this relationship experienced a notable break during the 2005–2010 period. In contrast, total liquids input continued to track the production of these fuels closely, indicating that non-crude liquids such as biofuels and NGLs indeed did directly replace crude oil, even in the production of high-value transportation fuels such as gasoline, diesel and jet fuel.

The aggregation of different oil liquids is not only important for achieving a framework with consistent quantities for oil production and fuel consumption but is also sensible from a macroeconomic perspective: similar to crude oil supply shocks, surprise shifts in the supply of non-crude liquids represent aggregate supply shocks. Like existing oil market models,

[11] The average absolute quarterly change in refinery gains during the 1988–2017 sample period is below 0.02 million barrels per day (mb/d), compared with an average absolute quarterly change in total oil production of about 0.75 mb/d.

[12] See, e.g., Kilian (2009), Kilian and Murphy (2014), and Baumeister and Hamilton (2019)

[13] The physical density of liquid hydrocarbons is typically measured according to the American Petroleum Institute (API) gravity formula. Often, liquid hydrocarbons with a gravity between 20 API ("heavy") and 50 API ("light") are considered crude oil.

[14] Non-crude oil liquids can be direct or indirect substitutes for crude oil. For example, condensates are too light to classify as crude oil, but are used in a similar fashion as crude oil to produce gasoline, diesel, and jet fuel. Condensate can also act as a diluent to enable the transportation of heavy oil, after which condensate and heavy oil are often refined jointly. In a similar fashion, some NGLs, in particular natural gasoline or butane, are directly used as refinery feedstock. Other NGLs are used as feedstock in the petrochemical industry and could thus crowd out the use of naphta or crude oil in this sector.

which aggregate different types of crude oil that are potentially imperfect substitutes into a single production number (Kilian 2016; Melek, Plante, and Yücel 2017), the aggregation in our data is useful to facilitate a comprehensive analysis of world oil supply and corresponding fuel demand.

2.2 How does the implied change in inventories compare with other measures of inventories?

For the empirical analysis, we use a standard filter (the U.S. Census X-13) to seasonally adjust the production and the consumption series, both of which exhibit seasonal patterns. The top panels of figure (5) in Appendix A depict the historical evolution of global oil production and fuel consumption in levels and in percentage changes. Quantities in the global oil market are slow moving, and almost all of the quarterly percentage changes in these series are within a range of ±2%. Also, these series clearly move together in the long run, indicating a cointegrating relationship between these variables.

By identity, the difference between flow production and flow consumption is equal to the change in inventories. The bottom panel of figure (5) depicts the change in oil inventories implied by IEA's total oil production and fuel consumption measure. Periods of sustained inventory accumulation seem to coincide with key episodes of oil price declines, such as the one around the 1997–1998 Asian crisis and the 2014–2015 oil price drop. Likewise, periods of inventory draws seem to coincide with episodes of oil price increases, notably during the 2007–2008 rise before the financial crisis and the recovery after 2010.

Due to the IEA's broad definition of total oil production and fuel consumption, the implied changes in global oil inventories include not only changes in commercial crude oil inventories, but also changes in inventories in Strategic Petroleum Reserves (SPRs), in non-crude refinery feedstock, and in refined petroleum products:

$$\begin{aligned}&\text{Total oil production}_t - \text{Fuel consumption}_t \equiv \text{Implied change in total oil inventories} =\\&\Delta\text{Crude oil inventories}_t + \Delta\text{Other refinery feedstock and blendstock inventories}_t +\\&\Delta\text{Fuel inventories}_t.\end{aligned} \tag{2}$$

The implied changes in total oil inventories thus acknowledge that storage of oil liquids can take place at different stages of the value chain. Importantly, the definition also includes inventories in non-OECD countries, which have become increasingly important over the last decades and by 2017 accounted for more than half of global oil consumption.

Although separate data for crude oil and finished petroleum products are available only for OECD countries, they are instructive in highlighting the importance of non-crude oil inventories in the oil market. Over our sample period, on average about 50% of all oil inventories in OECD countries consisted of crude oil, while fuel inventories accounted for about 40%.[15] Changes in OECD fuel inventories were more variable than OECD crude oil inventories and seemed to contribute importantly to the variability of total OECD petroleum products inventories.[16]

Figure (7) in Appendix A depicts changes in OECD crude oil and fuel inventories, along with the implied change in total oil inventories. It shows that while changes in OECD crude oil inventories and changes in total oil inventories are positively correlated (with a correlation coefficient of about 44%), changes in total oil inventories tend to be significantly larger and more persistent. As such, the accumulation of oil inventories in non-OECD countries seemed to have played an important role during the 1997–1998 oil glut, and, judging from the large overall stock draws, the global oil market appeared to be much tighter in 2007–2008 than is apparent from changes in OECD inventories alone. Taken together, the descriptive evidence shows that changes in non-OECD and fuel inventories are large and could play an important role in explaining the dynamics of global oil prices.

3 A simple model of the global oil market

3.1 Conceptual framework

Fluctuations in prices and quantities in the global oil market can originate from a variety of forces, and the distinction between different fundamental drivers is crucial for understanding oil market dynamics and the relationship between oil prices and macroeconomic outcomes (Kilian 2009). This paper proposes a simple structural framework that identifies surprise shifts in global oil supply, global fuel demand and global oil storage demand. Through the lens of this framework, patterns that are observable in aggregate fuel consumption data can help to identify key structural parameters in the global oil market.

To highlight the role of fuel demand in the global oil market, we present a stylized model of the global oil market that relates the standard upward-sloping crude oil supply to refining and storage decisions in the face of a downward-sloping demand for fuels.[17] In the standard linear setting and under the assumption of perfect substitutability between crude oil and

[15]Inventories of non-crude refinery feedstocks such as NGLs accounted for the remaining 10%.

[16]Based on calculations with seasonally adjusted data, the correlation between changes in fuel inventories and changes in total oil inventories over our sample period was larger than 80%, compared with about 70% for the correlation between changes in crude oil inventories and changes in total oil inventories. Consistent with this idea that fuel inventories are indeed useful for understanding crude oil price dynamics, it has been shown that crude oil prices react strongly to surprise changes in oil product inventories (Halova, Kurov, and Kucher 2014).

[17]See Appendix C for details.

other refinery blendstock in the production of fuels, we obtain the following expression of crude oil prices, P_t^o, as a function of oil supply, fuel demand and changes in inventories:

$$P_t^o = \frac{1}{\eta_S - (1+\tau)\eta_D^f} \left[\kappa + u_t^q - u_t^{x,t} + (\Delta I_t^o + \Delta I_t^f) \right], \tag{3}$$

where η_S is the slope of the short-run crude oil supply curve, η_D^f is the slope of the short-run fuel demand curve with respect to fuel prices, $u_t^{x,t}$ is a shifter of total oil supply, u_t^q is a fuel demand shifter, κ is a constant related to labor costs in the production of fuels as well as unit taxes, τ is taxes or subsidies that can drive a wedge between crude oil and fuel prices, and ΔI_t^o and ΔI_t^f denote changes in crude oil and fuel inventories, respectively. By identity, the change in total oil inventories, $\Delta I_t^o + \Delta I_t^f$, is equal to the difference between total oil production and fuel consumption. Thus, equation (3) suggests that a model based on total oil production and fuel consumption, along with the appropriate structural parameters, can provide an adequate description of the price of crude oil and its determinants. Moreover, by introducing shifts in storage demand as one potential source of shifts in total inventories, equation (3) shows that even in a framework with total oil production (instead of crude oil production) and fuel consumption (instead of crude oil refinery intake), crude oil prices can be expressed in terms of the typical flow supply, flow demand and storage demand shocks that form the basis of canonical models of commodity markets with storage. As shown below, this setting also suggests that standard sign restrictions can be used to disentangle these shocks.

3.2 VAR representation

We use a general dynamic simultaneous equation model in the form of a structural VAR to describe the dynamics of oil production, oil consumption and the price of crude oil. The vector of observed variables, $\mathbf{y}_t$,

$$\mathbf{y}_t = [x_t, q_t, p_t]', \tag{4}$$

comprises the log of total oil production, x_t, the log of fuel consumption, q_t, and the log of the real price of oil, p_t.[18] We assume that $\mathbf{y}_t$ evolves dynamically as a vector-autoregressive process:

$$\mathbf{y}_t = \boldsymbol{c} + \sum_{h=1}^{p} \boldsymbol{\Phi}_h \cdot \mathbf{y}_{t-h} + \boldsymbol{\epsilon}_t, \tag{5}$$

[18] The global oil production and consumption data are described in section (2). The real price of oil is computed as the quarterly average of real monthly oil prices, which are obtained by deflating EIA's monthly Brent spot prices by the Consumer Price Index provided by the US Bureau of Labor Statistics. A robustness exercise in which the quarterly average price was replaced by the average price during the last month of each quarter yielded almost identical results to the ones described below.

where $\boldsymbol{c}$ is a (3×1) vector of constants, the matrixes $\boldsymbol{\Phi}_1, \cdots, \boldsymbol{\Phi}_p$ contain the autoregressive parameters, and $\boldsymbol{\epsilon}_t \equiv [\epsilon_t^x, \epsilon_t^q, \epsilon_t^p]'$ is a (3×1) vector of (generally correlated) innovations following a white noise process. The reduced form is estimated with six quarterly lags, which reflects a trade-off between the 24 lags of monthly lags typically included in these models (Kilian and Murphy 2014) and the fact that we have a shorter sample period than in comparable studies.[19] The model is estimated for quarterly data from 1988Q1 to 2017Q3.

3.3 Identification with sign restrictions

In our framework, dynamics in the global oil market are driven by three different types of structural shocks: flow supply shocks, flow demand shocks and storage demand shocks. These shocks are linearly related to the reduced-form innovations of the VAR, $\boldsymbol{\epsilon}_t$ in equation (4), via

$$\boldsymbol{\epsilon}_t = \begin{bmatrix} \epsilon_t^x \\ \epsilon_t^q \\ \epsilon_t^p \end{bmatrix} = B \cdot \begin{bmatrix} u_t^x \\ u_t^q \\ u_t^i \end{bmatrix}, \tag{6}$$

where u_t^x, u_t^q and u_t^s are the structural innovations with diagonal variance-covariance matrix Σ_u and B is a (3×3) matrix governing the contemporaneous impact of structural shocks on production, consumption and the real price of oil. We refer to u_t^x as the flow supply shock, to u_t^q as the flow demand shock, and to u_t^i as the storage demand shock.

We identify the structural shocks and parameters via sign restrictions. The restrictions, displayed in table (1), follow readily from imposing an upward-sloping short-run oil supply curve and a downward-sloping short-run oil demand curve (e.g., Kilian and Murphy 2012; Baumeister and Peersman 2013; Kilian and Murphy 2014). As shown in Appendix C, these sign restrictions are able to uniquely identify flow supply, flow demand and storage demand shocks despite the fact that our framework relies on an aggregated measure of oil production and data on fuel consumption instead of the usual crude oil production and refinery intake data.

In our framework, negative flow supply shocks represent surprise shortfalls in total oil production that lead to increases in the real price of crude oil. Even without modeling fuel prices directly, our empirical model exploits the positive correlation between crude oil prices and fuel prices that arises from the fact that crude oil is an important cost component in the production of fuels. With a downward-sloping fuel demand curve, negative flow supply shocks are thus associated with a decrease in fuel consumption.

[19]Production and consumption are cointegrated, but the evidence for additional cointegrating relationships among the variables is inconclusive. Estimating the VAR model in levels allows for cointegration among the variables without taking a stance on the cointegrating relationship.

	Flow supply shock	Flow demand shock	Storage demand shock
Production	-	+	+
Consumption	-	+	-
Real price of crude oil	+	+	+

Table 1: Sign restrictions used to identify flow supply, flow demand and other shocks. All shocks are normalized to imply an increase in the real price of oil.

In contrast to existing models, which focus on more narrowly defined crude oil production, our setting also allows for the possibility that shifts in flow supply arise from changes in other refinery feedstock and blendstock supply. In Appendix C, we show that when crude oil and other refinery feedstock and blendstock are substitutes in the production of fuels, negative surprise shifts in other feedstock or in blendstock supply are associated with a decrease in total oil production, a decrease in fuel consumption, and higher crude oil prices. Classifying such surprise shifts as supply shocks is sensible because, just like crude oil supply shocks, such shifts will decrease the consumption of fuels and potentially change the desired level of oil inventories without shifting the short-run fuel demand or storage demand curves. Moreover, since changes in crude oil supply and surprise changes in other refinery feedstock and blendstock supply represent supply shifts from an aggregate macroeconomic perspective, the definition of oil supply shocks derived from total oil production is particularly useful for understanding the relationship between the global oil market and macroeconomic outcomes. In contrast, surprise changes in other refinery feedstock and blendstock supply constitute shocks to the flow demand for crude oil and are thus not identified as oil supply shocks in models with a narrower definition of crude oil.

Positive flow demand shocks represent surprise outward shifts in the flow demand for fuel. Such shifts also increase the flow demand for fuel production inputs such as crude oil and hence lead to an increase in crude oil prices and total oil production. Finally, storage demand shocks are associated with changes in market participants' willingness to hold above-ground oil inventories. Typically, such changes are related to expectations or uncertainty about the future oil supply relative to future oil demand (Alquist and Kilian 2010; Kilian and Murphy 2014). As shown in Appendix C, increases in storage demand for crude oil and increases in storage demand for fuels have similar effects on total oil production, crude oil prices and fuel consumption. In both cases, increases in inventories are achieved by increasing total oil production and decreasing fuel consumption, which requires higher equilibrium crude oil prices.

Similar to the case of flow supply, our framework offers definitions of flow demand and storage demand that differ from existing models focusing on the crude oil market. Existing models typically equate the flow consumption of oil with the refinery intake of crude oil.

However, this equality breaks down in the presence of changing fuel inventories. Our framework allows for the fact that oil is being stored both in the form of unrefined oils and in the form of fuels. As shown in Appendix C, this allows us to attribute shifts in the demand for fuel inventories to storage demand shocks. Instead, models of the narrower crude oil market might classify such shifts as flow demand shocks as they increase the refinery intake of crude oil along with the real price of oil.

3.4 Implementation and inference

Kilian and Murphy (2012) show that in sign-restricted VARs, additional restrictions are often necessary to properly identify the set of plausible models. Following existing practice, we also impose that negative flow supply shocks lower oil production for at least four quarters and that positive flow demand shocks raise oil consumption for at least four quarters. To ensure well-behaved dynamics, we also impose that the peak price impact of each structural shock occurs within the first four quarters. Finally, given existing evidence for a low short-run elasticity of oil supply, we restrict the short-run price elasticity of oil production to be lower than 5% after flow demand shocks and lower than 10% after storage demand shocks.

The estimation follows a standard procedure for sign-restricted SVAR models that allows for both parameter and identification uncertainty (see, e.g., Kilian and Lütkepohl 2017). Given a diffuse Gaussian-inverse Wishart prior distribution for the reduced form parameters, we draw a variance-covariance matrix, $\hat{\Sigma}_{\epsilon,i}$, from the posterior distribution of the implied variance-covariance matrix. For each posterior draw i, we construct $P_i = \text{chol}(\hat{\Sigma}_{\epsilon,i})$ and generate a set of random (3×3) matrices from $NID(0,1)$ random variables orthogonal matrices $W^{i,j}$. Using the QR decomposition such that $W_{i,j} = Q_{i,j}R_{i,j}$ and $Q_{i,j}Q'_{i,j} = I_3$, we construct an implied short-run impact matrix $B_{i,j} = P_i Q_{i,j}$. Finally, we generate the set of admissible structural models by retaining all candidate models that satisfy the sign and magnitude restrictions.

There are several options to present results from set-identified SVAR models. In the graphs below, we report impulse responses and historical decompositions of all admissible models, thus providing a comprehensive overview of the identified set of models. As standard in the literature, we also report the pointwise 0.16- and 0.84-quantiles along with these sets.[20] For the decomposition of oil price fluctuations during selected episodes, we follow Kilian and Zhou (2019) and report the posterior means of the variance decompositions and historical decompositions along with the posterior quantiles. Qualitatively similar results hold for the posterior medians.

[20] Baumeister and Hamilton (2018) show that such quantiles reflect the characteristics of an implicit prior distribution that can be rationalized under certain loss functions.

The results below are implemented for 2,000 draws of the posterior distribution, for each of which 5,000 random matrix and corresponding candidate models are generated. In total, 419 models are retained as admissible.

4 Estimation results

4.1 Elasticities and responses to structural shocks

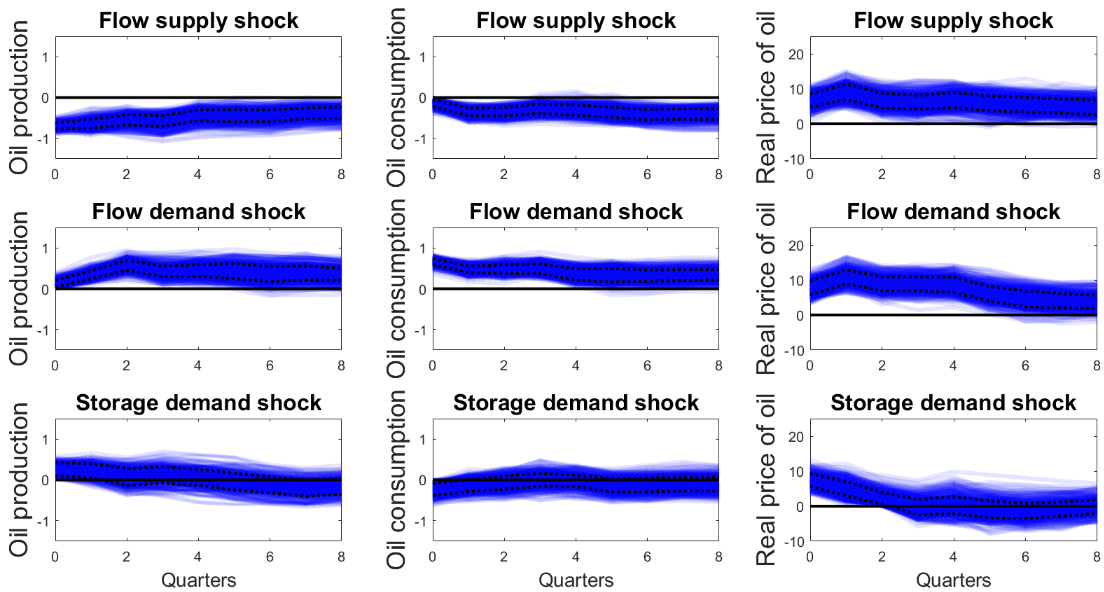

Figure 1: Structural impulse responses. The shocks are normalized to correspond to an increase in the real price of oil on impact. All responses are measured as cumulative log changes to a one standard deviation shock. The picture depicts impulse responses from all admissible models along with the pointwise 0.16 and 0.84 quantiles (dashed lines). The estimation period is 1988Q1 to 2017Q3.

Figure (1) plots the estimated impulse responses to oil supply, fuel demand and residual shocks. The shocks have been normalized such that they imply an increase in the real price of oil and are plotted along with the pointwise 0.16 and 0.84 quantiles. Supply shocks have a persistent impact on production, but also cause an immediate decline in consumption that slightly offsets the price impact of these shocks in the medium term. Consistently, the oil price impact is partially temporary, although the decline sets in only after several quarters. Fuel demand shocks have a qualitatively similar impact, but the immediate price impact is somewhat larger than that of supply shocks. In contrast, storage demand shocks seem to have a more transitory impact on oil prices, consistent with the view that these shocks mainly reflect temporary or one-off fluctuations in inventory demand.

The short-run elasticities of the oil supply and the oil demand take a crucial role in the identification of structural models of the oil markets and have received corresponding attention (Caldara, Cavallo, and Iacoviello 2019; Kilian and Zhou 2018b). In our model, the median short-run oil supply elasticity in response to oil demand shocks is 1.3%, with the 0.16 and 0.84 quantiles at 0.5% and 3%. The median short-run demand elasticity is -1.8% with corresponding -3.6% and -0.6% quantiles. Thus, both the short-run oil supply curve and the short-run oil demand curve appear to be very inelastic. A median short-run supply elasticity of 1.3% is consistent with the estimates and historical evidence presented in Kilian and Murphy (2012) and Kilian and Murphy (2014). Instead, the admissible models feature global fuel demand elasticities that are considerably lower (in absolute value) than much of the existing estimates of the crude oil demand elasticities, which are typically estimated to be of the order of -10% to -35% (Kilian and Murphy 2014; Baumeister and Hamilton 2019; Caldara, Cavallo, and Iacoviello 2019). Although the global fuel demand elasticity is generally different from the global crude oil demand elasticity, the magnitude of this difference is startling. As the narrow range of fuel demand elasticities across the set of admissible models suggest, a low demand elasticity is a common feature across all admissible models and is not the result of a particular prior or parameter bound that is imposed a priori. Instead, a low fuel demand elasticity directly reflects the smooth evolution of the raw consumption data and the low volatility of the reduced form innovations to consumption relative to a notoriously large oil price volatility.[21] This suggests that global fuel demand is indeed very inelastic in the short run and that these estimates are not the result of the bias that arises from inadequately identifying shifts along the demand curve (Kilian and Murphy 2014).

4.2 Do shifts in fuel consumption drive crude oil prices?

Figure (2) displays the historical decomposition of oil prices implied by our model. Qualitatively, the historical decompositions are in line with established accounts of key oil market

[21] In fact, a considerably more elastic short-run demand elasticity would be inconsistent with the smooth evolution of the raw consumption data and the reduced form estimates of the VAR model. The reduced form estimates of the VAR model show that surprise changes in global fuel consumption are small and cluster around -1% to 1%, with the largest changes (in absolute value) around 2%. Some of the largest surprise changes in the quarterly price of oil over our sample period, such as the nearly 50% price increase in 1990Q3, can plausibly be attributed to factors other than surprise shifts in flow demand (Kilian and Murphy 2014). A short-run price elasticity of fuel demand of the order of, say, -10% would imply a surprise decline in oil consumption of the order of -5% in 1991Q3—more than twice the largest surprise change observed over the entire sample period—while the actual surprise change was close to zero. More generally, the fact that the standard deviation of oil consumption shocks is almost 20 times smaller than the standard deviation of price shocks, in combination with existing evidence for a role of non-flow demand shocks during selected episodes of large price fluctuations, suggests that the fuel oil demand curve has to be very inelastic.

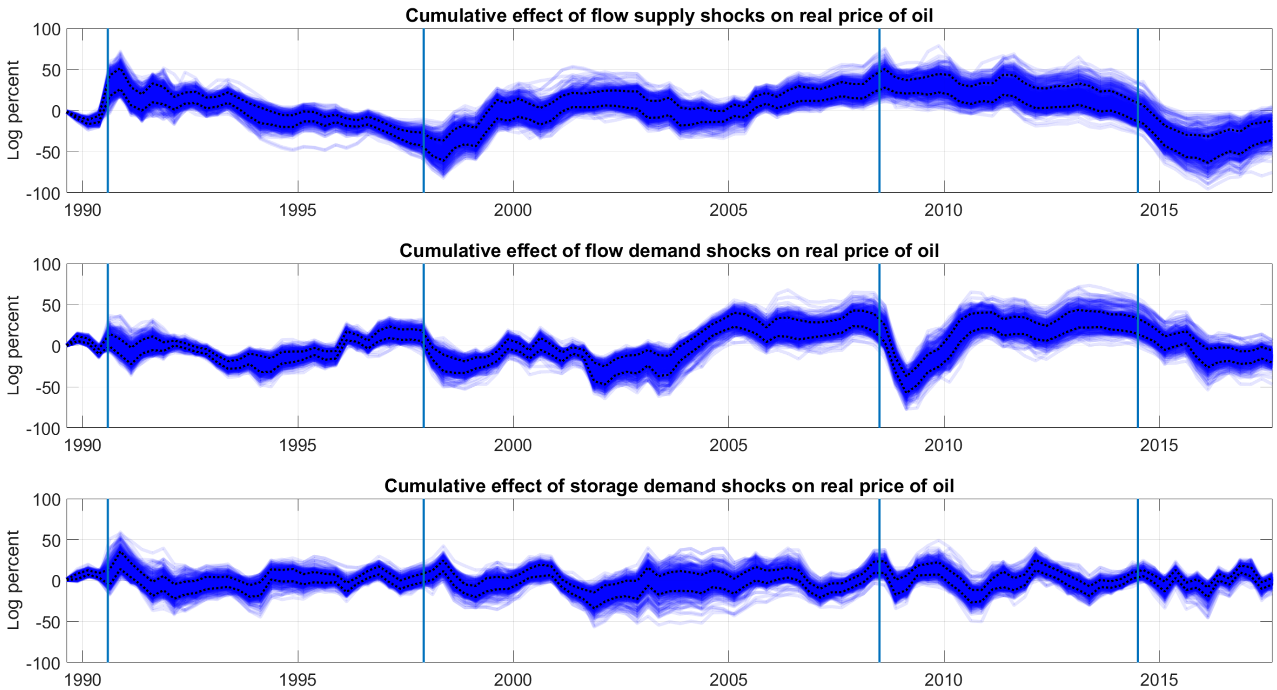

Figure 2: Historical decompositions of the real price of oil. The vertical bars indicate major events in oil markets, notably the outbreak of the Persian Gulf War in 1990Q3, the onset of the Asian Crisis in 1997Q4 and the Financial Crisis in 2008Q3, and the beginning of the 2014–2015 oil price drop in 2014Q3. The picture depicts decompositions for all admissible models along with the pointwise 0.16 and 0.84 quantiles (dashed lines). The sample period is 1989Q3 to 2017Q3.

episodes, while the role of fuel demand shocks is similar to those of crude oil flow demand shocks identified in Kilian and Murphy (2014). The interpretation of oil price fluctuations in 1990 broadly coincides with Kilian and Murphy (2014), who document that oil prices increased due to a combination of flow supply and inventory demand shocks around the outbreak of the Persian Gulf War. As shown in table (2), oil supply shocks raised the price of oil by 48% between 1990Q1 and 1990Q4, while storage demand shocks contributed to an additional increase of 19%. While flow demand shocks were not material during this episode, they contributed importantly to the decline in oil prices around the 1997 Asian crisis (-24%), the run-up in oil prices around the mid-2000s (+54%), the decline in oil prices in the wake of the financial crisis (-76%) and the decline in oil prices in late 2015 and early 2016 (-25%). During these episodes, shifts in oil demand were the main driver of oil price fluctuations, although strong oil production in 1997Q4 and stagnating supply in combination with storage demand shocks over the mid-2000s accentuated some of the price swings.

The model also suggests that oil supply shocks decreased the price of oil by 43% between 2014Q3 and 2015Q3, more than flow demand shocks (-16%) and storage demand shocks

Episode	Flow supply shock	Flow demand shock	Storage demand shock
1990Q1 - 1990Q4	47.5	-10.8	19.2
	(33.8,60.8)	(-18.9,-3.2)	(8.8,30.0)
1997Q4 - 1998Q1	-12.7	-23.6	7.5
	(-18.1,-7.6)	(-29.4,-17.7)	(1.9,13.7)
2002Q3 - 2008Q2	18.0	54.0	28.6
	(4.0,31.6)	(35.2,74.1)	(17.7,39.2)
2008Q3 - 2009Q1	-4.5	-76.1	-18.8
	(-13.7,4.8)	(-91.1,-60.8)	(-30.7,-6.5)
2014Q3 - 2015Q3	-43.1	-16.3	-13.4
	(-56.4,-30.1)	(-26.1,-7)	(-19.8,-6.5)
2015Q3 - 2016Q1	-4.9	-25.4	-7.5
	(-11.3,1.7)	(-32.8,-17.9)	(-13.9,-1.5)

Table 2: Cumulative effects on real price of oil for selected episodes. Posterior median based on all admissible models (with 0.16 and 0.84 quantiles in parentheses).

(-13%) combined. The dominant role of supply shocks during this period supports the popular narrative among policy makers (see, e.g., Baffes et al. 2015), but challenges some of the existing academic literature that suggests that the contribution of oil supply shocks has been more modest (Baumeister and Hamilton 2019; Baumeister and Kilian 2016b). A key reason why our model attributes a larger role to oil supply shocks over this period is that the increase in total oil production was significantly larger than suggested by the increase in crude oil production alone. Unlike existing studies that focus exclusively on global crude oil production, our model takes into account not only changes in the production of crude oil, which grew by about 3 million barrels per day (mb/d) between 2014Q2 and 2015Q3, but also in the production of non-conventional oils, condensates and NGLs, which grew an additional 2 mb/d over the same period and thus contributed to the overall glut in total refinery feedstock and finished petroleum products.

4.3 Decomposing changes in global fuel consumption

Understanding the evolution of global fuel consumption is important for several reasons. First, fuel consumption is likely to be an important driver of fluctuations of quantities in the oil market, which has important consequences for oil producers. Fuel consumption is also an important contributor to global emissions, and considerations about the future evolution of fuel consumption form an important part of climate change policies (see, e.g., IEA 2016).

Figure (3) shows the historical decomposition of (cumulative) changes in fuel consumption over our sample period. Consistent with the low short-run price elasticities documented above, we find that, in our model, much of the variation in global fuel consumption can be traced back to shifts in the demand curve itself. This is particularly true for short- and medium-term variations in fuel consumption, which seem to coincide with cyclical fluctu-

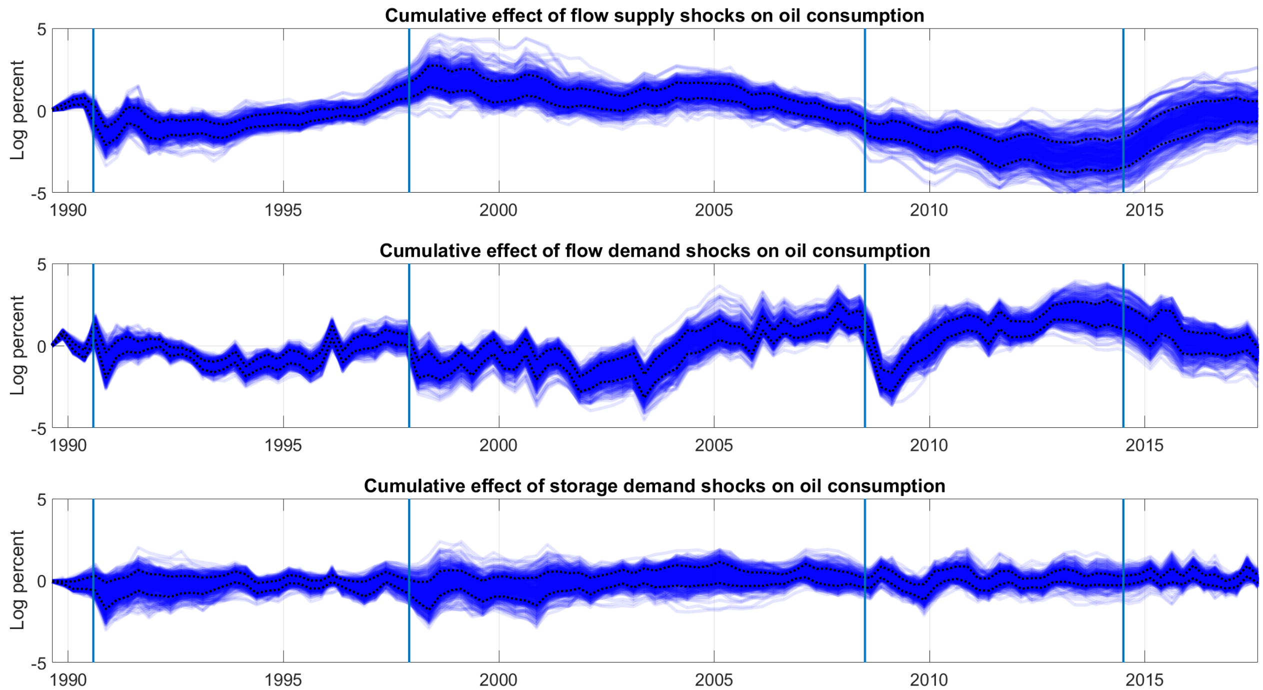

Figure 3: Historical decompositions of global oil consumption. The vertical bars indicate major events in oil markets, notably the outbreak of the Persian Gulf War in 1990Q3, the onset of the Asian Crisis in 1997Q4 and the Financial Crisis in 2008Q3, and the beginning of the 2014–2015 oil price drop in 2014Q3. The picture depicts decompositions for all admissible models along with the pointwise 0.16 and 0.84 quantiles (dashed lines). The sample period is 1989Q3 to 2017Q3.

ations in the global economic cycle. As such, these cyclical fluctuations appear to play a similar role for fuel and crude oil demand (Kilian 2009; Kilian and Murphy 2014). Some of the longer-term trends in global fuel consumption, however, seem to be driven also by changes in the global oil supply curve. According to our decomposition, surprise shifts in the supply curve played an important role in boosting global fuel consumption, in particular during the second half of the 1990s and in the aftermath of the 2014–2015 oil price drop. Also, stagnant oil supply during most of the 2000s had a very gradual but overall important role in curbing global fuel consumption over this decade. In contrast, the impact of storage demand shocks on flow quantities in the oil market appears to be negligible.

4.4 Structural oil price shocks and global economic activity

The relationship between oil price shocks and macroeconomic outcomes depends on the underlying drivers of such shocks (Kilian 2009). Unlike many existing models, the structural shocks identified in our framework can be used to investigate this relationship without imposing a priori restrictions on the impact of structural innovations on global economic activity.

Moreover, as our estimates of structural shocks are derived from movements in prices and quantities alone they do not rely on a particular choice of a particular economic activity indicator. This can be useful as the quantitative implications of different indicators often varies considerably (see, e.g., Kilian and Zhou 2018a).

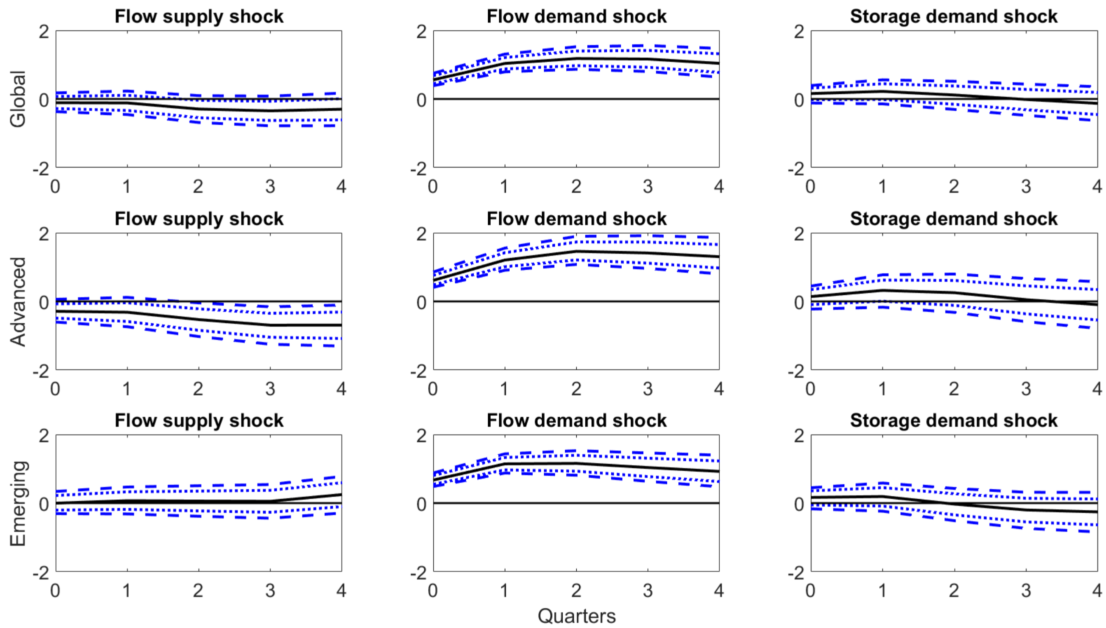

Figure 4: Relationship between structural shocks and cumulative industrial production growth at different horizons. Industrial production growth is measured in percent. *Advanced* refers to advanced economies, *Emerging* stands for emerging economies; the classification follows Caldara, Cavallo, and Iacoviello (2018). The solid line represents the median, the dotted line the 0.16 and 0.84 quantiles, and the dashed line the 0.05 and 0.95 quantiles obtained from 250,000 bootstrap replications that take into account serial correlation in error terms and model uncertainty. The shocks are normalized to imply an increase in the real price of oil. The estimation period is 1989Q3 to 2017Q3.

Figure (4) shows the relationship between the supply, flow demand and storage demand shocks identified in the previous section and global, advanced economies' and emerging economies' global economies industrial production growth at different horizons.[22] The inference on the response estimates is based on block bootstrap methods that allow for serial correlation in the error terms as well as for model uncertainty that arises from identification.[23] The results show that flow demand shocks are strongly positively correlated with

[22]We use the global industrial production series provided in Baumeister and Hamilton (2019) and the advanced and emerging economies' global industrial production series provided in Caldara, Cavallo, and Iacoviello (2019). The monthly data are converted to quarterly averages to maintain the frequency of the structural innovations. The parameters are estimated from univariate models that include a constant.

[23]The confidence bands are computed for a block size of 4 and a total of 250,000 bootstrap replications

industrial production growth in both advanced and emerging economies, consistent with the idea that changes in economic activity are an important source of shifts in commodity demand (Kilian and Zhou 2018a). In contrast, flow supply shocks and storage demand shocks are only weakly correlated with changes in global industrial production growth. Negative surprise shifts in global oil supply are associated with lower global industrial production growth, but the effect is small and statistically significant only at the 33% confidence level after two quarters. Moreover, the negative effect seems to arise entirely from the reaction of advanced economies, whereas industrial production growth in emerging economies is essentially uncorrelated with oil supply shocks. One explanation for this pattern is that during our sample period, the advanced economies were heavily reliant on oil imports while the sample of emerging economies used to construct the industrial production index was, on average, almost self-sufficient (Caldara, Cavallo, and Iacoviello 2019). The point estimates also seem suggest that storage demand shocks initially have a positive relationship with industrial production growth that turns negative after three quarters, but the magnitude of the effects is economically negligible and not statistically different from zero at conventional significance levels.

Overall, the distinct relationship between demand shocks and industrial production growth shows that our model is able to recover economically meaningful structural shocks that are largely consistent with economic theory and existing empirical evidence. However, oil supply and storage demand shocks seem to have a weaker effect on global economic activity than implied by models that impose restrictions on the sign of this effect a priori.

5 Interpretation

5.1 Why is the global fuel demand elasticity low?

Our model suggests that the short-run elasticity of global fuel demand with respect to the real price of crude oil is about -2%. This estimate is not only considerably lower (in absolute value) than existing estimates of the global short-run crude oil demand elasticity, but also lower than estimates of the short-run gasoline demand elasticity in the US, which is estimated to be larger than -30% (Levin, Lewis, and Wolak 2017; Coglianese et al. 2017).[24] Clearly, the difference between the elasticity estimates is large enough to matter economically and raises the question of whether our estimates are at odds with the evidence provided in micro-studies.

that originate from 250 bootstrap replications for each of 1,000 random draws from all admissible models.

[24]Kilian and Murphy (2014) and Baumeister and Hamilton (2019) provide point estimates of the global crude oil demand elasticity of -26% and -35%, respectively.

This section shows that the fact that we measure the fuel demand elasticity with respect to global crude oil prices—instead of retail fuel prices—can account for much of this difference. Empirically, only a fraction of percent changes in global crude oil prices are passed on to percent changes in the retail price of the "average" barrel of fuel. Since the elasticity is defined as the change in quantity over the change in the price, an imperfect pass-through between global crude oil prices and local retail prices can explain the concurrence of a low global demand elasticity and a considerably larger local elasticity.

To relate the elasticity estimates from our model to the existing micro-evidence, it is instructive to define a percent pass-through, $\frac{\Delta p^{i,j}}{\Delta p^{crude}}$, which relates local fuel price elasticities to global crude price elasticities through the relationship

$$\eta_D^{global} = \sum_i \sum_j \omega^{i,j} \cdot \eta_D^{i,j} \cdot \frac{\Delta p^{i,j}}{\Delta p^{crude}}, \tag{7}$$

where η_D^{global} is the global short-run demand elasticity with respect to the price of crude oil, $\eta_D^{i,j}$ denotes a local fuel price elasticity for fuel in country i (such as the US gasoline demand elasticity), $\omega^{i,j}$ is the weight of fuel j in country i in the global fuel consumption basket, and $\frac{\Delta p^{i,j}}{\Delta p^{crude}}$ denotes the percent change in the price of fuel j in country i divided by the percent change in the price of crude oil. The identity in equation (7) states that the global fuel demand elasticity with respect to crude oil prices can be expressed as the consumption-weighted fuel demand elasticity with respect to local price times the percent pass-through from crude oil to local fuel prices. Assuming further that the local elasticities with respect to different fuels in non-US countries are of similar magnitudes to the US gasoline demand elasticity, we can decompose (7) into a local elasticity component, η_D^{local}, common to all countries and fuels, and an average percent pass-through:

$$\eta_D^{global} = \eta_D^{local} \cdot \underbrace{\sum_i \sum_j \omega^{i,j} \cdot \frac{\Delta p^{i,j}}{\Delta p^{crude}}}_{\text{average percent pass-through}}. \tag{8}$$

The relationship between the local fuel demand elasticity and the global fuel demand elasticity described in equation (8) has been recognized by the existing literature, but much of the empirical evidence has focused exclusively on the specific case of US gasoline consumption. In the US, most of the dollar changes in the global price of crude oil are passed on to gasoline prices (Coglianese et al. 2017; Baumeister and Kilian 2016a). Since the cost of crude oil purchases constitutes, on average, slightly more than half of all costs in US gasoline production, the percent pass-through for US gasoline is around 50–60%. It is therefore tempting to conclude that the global crude oil demand elasticity is about half the size of the

US gasoline demand elasticity (Hamilton 2009; Coglianese et al. 2017; Caldara, Cavallo, and Iacoviello 2019). However, US gasoline consumption accounts for only a fraction of global fuel consumption. The validity of this extrapolation to global oil consumption hence depends on the pass-through in non-US countries and on the pass-through for other fuels.

To shed light on the magnitude of the percent pass-through for non-US countries, we rely on a panel of gasoline and diesel prices in 21 major oil-consuming economies.[25] We measure the pass-through by estimating country-specific regressions of the form

$$\Delta p_t^{i,j} = \beta_0^{i,j} + \beta_1^{i,j} \Delta p_t^{crude} + \epsilon_t^{i,j}, \tag{9}$$

where $p_t^{i,j}$ represents the log difference in prices per litre in local currency in country i in quarter t for $j = \{\text{gasoline, diesel}\}$, $\beta_1^{i,j}$ is the country-specific percent pass-through coefficient, and p_t is the log difference in Brent prices in quarter t.[26] The regression results are displayed in table (3) in Appendix A. Reassuringly, our point estimated for the pass-through for US gasoline consumption is 61%, in line with previous estimates (Baumeister and Kilian 2016a). In contrast, the estimated percent pass-through for most European and Asian countries is around 20%–35% and thus considerably lower. For major oil-exporting countries with the exception of Canada, the estimated percent pass-through is close to zero.[27] The results for the percent pass-through for diesel follow a similar pattern, with much lower pass-through rates for non-US countries, in particular oil exporters. Relatively to the pass-through to gasoline prices, the estimated percent pass-through to diesel prices is lower for the US (48%) and Canada, but slightly higher for most other countries.[28] Overall, the empirical results for the gasoline and diesel pass-through show that the average global percent pass-through is likely to be much lower than implied by US gasoline consumption alone.

To gauge the total average percent pass-through to gasoline and diesel prices, we must

[25] Gasoline and diesel retail prices are obtained from GlobalPetrolPrices.com. The dataset comprises prices for 21 major oil-consuming countries, which together accounted for about 50% of global total product consumption in 2016. The original price series are weekly and were averaged to a quarterly frequency to ensure the comparability with the quarterly real price of oil.

[26] We measure the pass-through in local currency rather than US$ because the prices of the consumer end products are also quoted in local currency.

[27] The data availability for these estimations varies by country and, for some countries, only comprises a few quarters. However, as shown in table (3), for those countries where more observations are available, the percent pass-through estimates for a reduced sample that only contains 11 observations are close to the full-sample estimates. This suggests that even the regressions that are based on a limited sample size contain useful information about the historical pass-through.

[28] There are several reasons for why the percent pass-through is considerably lower for non-US countries. First, the US has very low gasoline taxes by international standards (Sterner 2007), which implies a lower cost-share of crude oil in retail fuel prices in many non-US countries. Other countries heavily subsidize fuel consumption, thus preventing a complete price pass-through (Davis 2014). Finally, the US dollar exchange rate is on average negatively correlated to oil price movements (Kilian and Zhou 2019), implying that oil price fluctuations are partially absorbed by exchange rates instead of being fully transmitted to local retail prices.

also provide estimates of the pass-through to countries and fuels for which no suitable data is available. For the countries not included in our sample, we assume that the pass-through is of the same magnitude as the average pass-through from all non-US countries for which we do have empirical estimates. Aggregating with weights given by the average share of each country in the global consumption of gasoline and diesel, this procedure yields a global price pass-through coefficient of approximately 26% for retail gasoline prices and 23% for retail diesel prices. These estimates are less than one-half the typical estimates for the percent pass-through from global oil prices to US motor gasoline prices. Over our sample period, gasoline and diesel consumption accounted for about 56% of global fuel consumption.[29] Although we do not have the data to estimate the pass-through for all fuel products, it is plausible that the pass-through is much lower for other fuels. For example, Kilian (2009) and Kilian and Zhou (2018a) argue that the contemporaneous pass-through from global crude oil prices to bunker fuel prices is negligible. To construct a back-of-the-envelope calculation of the total pass-through of crude oil to the "average" barrel of fuel consumed globally, we hence further assume that the pass-through to products other than gasoline and diesel is, on average, about half the pass-through to global diesel and gasoline prices.

An estimate of the overall global average percent pass-through can be computed from the consumption-weighted pass-through for gasoline, diesel and other oil products. With the empirical pass-through estimates and the additional assumptions on the pass-through in the remaining countries and for the remaining fuels, the estimate for the average contemporaneous percent pass-through from global crude oil to local fuel prices is close to 20%.[30] This number is considerably lower than the pass-through estimate for US motor gasoline, which is close to 60%. A low *global* fuel demand elasticity with respect to crude oil prices is hence generally consistent with significantly larger *local* elasticities with respect to retail prices: the imperfect pass-through alone can account for a five-fold difference between global and local elasticities.[31] Our analysis also shows that the global percent pass through is lower than the percent pass-through for US gasoline prices, which implies that the extrapolations from US gasoline prices to global fuel prices made in previous studies could be inaccurate.

[29] According to the IEA, gasoline (30%) and diesel (26%) consumption accounted for about 56% of global fuel consumption, with the remainder shared by LPG and Ethane (10%), Naphta (6%), Jet and Kerosene Fuel (8%), Residual Fuel (10%) and Other Products (10%).

[30] This calculation assumes that the short-run demand elasticities for other fuels and countries are of similar magnitude to the US gasoline demand elasticity. However, a larger share of the consumption of other fuels takes place in the industrial sector, where prices are often hedged and, as a result, short-run demand could be more inelastic (see, e.g., Carter, Rogers, and Simkins (2006) for the airline industry). Since hedging reduces the impact of short-run price fluctuations, it is plausible that the local elasticities for other fuels are lower than the US gasoline demand elasticity.

[31] Related, Muehlegger and Sweeney (2017) show that under imperfect competition, the consumer price pass-through of local cost shocks is much smaller than the pass-through of global cost shocks. This indicates that the demand elasticity with respect to global price shocks is considerably larger than the elasticity with respect to local price shocks.

5.2 Relationship to estimates of the crude oil supply and demand elasticities

The total oil supply and fuel demand elasticities identified in our framework are generally different from the crude oil supply and demand elasticities identified in benchmark models of the global oil market. Nevertheless, because these elasticities are related, our estimates can also provide useful insights into the magnitudes of the crude oil elasticities.

In the case of supply, the total oil supply elasticity is generally not equal to the crude oil supply elasticity because the latter measures only the reaction of crude oil production to oil price changes, whereas the former also includes the reaction of other refinery feedstock and blendstock production to oil price changes. However, there is reason to believe that these elasticities are not far apart. The share of crude oil in total oil production was, on average over our sample period, almost 90%, suggesting that most of the adjustments in total oil production are likely to reflect changes in crude oil production. Thus, our median estimate of the contemporaneous total oil supply elasticity in response to oil demand shocks of 1.3% is fully consistent with existing evidence that crude oil supply is very inelastic in the short run (Kilian and Murphy 2012; Anderson, Kellogg, and Salant 2018; Newell and Prest 2019).

Similarly, the fuel demand elasticity and the crude oil demand elasticity are different because they rely on different notions of flow consumption. In our framework, flow consumption refers to the oil content of fuels that are being consumed, whereas most existing studies define oil consumption as the refinery intake of crude oil. While these measures of flow consumption are not the same, they are related. In fact, the difference between the refinery intake of crude oil and the flow consumption of fuels is approximately equal to the change in oil product inventories.[32] As a result, any differences between the global fuel demand elasticity and the global crude oil demand elasticity must be reflected the systematic response of oil product inventories to oil prices. The stronger the response of oil product inventories, the larger becomes the difference between the fuel demand and the crude oil demand elasticity.

Given our estimates of the fuel demand elasticity, we can thus infer plausible values for the short-run elasticity of the demand for crude oil by bounding the response of changes in oil product inventories to oil supply shocks.[33] An upper bound for the crude oil demand elasticity (in absolute value) can be obtained by assuming that the entire change in total oil inventories is attributable to changes in oil product inventories. Under this assumption,

[32] The relationship only holds approximately because of the possible additions of non-crude refinery feedstock and blendstock, and refinery gains. Empirically, however, the variations in non-crude refinery feedstock and blendstock, and refinery gains are relatively small, implying that changes in crude oil product inventories account for most of the difference between fuel consumption and crude oil refinery intake.

[33] Since no data on global fuel inventories exists, it is not possible to estimate this response directly.

refinery intakes of crude oil are equal to oil production, and hence the short-run crude oil demand elasticity is given by the inverse of the short-run price impact of oil supply shocks. Over all admissible models, the inverse of the price impact of a 1% supply shock has a median of -10.4%, with 0.84 and 0.16 quantiles at -7.4% and -15.3%, respectively. Again, these bounds are likely to be very conservative: given the existing theoretical and empirical evidence for a significant reaction of crude oil inventories to global oil supply shocks, the adjustment in fuel inventories is likely to be smaller than the adjustment in total oil inventories, and hence the true crude oil demand elasticity is likely to be lower than these upper bounds.[34]

In a similar fashion, a lower bound (in absolute value) for the crude oil demand elasticity can be obtained by assuming that the entire response of total oil inventories to oil supply shocks takes place in the form of crude oil inventories. In this case, the global crude oil demand elasticity would be of a similar magnitude as the global fuel demand elasticity, and hence around -2%. Again, given the strong, positive correlation between crude oil and fuel inventories in OECD countries which indicates that both types of inventories respond to structural shocks, this lower bound is likely to be conservative. All told, the range of the short-run crude oil demand elasticities consistent with our estimates of the fuel demand elasticity and the reaction of total oil inventories to flow supply shocks is -2% to -15%. This is lower than suggested by most other existing benchmark studies, which often imply crude oil elasticities of the order of -30% (Kilian and Murphy 2014; Baumeister and Hamilton 2019).[35]

5.3 Implications for models of the global oil market

Prior information on short-run demand and supply elasticities plays an important role in the identification and in the quantitative features of oil market models.[36] Even small differences in the assumptions about the crude oil supply and demand elasticities can lead to large differences in the conclusions about the relative importance of crude oil supply and oil demand shocks (Caldara, Cavallo, and Iacoviello 2019; Herrera and Rangaraju 2019). Yet in many existing models, the prior information about these structural parameters relies on evidence from micro-studies that measure local parameters and fuel demand elasticities

[34] For example, the estimates provided in Kilian and Murphy (2014) provide empirical evidence for a significant reaction of crude oil inventories to global oil supply shocks. Moreover, most existing oil market models document that at least part of the initial price impact of oil supply shocks is mean-reverting. The theory of storage suggests that this pattern should coincide with an initial reaction of crude oil inventories.

[35] Using a narrative approach, Caldara, Cavallo, and Iacoviello (2019) estimate a short-run demand elasticity in OECD countries of around -8%, which is very much consistent with our estimates.

[36] For example, Kilian (2009) restricts the short-run supply elasticity to zero, Kilian and Murphy (2012) introduce bounds on the magnitude of short-run elasticities and Baumeister and Hamilton (2019) introduce magnitudes restrictions in form of Bayesian priors.

instead of crude oil demand elasticities. For example, to gauge plausible values of the global short-run crude oil demand elasticity, Kilian and Murphy (2014) rely on evidence on US retail gasoline demand elasticities; Baumeister and Hamilton (2019) use cross-country variation in gasoline prices and gasoline consumption; and Caldara, Cavallo, and Iacoviello (2019) measure the reaction of OECD fuel consumption to exogenous supply shocks. Our results show that such estimates might bear limited information about the magnitude of the *global crude oil* demand elasticity, which is likely to be very different.

The discrepancy between local and global estimates is also consequential for evaluating the role of speculation in the oil market. The more elastic the short-run supply and short-run demand curve, the more quantities and hence inventories respond to prices. This makes it easier to detect price impacts that arise from speculation (Hamilton 2009). Overall, the existing evidence suggests that speculation had only negligible effects on crude oil prices (Fattouh, Kilian, and Mahadeva 2013; Knittel and Pindyck 2016). However, while these studies investigate the effect of speculation in the crude oil market, they often rely on estimates of local fuel elasticities. As discussed above, there is reason to believe that global elasticities are considerably smaller. Although our results show that most of the oil price fluctuations over the last decades can be attributed to shifts in the oil supply and oil demand curve, our historical decomposition of crude oil prices—which is associated with much smaller elasticity estimates—is not able to rule out significant price effects from shifts in speculative demand during selected periods, such as the rapid increase in the real price of oil in the first half of 2008.

Finally, a low global fuel demand elasticity also has important distributional consequences for global energy and environmental policies that act through the price of oil (Davis and Kilian 2011).[37] Our estimates suggest that in the short run, global fuel consumption might react much less to changes in global crude oil prices than suggested by recent estimates, and that hence a greater share of the tax incidence would accrue to oil consumers and distributors.

6 Conclusion

We present a structural model of the global oil market that relies on information on global fuel consumption to identify oil demand. The model provides new estimates of key structural parameters in the oil market that suggest that in the short run, both oil supply and oil demand are very inelastic with respect to crude oil prices. This is important for two reasons. First, these parameters govern the evolution of prices and quantities in the global oil market and are key to disentangling the various forces acting upon the oil market and to conducting

[37] One such global climate change policy that is frequently considered is a global carbon tax (IPCC 2014; Paltsev et al. 2015).

counterfactual analysis. Second, they shed light on the effectiveness of global environmental or climate policies that act through the price of crude oil. Ceteris paribus, a lower global demand elasticity implies that larger changes in global taxes or subsidies would be needed to affect fuel consumption, and that a larger fraction of the associated tax incidence would fall on consumers, refiners or distributors as opposed to oil producers.

Our results also show that it is important to distinguish between global elasticities and local elasticities. Models of the global oil market often rely on micro- or cross-country-estimates of the local elasticity to provide the bounds or priors for global elasticities that identify structural parameters. When global and local elasticities are very different, this practice can distort the estimation and inference in such models.

The framework presented in this paper is simple in the sense that it relies on aggregate data and minimal assumptions to identify global oil supply and demand. This approach facilitates transparency and closely reflects the view of policy makers and market participants who frequently rely on global oil production and consumption data. At the same time, it abstracts from compositional factors such as the potential imperfect substitutability of refinery inputs and fuels or exchange rates, which represent natural extensions to the basic framework presented here.

Our model is well-suited for scenario analysis, in particular when the underlying scenario is based on an explicit specification of the volume of oil consumption. This complements existing frameworks that rely on real economic activity indicators to compare alternative scenarios of future oil demand (see, e.g., Baumeister and Kilian 2014). The framework can also be used to re-evaluate the role of speculation by applying the methodology proposed in Knittel and Pindyck (2016) to a setting that also allows for speculation in the fuel market. We leave these applications for further research.

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Appendix A: Additional figures

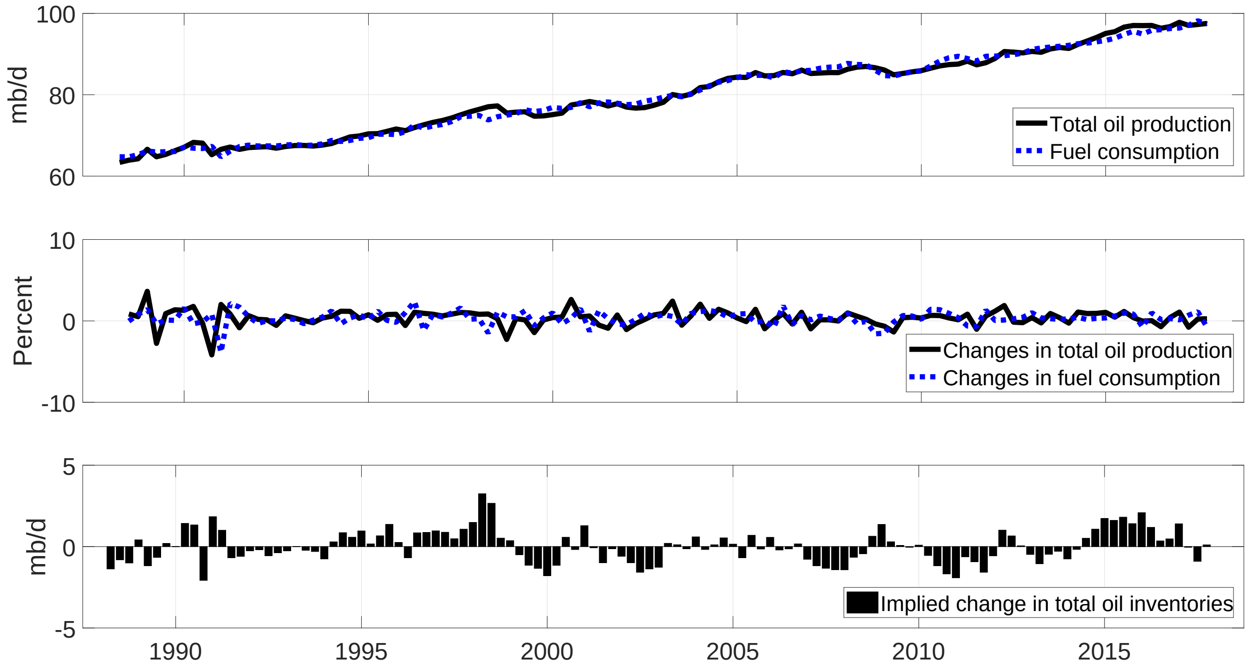

Figure 5: Description of aggregate total oil production and fuel consumption data. *Total oil production* includes crude oil, natural gas liquids, biofuels and refinery gains. *Fuel consumption* refers to total refined oil products consumption. The data is provided by the IEA and is seasonally adjusted using the U.S. Census X-13. *Implied change in total oil inventories* is calculated as the difference between total oil production and fuel consumption. *mb/d* stands for million barrels per day. The sample period is 1988Q1 to 2017Q3.

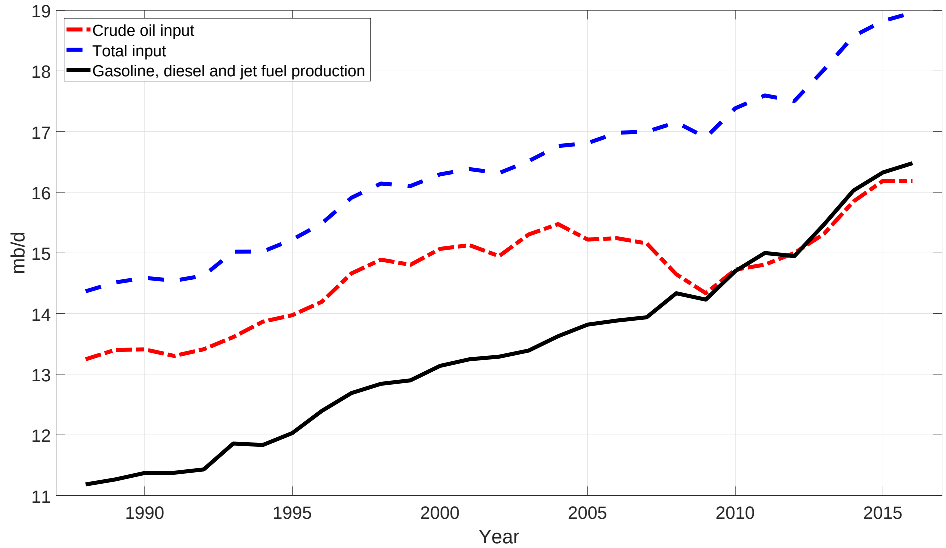

Figure 6: US refinery and blender net input of crude oil, total US petroleum refinery and blender net inputs, and production of gasoline, diesel and jet fuel. Source: US Energy Information Administration. Yearly data from 1988 to 2016.

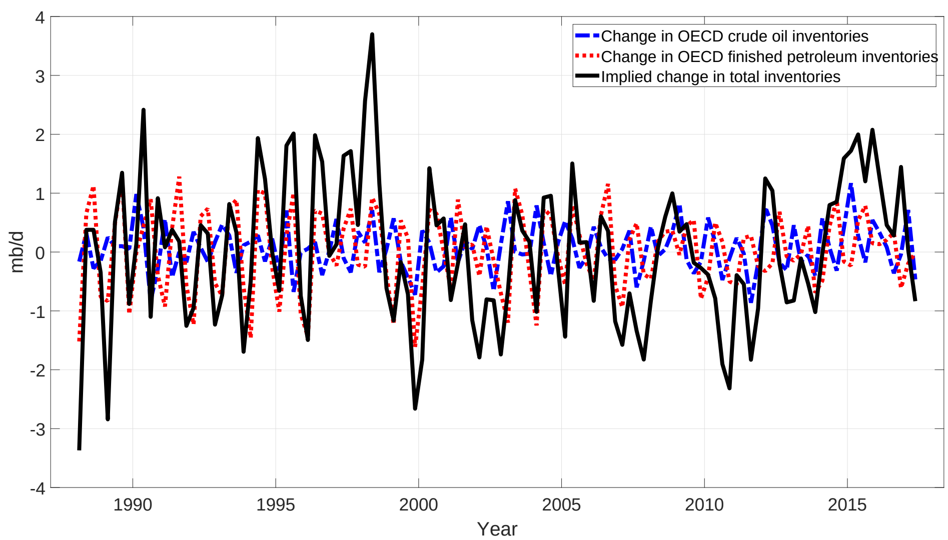

Figure 7: Changes in different types of oil inventories. Changes in the level of inventories are divided by 90. *Implied change in total oil inventories* is calculated as the difference between the (not seasonally adjusted) total oil production and fuel consumption series. *mb/d* stands for million barrels per day. Source: International Energy Agency. The sample period is 1988Q1 to 2017Q3.

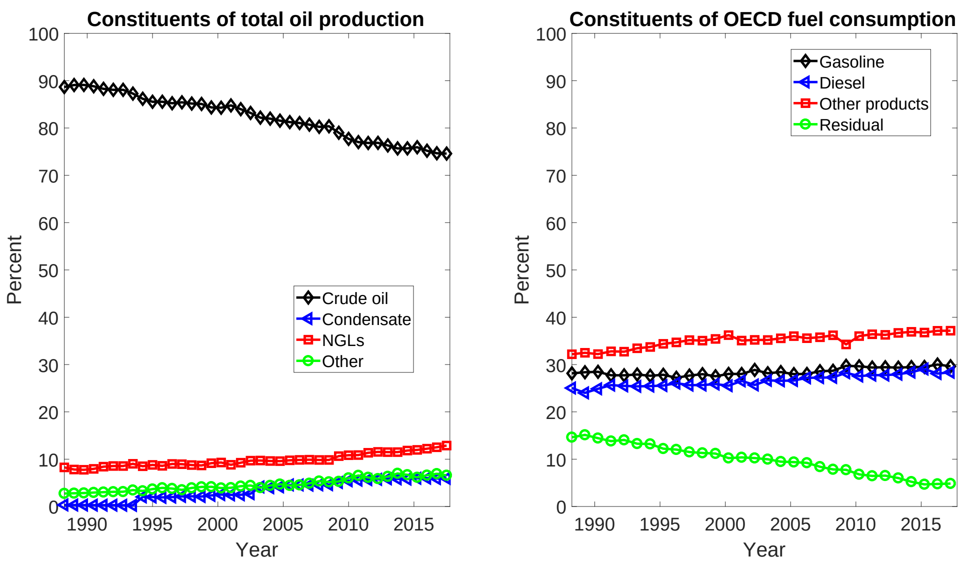

Figure 8: Constituents of total oil production and of OECD fuel consumption. *NGLs* stands for Natural Gas Liquids. *Other* oil production includes nonconventional oil production, biofuels and refinery gains. *Other products* includes jet fuel and kerosene, liquified petroleum gas, ethane and naphtha. Source: International Energy Agency. The graph displays production and consumption in the first quarter of each year from 1988 to 2017.

Appendix B: Additional tables

	Full sample			Reduced sample		
	Gasoline	Diesel	N	Gasoline	Diesel	N
USA	0.614***	0.488***	87	0.606***	0.364**	11
	(0.056)	(0.038)		(0.083)	(0.090)	
Brazil	-0.065	-0.053	11	-0.065	-0.053	11
	(0.037)	(0.035)		(0.037)	(0.035)	
Canada	0.353***	0.222***	119	0.369***	0.193**	11
	(0.051)	(0.041)		(0.060)	(0.052)	
Chile	0.268***	0.314**	11	0.268***	0.314***	11
	(0.052)	(0.071)		(0.052)	(0.071)	
Germany	0.276***	0.282***	47	0.282***	0.284***	11
	(0.016)	(0.026)		(0.048)	(0.035)	
Italy	0.252***	0.277***	47	0.230***	0.249***	11
	(0.019)	(0.026)		(0.040)	(0.036)	
France	0.229***	0.264***	103	0.229***	0.247***	11
	(0.018)	(0.021)		(0.035)	(0.025)	
UK	0.270***	0.247***	54	0.258***	0.249***	11
	(0.019)	(0.020)		(0.044)	(0.027)	
India	0.238***	0.285***	11	0.238***	0.285***	11
	(0.035)	(0.039)		(0.035)	(0.039)	
Japan	0.328***	0.294***	47	0.313***	0.270**	11
	(0.037)	(0.043)		(0.064)	(0.078)	
South Korea	0.234**	0.272**	11	0.234**	0.272***	11
	(0.068)	(0.057)		(0.068)	(0.057)	
Mexico	0.001	0.020	27	-0.001	0.003	11
	(0.026)	(0.030)		(0.030)	(0.033)	
South Africa	0.327*	0.336***	11	0.327*	0.336***	11
	(0.117)	(0.067)		(0.117)	(0.067)	
Singapore	0.291*	0.385***	11	0.291*	0.385***	11
	(0.101)	(0.071)		(0.101)	(0.070)	
Thailand	0.308**	0.301**	11	0.308**	0.301**	11
	(0.067)	(0.086)		(0.067)	(0.086)	
Venezuela	-2.573	0	7	-2.573	0	7
	(3.408)	(.)		(3.408)	(.)	
Indonesia	0.196	0.242	11	0.196	0.242	11
	(0.145)	(0.165)		(0.145)	(0.165)	
Egypt	-0.341	-0.215	11	-0.341	-0.215	11
	(0.322)	(0.203)		(0.322)	(0.203)	
Kuwait	0.119	0.134	7	0.119	0.134	7
	(0.219)	(0.248)		(0.219)	(0.248)	
Russia	0.068*	0.081	47	0.007	-0.037	11
	(0.033)	(0.041)		(0.029)	(0.012)	
Saudi Arabia	-0.435	-1.371	7	-0.435	-1.371	7
	(0.371)	(1.124)		(0.371)	(1.124)	

Table 3: Pass-through estimates from log changes in the Brent crude oil price to log changes in local gasoline and diesel prices. The estimates are based on OLS regressions that include a constant, which is suppressed in the table to improve readability. The final observation is in 2016Q3 for all series, and the starting observation is determined by data availability, which varies across countries. The second set of results displays estimations over the period 2014Q1 to 2016Q3 for the regressions with 11 observations, and 2015Q1 to 2016Q3 for the regressions with 7 observations. Robust standard errors in parentheses.

Appendix C: A stylized model of the global oil market

This section presents a stylized framework of the global oil market that models the relationship between production of crude oil and other oil liquids, refining, fuel consumption and the storage of oil liquids and fuels. The analysis, which should be interpreted as strictly short term, motivates the impact restrictions used to identify our structural model of the oil market. Moreover, it clarifies the definition of flow supply, flow demand and storage demand shocks in our setting.

Setup

Unrefined oil supply: Crude oil is supplied along the standard upward-sloping supply curve with slope η_S and curve shifter $u_t^{x,o}$:

$$X_t^o = u_t^{x,o} + \eta_S P_t^o, \tag{10}$$

where X_t^o is the flow production of crude oil at time t and P_t^o is the real price of crude oil. We assume that other refinery feedstock and blendstock, X_t^b, is supplied inelastically with supply shifter $u_t^{x,b}$[38]:

$$X_t^b = u_t^{x,b}. \tag{11}$$

Refining: The representative refiner combines crude oil with other feedstock and blendstock to produce fuels with the Leontief production function:

$$X_t^f = \min\left[(Q_t^o + Q_t^b), L_t\right], \tag{12}$$

where Q_t^o represents the unrefined oil intakes by refineries, Q_t^b represents refining blendstock, L_t represents the refiner's input of labor, and X_t^f represents the refiner's production of fuels. The refiner maximizes profits Π_t choosing Q_t^o, Q_t^b and L_t:

$$\max_{Q_t^o, Q_t^b, L_t} \Pi_t = P_t^f \min\left[(Q_t^o + Q_t^b), L_t\right] - P_t^o Q_t^o - P_t^b Q_t^b - bL_t, \tag{13}$$

where b represents the costs of labor and P_t^f is the retail price of finished fuels.[39] Optimality requires that

$$L_t = (Q_t^o + Q_t^b), \tag{14}$$

[38]The assumption of inelastic supply facilitates the tractability of the model but does not drive the qualitative implications derived in this section.

[39]This production assumes that one barrel of unrefined oil yields one barrel of fuels, which is an approximation. As argued above, while in reality there are volumetric differences between total refinery intakes and total refinery output, these differences have been relatively small and stable over time.

such that the optimal production of fuels is

$$X_t^f = (Q_t^o + Q_t^b). \tag{15}$$

Under the empirically relevant assumption that total refinery intakes are larger than intakes of other refinery feedstock and blendstock, it follows that $X_t^b = Q_t^b$, such that marginal quantity will be determined by crude oil. Moreover, it follows readily from the first-order condition of the refiner's maximization problem that

$$P_t^f = P_t^o + b. \tag{16}$$

Fuel demand: Consumption of fuel, Q_t^f, is governed by a downward-sloping demand curve,

$$Q_t^f = u_t^q + \eta_D^f P_t^*, \tag{17}$$

where u_t^q is a demand shifter and η_D^f denotes the price elasticity of fuel demand, and P_t^* is the consumer price of gasoline. P_t^* differs from producer prices, P_t^f, because of taxes, τ, such that

$$P_t^* = (1+\tau)P_t^f \quad = (1+\tau)(P_t^o + b). \tag{18}$$

Storage: Changes in crude oil inventories, ΔI_t^o, are given by

$$\Delta I_t^o = u_t^{i,o} + a^o E_t(\Delta P_{t+1}^o), \tag{19}$$

where $u_t^{i,o}$ is a shifter for the demand for crude oil inventories, a^o is a parameter that governs the relationship between changes in current inventories and expectations about future price changes, and Δ is the usual first-difference operator. Equation (19) reflects standard assumption of commodity storage models that relates inventories to expected future price changes and other factors such as technology, which are summarized in $u_t^{i,o}$. Theory suggests that inventories should be an increasing function of future price changes, implying that a^o is larger than zero.[40] Similar to changes in crude oil inventories, changes in fuel inventories, ΔI_t^f, follow

$$\Delta I_t^f = u_t^{i,f} + a^f E_t(\Delta P_{t+1}^f), \tag{20}$$

where $u_t^{i,f}$ is a gasoline inventory demand shifter.

By identity, the changes in inventories can be expressed as the difference between current

[40] The functional form in equation (19) can be motivated by the maximization problem of a representative inventory holder who maximizes period-by-period profits subject to quadratic adjustment costs.

flow production and consumption, such that

$$
\begin{aligned}
Q_t^o &= X_t^o - \Delta I_t^o \quad \text{and} \qquad (21)\\
Q_t^f &= X_t^f - \Delta I_t^f. \qquad (22)
\end{aligned}
$$

Equilibrium crude oil prices

In this setting, equilibrium crude oil prices are related to unrefined oil supply, fuel demand and changes in oil inventories via

$$P_t^o = \frac{1}{\eta_S - (1+\tau)\eta_D^f}\left[(1+\tau)\eta_D^f b + u_t^q - (u_t^{x,o} + u_t^{x,b}) + (\Delta I_t^o + \Delta I_t^f)\right], \qquad (23)$$

where $\Delta I_t^o + \Delta I_t^f = (u_t^{i,o} + u_t^{i,f}) + (a^o + a^f)E_t(\Delta P_{t+1}^o)$.

Impact of supply shocks, fuel demand shocks and storage demand shocks on equilibrium prices and quantities

Fuel demand shocks: Fuel demand shocks appear as surprise changes in u_t^q. Under the maintained assumption that the equilibrium impact on $E_t(\Delta P_{t+1}^o)$ is sufficiently small, we have that[41]

$$\text{sign}\left(\frac{\partial P_t}{\partial u_t^q}\right) = \text{sign}\left(\frac{1}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \qquad (24)$$

where sign refers to the sign function, i.e., crude oil prices increase;[42]

$$\text{sign}\left(\frac{\partial X_t^o}{\partial u_t^q}\right) = \text{sign}\left(\frac{\eta_S}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \qquad (25)$$

[41] This section derives the signs of the impacts of supply shocks, fuel demand shocks and storage demand shocks. In models with storage, these impacts will depend also on expected future equilibrium price changes. A proper quantitative analysis with rational expectations would hence require a full specification of the dynamic properties of shocks and the dynamic adjustments of the oil supply, fuel demand and storage demand curves. Consistent with standard assumptions in models of storable commodities, we assume that inventory adjustments are used to smooth shocks and hence might dampen, but do not reverse, the signs of the impact of fundamental shocks on prices on quantities (see, e.g., Kilian and Murphy 2014; Kilian and Zhou 2019). This allows us to disregard the effect on equilibrium expected future price changes throughout the subsequent exercises, as it focuses only on the signs but not the magnitudes of the respective effects.

[42] The sign function is defined as

$$\text{sign}(x) = \begin{cases} -1 & \text{if } x < 0 \\ 0 & \text{if } x = 0 \\ 1 & \text{if } x > 0. \end{cases}$$

.

i.e., crude oil production and hence total unrefined oil production, $X_t^o + X_t^b$, increases; and

$$\operatorname{sign}\left(\frac{\partial Q_t^f}{\partial u_t^q}\right) = \operatorname{sign}\left(1 + \frac{(1+\tau)\eta_D^f}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{26}$$

i.e., fuel consumption increases.

Oil supply shocks: Unrefined oil supply shocks can show up a surprise shifts in the crude oil supply curve, $u_t^{x,o}$ or as shifts in other refinery feedstock and blendstock supply, $u_t^{x,b}$. To see that both types of shifts have similar effects on total oil production, crude oil price and fuel consumption, note that after shifts in crude oil supply,

$$\operatorname{sign}\left(\frac{\partial P_t}{\partial u_t^{x,o}}\right) = \operatorname{sign}\left(\frac{-1}{\eta_S - (1+\tau)\eta_D^f}\right) = -1, \tag{27}$$

i.e., crude oil prices decrease;

$$\operatorname{sign}\left(\frac{\partial X_t^o}{\partial u_t^{x,o}}\right) = \operatorname{sign}\left(1 + \frac{-\eta_S}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{28}$$

i.e., crude oil production and hence total production increases; and

$$\operatorname{sign}\left(\frac{\partial Q_t^f}{\partial u_t^{x,o}}\right) = \operatorname{sign}\left(\frac{-\eta_D^f(1+\tau)}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{29}$$

i.e., fuel consumption increases. In a similar fashion, the reaction of prices and quantities to shifts in other refinery feedstock and blendstock are

$$\operatorname{sign}\left(\frac{\partial P_t}{\partial u_t^{x,b}}\right) = \operatorname{sign}\left(\frac{-1}{\eta_S - (1+\tau)\eta_D^f}\right) = -1, \tag{30}$$

i.e., crude oil prices decrease;

$$\operatorname{sign}\left(\frac{\partial X_t^c}{\partial u_t^{x,b}}\right) = \operatorname{sign}\left(\frac{-\eta_S}{\eta_S - (1+\tau)\eta_D^f}\right) = -1, \tag{31}$$

and

$$\operatorname{sign}\left(\frac{\partial (X_t^o + X_t^b)}{\partial u_t^{x,b}}\right) = \operatorname{sign}\left(1 + \frac{-\eta_S}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{32}$$

i.e., crude oil production decreases but total production increases; and

$$\text{sign}\left(\frac{\partial Q_t^f}{\partial u_t^{x,b}}\right) = \text{sign}\left(\frac{-\eta_D^f(1+\tau)}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{33}$$

i.e., fuel consumption increases.

Storage demand shocks: Storage demand shocks appear either as shifts in the demand for crude oil inventories, i.e., in $u_t^{i,o}$, or as shifts in the demand for fuel inventories, i.e., in $u_t^{i,f}$. To see that both types of shifts have similar effects on total oil production, crude oil prices and fuel consumption, note that

$$\text{sign}\left(\frac{\partial P_t^o}{\partial u_t^{i,o}}\right) = \text{sign}\left(\frac{1}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{34}$$

i.e., crude oil prices increase;

$$\text{sign}\left(\frac{\partial X_t^o}{\partial u_t^{i,o}}\right) = \text{sign}\left(\frac{\eta_S}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{35}$$

i.e., crude oil production and hence total production increases; and

$$\text{sign}\left(\frac{\partial Q_t^f}{\partial u_t^{i,o}}\right) = \text{sign}\left(\frac{(1+\tau)\eta_D^f}{\eta_S - (1+\tau)\eta_D^f}\right) = -1, \tag{36}$$

i.e., fuel consumption decreases. Moreover, the change in total inventories (in appropriate units) becomes larger, since

$$\frac{\partial \tilde{c}\Delta I_t^o + \Delta I_t^f}{\partial u_t^{i,o}} = \tilde{c}\left(\frac{\partial X_t^o}{\partial u_t^{i,o}} - \frac{\partial Q_t^o}{\partial u_t^{i,o}}\right) + \frac{\partial X_t^f}{\partial u_t^{i,o}} - \frac{\partial Q_t^f}{\partial u_t^{i,o}} \tag{37}$$

$$= \underbrace{\frac{\partial X_t^o}{\partial u_t^{i,o}} - \frac{\partial Q_t^f}{\partial u_t^{i,o}}}_{>0} + \underbrace{\frac{\partial X_t^f - Q_t^o}{\partial u_t^{i,o}}}_{=0}. \tag{38}$$

This is intuitive, since the total flow production of unrefined oil increases and fuel consumption decreases.

In a similar fashion, fuel storage demand shocks imply that

$$\text{sign}\left(\frac{\partial P_t^o}{\partial u_t^{i,f}}\right) = \text{sign}\left(\frac{1}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{39}$$

i.e., crude oil prices increase;

$$\operatorname{sign}\left(\frac{\partial X_t^o}{\partial u_t^{i,f}}\right) = \operatorname{sign}\left(\frac{\eta_S}{\eta_S - (1+\tau)\eta_D^f}\right) = 1, \tag{40}$$

i.e., crude oil production and hence total production increases; and

$$\operatorname{sign}\left(\frac{\partial Q_t^f}{\partial u_t^{i,f}}\right) = \operatorname{sign}\left(\frac{(1+\tau)\eta_D^f}{\eta_S - (1+\tau)\eta_D^f}\right) = -1, \tag{41}$$

i.e., fuel consumption decreases. Moreover, the change in total inventories (in appropriate units) becomes larger, since

$$\frac{\partial \tilde{c}\Delta I_t^c + \Delta I_t^g}{\partial u_t^{I,g}} = \tilde{c}\left(\frac{\partial X_t^c}{\partial u_t^{I,g}} - \frac{\partial Q_t^o}{\partial u_t^{I,g}}\right) + \frac{\partial X_t^g}{\partial u_t^{I,g}} - \frac{\partial Q_t^g}{\partial u_t^{I,g}} \tag{42}$$

$$= \underbrace{\frac{\partial X_t^c}{\partial u_t^{I,g}} - \frac{\partial Q_t^g}{\partial u_t^{I,g}}}_{>0} + \underbrace{\frac{\partial X_t^g - Q_t^o}{\partial u_t^{I,g}}}_{=0}. \tag{43}$$

Again, this is intuitive, since the total flow production of unrefined oil increases and fuel consumption decreases.