Federal Reserve Bank of Dallas

Geopolitical Oil Price Risk and Economic Fluctuations

Lutz Kilian, Michael D. Plante and Alexander W. Richter

Working Paper 2403 May 2024 (Revised November 2024)

Research Department

https://doi.org/10.24149/wp2403r1

Geopolitical Oil Price Risk and Economic Fluctuations*

Lutz Kilian†, Michael D. Plante‡ and Alexander W. Richter§

May 21, 2024
Revised: November 6, 2024

Abstract

This paper studies the general equilibrium effects of time-varying geopolitical risk in the oil market by simultaneously modeling downside risk from disasters, oil storage, and the endogenous determination of oil price and macroeconomic uncertainty in the global economy. Notwithstanding the attention geopolitical events in oil markets have attracted, we find that geopolitical oil price risk is not a major driver of global macroeconomic fluctuations. Even when allowing for the possibility of an unprecedented 20% drop in global oil production, it takes a large increase in the probability of such a disaster to cause a sizable recessionary impact.

Keywords: Geopolitical risk, macroeconomic risk, time-varying uncertainty, rare disasters, oil, endogeneity, shock propagation, economic fluctuations, precautionary savings, inventories

JEL Classifications: E13, E22, E32, Q43

---

*We thank María Aristizábal-Ramírez and Michael Siemer for discussing our paper at the 2024 System Macro and System Energy meetings. We also thank Steven Davis, Paulina Restrepo-Echavarría, Zheng Liu, and numerous conference and seminar participants for helpful comments. This work was supported by computational resources provided by the BigTex High Performance Computing Group at the Federal Reserve Bank of Dallas. The views in this paper do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

†Lutz Kilian, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201, and CEPR (lkilian2019@gmail.com).

‡Michael D. Plante, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201 (michael.plante@dal.frb.org).

§Alexander W. Richter, Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201 (alex.richter@dal.frb.org).

1 INTRODUCTION

Time-variation in geopolitical risk is widely considered an important determinant of fluctuations in economic activity. The financial press, international organizations, rating agencies and the investment community all vie to assess these risks and their impact on the economy. Clearly, major geopolitical disruptions matter not only when they occur on rare occasions, but also when investors and consumers make decisions in anticipation of the possibility of such events. This fact is nowhere more apparent than when it comes to geopolitical risk in energy markets. For example, many market analysts list risks to energy security as one of the top geopolitical risks of 2024. This assessment is driven in no small part by concerns about OPEC quota decisions, global access to Russian oil amidst Ukrainian attacks on Russian oil infrastructure and efforts to tighten the G7 price cap, dwindling strategic oil reserves, disruptions of oil shipments in the Red Sea and possibly in the Persian Gulf, and concerns about a widening conflict between Israel and Iran.

There is a deep-rooted belief in macroeconomics that higher oil price uncertainty driven by geopolitical risk lowers domestic investment and consumption and hence real GDP.[1] The focus of our paper is to develop a better understanding of how time-variation in geopolitical risk in oil markets affects oil price uncertainty and economic fluctuations. Our analysis recognizes that, while downside geopolitical risk raises oil price uncertainty, not all surges in oil price uncertainty are driven by geopolitical events. In particular, a major downturn in the economy or simply the possibility of such a downturn may cause surges in oil price uncertainty.

We present results from a calibrated dynamic stochastic general equilibrium (DSGE) model of the global economy that is designed to address the question of how geopolitical oil price risk is linked to economic fluctuations. The model includes risk averse economic agents, an oil pro-

[1]For example, Bernanke (1983), Lee et al. (1995), Ferderer (1996), Edelstein and Kilian (2009), Elder and Serletis (2010), Baumeister and Kilian (2016a), Ready (2018), Gao et al. (2022), and Alfaro et al. (2024) discuss the impact of oil price uncertainty on U.S. real activity, while Kilian (2009), Jo (2014), and Cross et al. (2022) discuss its impact on global real activity. The perception that oil price volatility matters for the transmission of oil price shocks to the economy also helped spawn a large literature on the asymmetric transmission of oil price shocks (see, e.g., Bernanke et al., 1997; Davis and Haltiwanger, 2001; Hooker, 1996, 2002; Kilian and Vigfusson, 2011; Leduc and Sill, 2004; Lee and Ni, 2002; Mork, 1989; Ramey and Vine, 2010).

duction sector, oil storage, and limited substitutability between oil and capital. The price of oil is determined endogenously. Since the model is global, we abstract from oil imports and exports and international capital flows.[2] One key difference from earlier studies is that our model allows for both macroeconomic and oil price uncertainty and that uncertainty is determined endogenously.

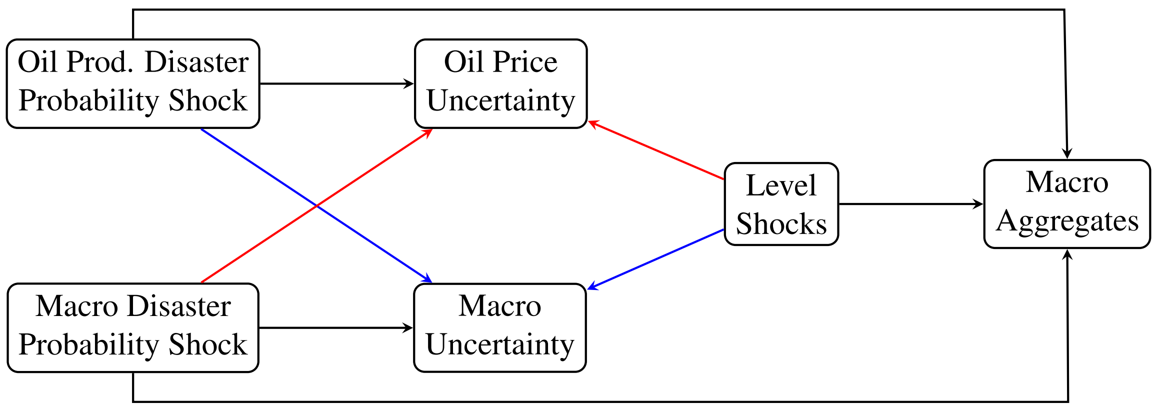
Building on Gourio (2012), downside risk emanates from macroeconomic and oil production disasters of stochastic length that occur with time-varying probabilities. Macroeconomic disasters are modeled as sharp declines in economic growth and may be viewed as the result of an economic crisis such as the financial crisis of 2008 or the Covid-19 pandemic of 2020. Oil production disasters are modeled after historical events such as the Arab-Israeli War in 1973, the Iranian Revolution in 1979, or the invasion of Kuwait in 1990. The size (5% drop in global oil production) and duration (3 quarters on average) of these disasters is set to match the behavior of global oil production during major geopolitical events in the oil market over the past 50 years.

We find that shocks to the probability of an oil production disaster have persistent, albeit modest, effects on oil inventories, the price of oil, and oil price uncertainty, whether this disaster is realized or not. These shocks also have modest effects on investment and output, and they are not a major driver of fluctuations in macroeconomic aggregates because large probability shocks are rare. Nor do they have much of an effect on macroeconomic uncertainty. Shocks to the probability of a growth disaster, which increase macroeconomic uncertainty, in contrast have larger effects on both the price of oil and the macroeconomy. These shocks also play a major role in the determination of oil price uncertainty, which helps explain why higher oil price uncertainty has historically been associated with lower real activity. Our analysis highlights that this association should not be interpreted as evidence of a causal link.

We also explore the possibility that agents might be concerned about larger oil production disasters than observed historically. While this increases the importance of geopolitical oil price risk, even when considering a temporary 20% drop in global oil production, which roughly corresponds

[2] While a multi-country model would allow us to assess the differential effects of oil production disasters across countries, our focus in this paper is the aggregate effects of oil production disasters on the global economy rather than their distributional implications.

Figure 1: Sources of uncertainty



to the cessation of oil supplies from the Persian Gulf, it takes a large increase in the probability of this disaster or its realization to cause sizable recessionary impacts.

Incorporating downside risk is crucial for our results. While increases in oil price uncertainty may alternatively be explained by stochastic volatility shocks to oil production growth, these shocks have very small effects on the economy because they do not generate risk tilted to the downside. We also show that the ability to store oil plays a central role. Without storage the responses of both oil market variables and macroeconomic aggregates to higher oil production risk tend to be muted, suggesting that DSGE models without storage fail to capture the full effects of shifts in oil production risk. Oil storage also matters for the responses of the global economy to growth disaster probability shocks, underscoring the importance of jointly modeling oil production disasters and macroeconomic disasters.

Our model shows that changes in oil price uncertainty need not be an indication of exogenous shifts in the uncertainty about future oil supplies. As illustrated in Figure 1, oil price uncertainty also reflects exogenous macroeconomic uncertainty shocks, mirroring the standard result that the real price of oil responds to shifts in the demand for oil. In addition, oil price uncertainty responds to level shocks in the oil market and the macroeconomy, such as realizations of disasters. Thus, not only are level and uncertainty shocks not the same, as implicitly assumed in VAR-GARCH models, but the effects of a level shock are not separable from those of an uncertainty shock, as assumed in VAR models with stochastic volatility. Similarly, it does not make sense to employ recursive linear VAR models with oil price uncertainty either ordered first or last, since oil price uncertainty is simultaneously determined with macroeconomic aggregates. These results call into question a large body of empirical work that has produced seemingly robust evidence of large recessionary effects of oil price uncertainty shocks and shaped the policy debate about geopolitical risk.

Related Literature Our work relates to several strands of the literature. First, it contributes to the large literature on the effects of uncertainty shocks on the macroeconomy (e.g., Berger et al., 2020; Bernstein et al., 2024; Bianchi et al., 2018; Bloom, 2009; Bloom et al., 2018; Fernández-Villaverde et al., 2015, 2011; Gourio, 2012; Jurado et al., 2015; Leduc and Liu, 2016; Ludvigson et al., 2021) by focusing on the interaction between macroeconomic and oil price uncertainty, which has received little attention to date. We show that modeling geopolitical oil production risk and macroeconomic risk jointly is necessary for understanding the evolution of oil price uncertainty.

Second, our analysis contributes to the literature making the case that oil price uncertainty shocks driven by geopolitical events are recessionary (e.g., Alfaro et al., 2024; Başkaya et al., 2013; Bernanke, 1983; Drakos and Konstantinou, 2013; Gao et al., 2022; Guo and Kliesen, 2005; Ready, 2018) and affect oil production and storage (e.g., Cross et al., 2022; Kellogg, 2014). We examine this question within a general equilibrium model with an endogenous price of oil and endogenous oil price uncertainty. Unlike earlier DSGE studies with stochastic volatility shocks to either oil production or the price of oil, we account for the fact that geopolitical oil price risk is inherently one-sided and reflects the stochastic arrival of oil production disasters driven by geopolitical events. We find that shifts in the probability of an oil production disaster are associated with changes in oil price uncertainty. However, they have modest effects on real activity and are too infrequent to generate much volatility in macroeconomic aggregates.

Third, we contribute to the literature emphasizing the endogeneity of fluctuations in the price of oil with respect to macroeconomic aggregates (e.g., Braun, 2023; Kilian, 2009; Kilian and Murphy, 2014; Zhou, 2020). Whereas this earlier literature focused on showing that the level of the real price of oil is endogenously determined by oil demand and supply, our analysis shows that oil price uncertainty responds to both level and uncertainty shocks to macroeconomic aggregates, complicating the identification of oil price uncertainty shocks. These findings have important implications for empirical work seeking to establish the macroeconomic effects of shocks to oil price uncertainty (e.g., Cross et al., 2022; Elder and Serletis, 2010; Ferderer, 1996; Gao et al., 2022; Jo, 2014).

Outline The remainder of the paper is organized as follows. In Section 2, we highlight the importance of geopolitical risk for the economy. We propose an index of the uncertainty in the real price of oil building on Jurado et al. (2015), trace its evolution since the 1970s, and discuss the relationship between downside risk in oil production and oil price uncertainty. We also show that our index is highly correlated with the OVX measure of implied volatility when that index is available. Section 3 reviews why many economists expect oil price uncertainty to slow economic activity. Section 4 introduces a calibrated DSGE model of the global economy that elucidates the determination of oil price uncertainty and macroeconomic uncertainty. In Section 5, we study the relationship between oil price uncertainty and macroeconomic uncertainty, the transmission of uncertainty shocks to the economy, and the ability of these shocks to explain fluctuations in economic growth and the oil price. Our analysis also sheds light on the key economic mechanisms in the model, the importance of modeling downside risk, and the sensitivity of our results to the specification of the oil production disaster. In Section 6, we discuss the relationship between our work and earlier DSGE models of the transmission of oil price uncertainty shocks. Section 7 discusses implications of our analysis for empirical models of the effects of oil price uncertainty shocks. The concluding remarks are in Section 8.

2 MEASURING OIL PRICE UNCERTAINTY

There has been growing interest in the impact of shifts in geopolitical risk in global commodity markets, in general, and in the oil market in particular in recent years. Historically, increases in oil price risk have been associated, for example, with uncertainty about the implications of the Iranian Revolution in 1979 and the outcome of the invasion of Kuwait in 1990. More recently, there was a surge in uncertainty about the possibility of Russia refusing to sell oil to Europe after the invasion of Ukraine in 2022 and then about the effectiveness of a price cap on Russian oil exports. Other recent sources of oil price uncertainty have included concerns in 2024 about a war between Israel and Iran disrupting global oil exports, changes in OPEC production quotas, and the ability of U.S. shale oil producers to maintain their production increases.

The focus of our paper is to develop a better understanding of how time-variation in geopolitical risk in oil markets affects oil price uncertainty and hence economic fluctuations. Our starting point is the downside risk to oil production caused by these events. These downside risks are inherently subjective because they relate to events that have not occurred. In contrast, oil price uncertainty can be quantified using econometric methods. This does not make oil price uncertainty a good indicator of geopolitically driven downside risk in oil production, however, because these two variables need not go hand-in-hand. While downside geopolitical risk to oil production raises oil price uncertainty, not all surges in oil price uncertainty are driven by geopolitical events.

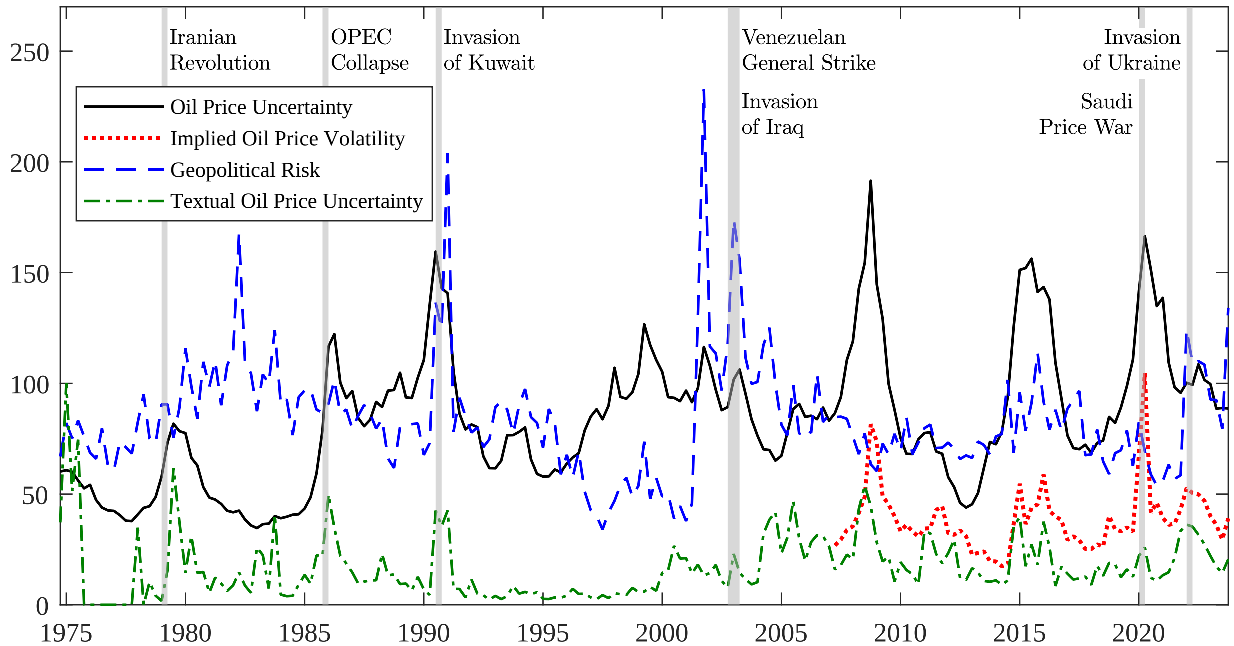
Figure 2 quantifies the uncertainty about the real price of oil in global oil markets since the modern oil market emerged in the early 1970s. We follow Jurado et al. (2015) in measuring oil price uncertainty ($\mathcal{U}_{p^o}$) as the one-quarter ahead conditional volatility of the unpredictable component from a predictive model of the real price of oil.[3] This definition highlights the fact that what matters for economic decision making is not whether the price of oil has become more or less variable, but whether it has become more or less predictable.[4] The real price of oil is defined as the U.S. refiners' acquisition cost for oil imports deflated by the implicit GDP deflator and is plotted in Appendix C for reference. The predictable component of the growth rate of the real price of oil is approximated using a diffusion index based on largely the same set of variables used by Jurado et al. (2015), augmented by the real price of oil, updated, and aggregated to quarterly frequency.

We estimate the uncertainty about the price of oil from 1974Q4 to 2023Q4. There are large spikes in 1979, 1986, and 1990 at the time of the Iranian Revolution, the collapse of OPEC, and the invasion of Kuwait. Not all geopolitical events are associated with surges in oil price uncertainty,

[3]Details of the construction of the uncertainty measure can be found in Appendix A.

[4]The definition of uncertainty in Jurado et al. (2015) is closely related to the formal measure of predictability in Diebold and Kilian (2001), since lack of predictability implies uncertainty.

Figure 2: Measures of oil price uncertainty



Notes: All series are indices. The solid line shows the uncertainty about the percent change in the real price of oil obtained by deflating the U.S. refiners' acquisition cost for oil imports by the U.S. CPI for all urban consumers. The method used to quantify this uncertainty is based on Jurado et al. (2015). The dotted line is the option-implied crude oil price volatility index (OVX) published by the Chicago Board Options Exchange. The dash-dotted line shows the (rescaled) text-based oil price uncertainty index in Abiad and Qureshi (2023). The dashed line is the quarterly average of the historical GPR series in Caldara and Iacoviello (2022).

however. For example, neither the outbreak of the Iran-Iraq War in late 1980 nor the outbreak of the Israel-Hamas War in the last quarter of 2023 had a discernible impact on the index.[5]

The largest spike in oil price uncertainty in 2008 was not driven by geopolitical risk, but by macroeconomic risk created by the Great Recession. Similarly, the surge in oil price uncertainty in 2015 appears to be driven by market forces rather than geopolitics (see Baumeister and Kilian,

[5]Our analysis of oil price uncertainty cannot be extended back further because the U.S. refiners' acquisition cost for crude oil imports we use as a proxy for the global price of oil is only available starting in early 1974. While the WTI price of oil is available much further back, that price only captures the domestic price of oil in the United States. Since the WTI price remained regulated until the early 1980s and because arbitrage between the U.S. oil market and the global oil market temporarily broke down during the U.S. shale oil boom in the 2010s, the WTI price is not a good proxy for the global price of oil even after 1974. These problems are compounded in the pre-1974 era. The nominal WTI price of oil price prior to 1974 was fixed for extended periods, followed by discrete jumps, reflecting the regulation of the U.S. oil market. As a result, not only is there a major structural change in the distribution of the real price of oil in late 1973, but there is a structural break in the predictive correlation between U.S. real GDP growth and the real price of oil. Combining the pre- and post-1974 oil price data thus would be inappropriate (see Alquist et al., 2013).

2016b), as was a smaller spike during the Asian Financial Crisis of the late 1990s. Sometimes, geopolitical events coincide with surges in macroeconomic risk, as was the case in early 2020 when the Covid-19 recession occurred at the same time as the Saudi price war in the oil market or in 1979 when rising geopolitical uncertainty coincided with uncertainty about monetary policy.

An alternative way to measure oil price uncertainty is to use the implied volatility index (OVX) published by the Chicago Board Options Exchange. While these data are only available starting in 2007, we find a correlation of 0.71 between our index and the OVX when both series are available.[6]

Figure 2 also shows that our oil price uncertainty index differs systematically from the geopolitical risk (GPR) index of Caldara and Iacoviello (2022), which quantifies the newspaper coverage of geopolitical events not limited to oil markets. The GPR index does not capture oil price uncertainty associated with macroeconomic risk, nor does it capture variation in oil price uncertainty clearly driven by geopolitical risk in oil markets. For example, the direction of these indices differs in the early 1980. In addition, the changes in these indices are quite different, and the correlation between the two indices is close to zero. Similarly, the text-based oil price uncertainty index in Abiad and Qureshi (2023) based on the methodology in Baker et al. (2016) differs substantially from our data-based index. The low correlation of 0.3 with our index suggests that the text-based oil price uncertainty index fails to capture changes in the predictability of the real price of oil.

3 WHY ECONOMISTS THINK OIL PRICE UNCERTAINTY MATTERS

Interest in fluctuations in oil price uncertainty dates to the mid-1980s. Economists at the time observed that the economy entered a steep recession after the 1979/80 oil price surge, but a similarly large drop in the price of oil in 1986 did not cause a large economic expansion. This fact is consistent with two mutually exclusive narratives. One is that the relationship between oil prices and the U.S. economy is linear, which implies that the effect of oil price shocks on the economy is modest at best and that the recession in the early 1980s is explained in substantial part by other shocks

[6] In related work, Gao et al. (2022) derive an index similar to the OVX series using oil options back to 1990Q1. The relationship between these indices is similar over the extended sample.

(e.g., Barsky and Kilian, 2002). This explanation is consistent with DSGE models of the transmission of oil price shocks that predict that a rising price of oil will only modestly slow growth in oil-importing economies, as consumers' income is reduced and firms face higher production costs, and, conversely, falling oil prices will only modestly stimulate growth in oil-importing economies (e.g., Backus and Crucini, 2000).[7]

The other narrative is that this relationship is nonlinear with positive oil price shocks having disproportionately larger effects on the economy. Macroeconomists for many years have been partial to this interpretation. A leading explanation of the nonlinearity required to explain the disproportionately large effect of positive oil price shocks and the negligible effects of negative oil price shocks, is that the rise in oil price uncertainty associated with the 1979/80 oil price surge caused consumer spending and business fixed investment to drop, amplifying the effects of rising oil prices, whereas in 1986 an increase in oil price uncertainty associated with the fall in oil prices largely offset the stimulus from lower oil prices.

The theoretical justification for this explanation relies on the real options theory of investment in Bernanke (1983) as well as the effect of rising uncertainty on precautionary savings and consumer spending (e.g., Başkaya et al., 2013; Edelstein and Kilian, 2009; Plante and Traum, 2012). A closely related third argument is that firms build oil inventories when oil price uncertainty rises, which raises the real price of oil, lowers oil consumption, and hence depresses economic activity (e.g., Cross et al., 2022; Gao et al., 2022; Kilian, 2009; Kilian and Murphy, 2014).

3.1 REAL OPTIONS THEORY

The most commonly cited reason why oil price uncertainty shocks matter for economic activity was articulated by Bernanke (1983) in a partial equilibrium setting.[8] Bernanke's point is that—to the extent that the cash flow from an irreversible investment project depends on the price of oil or its derivatives—all else equal, increased uncertainty about the price of oil prompts firms to delay investments. As a result, investment expenditures drop and real output

[7] There have been many attempts to design macroeconomic models that amplify the transmission of oil price shocks (e.g., Aguiar-Conraria and Wen, 2007; Atkeson and Kehoe, 1999; Finn, 2000; Rotemberg and Woodford, 1996). These theoretical models are not necessarily supported by the data, however. More importantly, being able to generate a larger recession after 1979/80 makes it even more difficult to explain the absence of an economic expansion in 1986.

[8] For related discussion of the effects of uncertainty shocks more generally see Pindyck (1991) and Bloom (2014).

declines. Uncertainty for this purpose may be measured by the expected conditional volatility of the real price of oil over the relevant investment horizon. Exactly the same reasoning applies to purchases of energy-intensive consumer durables such as cars (see Edelstein and Kilian, 2009).

There are several caveats to this application of real options theory. First, the quantitative importance of this cash flow channel depends on how important the real price of oil is for investment and durable consumption decisions and on the share of such expenditures in aggregate spending. For example, it seems intuitive that uncertainty about the price of oil would be important for decisions about oil drilling in Texas (see Kellogg, 2014). It is less obvious that it would be as important for investment in other sectors of the economy such as textile production or information technology, the expected profitability of which does not depend as much on oil prices.

Second, there is reason to believe that for longer-term investment projects, the variation over time in the uncertainty about the real price of oil is small. Consider an airline purchasing new planes that are expected to fly for 20 years. The cash flow from this investment clearly depends on fuel prices and an increase in expected fuel price uncertainty, all else equal, should cause the airline to delay the investment. However, the predictable component of the variance of the real price of oil quickly reverts to the unconditional variance at longer horizons, so one would not expect variation in the conditional variance at a monthly or quarterly frequency to have a large effect on the investment decision.

Third, Bernanke (1983) takes the real price of oil as exogenously given. This simplifying assumption does not hold in practice, complicating the analysis. The concern is that we may attribute to oil price uncertainty the effects of macroeconomic uncertainty, which is more likely to affect the cash flow from the investment. As discussed in Section 4.4, it is also unclear whether the importance of the real options channel survives in general equilibrium. Thus, the overall importance of this channel for the aggregate economy is open to question.

3.2 PRECAUTIONARY SAVINGS

A complementary reason first articulated in Edelstein and Kilian (2009) is that households' increased uncertainty about their future income in the wake of unexpected changes in the real price of oil will cause an increase in precautionary savings. In this interpretation, oil price uncertainty may affect a wide range of consumer expenditures. This argument has subsequently been formalized in Plante and Traum (2012) and Başkaya et al. (2013).

While a response of precautionary savings to oil price uncertainty shocks may seem persuasive in a partial equilibrium setting, its quantitative importance becomes less obvious when moving to general equilibrium models. For example, in many general equilibrium models with stochastic volatility shocks, consumption barely declines or even increases in response to higher uncertainty (e.g., Born and Pfeifer, 2021; de Groot et al., 2018).

3.3 Precautionary inventory demand

A third channel by which increased oil price uncertainty can reduce economic activity operates through precautionary demand for oil inventories. This channel was introduced in Kilian (2009) and expanded on in Kilian and Murphy (2014) and Cross et al. (2022). These studies emphasized that higher precautionary demand driven by increases in oil price uncertainty, all else equal, will raise the real price of oil and reduce global economic activity by discouraging oil consumption.[9] DSGE models incorporating oil storage have been presented in Olovsson (2019) and Gao et al. (2022). The latter study considers stochastic volatility shocks to oil production and finds that firms increase their oil inventory holdings in response to an increase in oil price uncertainty.

4 A Model of the Propagation of Uncertainty Shocks

In this section, we introduce a DSGE model of the global economy designed to elucidate the determinants of oil price uncertainty and to uncover the macroeconomic implications of downside risk. Focusing on the global economy allows us to sidestep the complications involved in modeling oil importing and exporting economies and to concentrate on the key research questions.

4.1 Environment

The model is a nonlinear stochastic growth model augmented to include oil production. Oil is used as an intermediate input by a representative firm that produces a final

[9] This analysis in turn builds on the theoretical insights in Alquist and Kilian (2010) of how mean-preserving shifts in the uncertainty about future oil supply shortfalls affect the real price of oil through inventory accumulation.

good. The model allows for precautionary savings as well as oil storage, which has been shown to play an important role in driving fluctuations in oil prices (see Kilian and Murphy, 2014). The distinguishing feature of the model is that it includes downside risk to both oil production and output growth. While downside risk to oil production can be thought of as arising from geopolitical events, downside risk to the macroeconomy involves rare, sharp economic downturns, such as the Great Recession or the COVID-19 Recession that are not otherwise captured by the model.

We follow Gourio (2012) in modeling such events as disasters that arrive with a time-varying probability.[10] Time-variation in the probability of oil production and output growth disasters induces exogenous variation in oil price uncertainty and macroeconomic uncertainty. While the idea of modeling downside risk in the economy as growth disasters with time-varying probability is not new, we are the first to apply this approach to modelling geopolitical risk in the oil market.[11] One advantage of this approach compared to the more traditional approach of subjecting oil production to a stochastic volatility shock is that it accounts for the fact that the risk agents are typically concerned with in practice is not two-sided. Rather these risks involve a sharp reduction in oil production. Such rare disasters matter not only because of their impact when they occur, but, more importantly, because agents' behavior reflects the anticipation of these disasters even when they are not realized in the data.

Productivity and Growth Disasters The growth rate of productivity, $g_t = a_t/a_{t-1}$, follows

$$\ln g_t = \ln \bar{g} + \sigma_g \varepsilon_{g,t} - \zeta_g (v_t^g - \bar{\pi}_1^g), \quad \varepsilon_{g,t} \sim \mathbb{N}(0,1),$$

where $\bar{g}$ is the steady-state growth rate. The indicator variable v_t^g equals 1 if a growth disaster occurs and 0 otherwise. The transition matrix for v_t^g is summarized by

$$\Pr(v_{t+1}^g = 1 | v_t^g = 1) = \bar{q}^g, \quad \Pr(v_{t+1}^g = 1 | v_t^g = 0) = p_t^g,$$

[10] Applications of disaster risk include Barro and Ursúa (2012), Gourio (2013), Gourio et al. (2013), Wachter (2013), Shen (2015), Farhi and Gabaix (2016), Olovsson (2019), Berger et al. (2020), Kim (2022), and Kilian et al. (2024).

[11] Olovsson (2019) uses a related approach, except his model treats the probability of an oil disaster as constant.

where the probability of a growth disaster follows

$$\ln p_t^g = (1-\rho_p^g)\ln \bar{p}^g + \rho_p^g \ln p_{t-1}^g + \sigma_p^g \varepsilon_{p,t}^g, \quad \varepsilon_{p,t}^g \sim \mathbb{N}(0,1).$$

The size of the disaster is determined by ζ_g, and $\bar{\pi}_1^g = \frac{\bar{p}^g}{1+\bar{p}^g-\bar{q}^g}$ is the unconditional probability of the disaster. Following Gourio (2012), capital is destroyed when the disaster occurs. As in that paper, we use a broad interpretation of capital destruction that can represent a sharp reduction in capital quality due to the loss of intangible capital during economic downturns or the destruction of physical capital during wars, natural disasters, or sectoral reallocations. Let k_t denote the inherited stock of capital and i_t denote investment. The capital stock evolves according to

$$k_{t+1} = e^{-\zeta_g v_{g,t+1}}((1-\delta)k_t + i_t - \phi(i_t/k_t)k_t).$$

The functional form of the adjustment cost follows Jermann (1998) and is given by

$$\phi(i_t/k_t) = i_t/k_t - (\mu_1 + \tfrac{\mu_2}{1-1/\nu}(i_t/k_t)^{1-1/\nu}),$$

where $\mu_1 = (\bar{g}-1+\delta)/(1-\nu)$ and $\mu_2 = (\bar{g}-1+\delta)^{1/\nu}$.

Final Goods Firm A representative firm maximizes profits by choosing investment (i_t), capital (k_{t+1}), labor (n_t), and oil (o_t) inputs. Following Kim and Loungani (1992) and Backus and Crucini (2000), the firm produces a final good y_t using a Cobb-Douglas technology that aggregates labor and capital services, which are produced using a normalized CES production function that aggregates capital and oil. The firm's profit maximization problem is given by

$$V_t = \max_{i_t,k_{t+1},n_t,o_t} y_t - i_t - p_t^o o_t - w_t n_t + E_t[x_{t+1}V_{t+1}]$$

subject to

$$k_{t+1} = e^{-\zeta_g v_{g,t+1}}((1-\delta)k_t + i_t - \phi(i_t/k_t)k_t),$$
$$y_t = y_0(a_t n_t)^{1-\xi}\left((1-\alpha)(k_t/k_0)^{1-1/\sigma} + \alpha(o_t/o_0)^{1-1/\sigma}\right)^{\xi/(1-1/\sigma)},$$

where σ is the elasticity of substitution between capital and oil, δ is the depreciation rate of capital, $1-\xi$ is the share of labor in gross output, and α controls the share of oil in the capital services aggregate. The scalars y_0, k_0, and o_0 are set so that α is equal to the cost share of oil in the capital services aggregate. These normalizations do not affect the results but simplify the model calibration.[12]

The first-order conditions for the firm's problem are given by

$$w_t = (1-\xi)y_t/n_t,$$
$$p_t^o = \xi\alpha\frac{(o_t/o_0)^{1-1/\sigma}}{(1-\alpha)(k_t/k_0)^{1-1/\sigma}+\alpha(o_t/o_0)^{1-1/\sigma}}\frac{y_t}{o_t},$$
$$E_t[x_{t+1}r_{t+1}^i] = 1,$$

where

$$r_{t+1}^i \equiv e^{-\zeta_g v_{g,t+1}}(r_{t+1}^k + (1-\delta+\mu_1+\tfrac{\mu_2}{\nu-1}(i_{t+1}/k_{t+1})^{1-1/\nu})p_{t+1}^k)/p_t^k,$$
$$r_t^k \equiv \xi(1-\alpha)\frac{(k_t/k_0)^{1-1/\sigma}}{(1-\alpha)(k_t/k_0)^{1-1/\sigma}+\alpha(o_t/o_0)^{1-1/\sigma}}\frac{y_t}{k_t},$$
$$p_t^k \equiv \frac{1}{1-\phi'(i_t/k_t)} = \frac{1}{\mu_2}(\tfrac{i_t}{k_t})^{1/\nu}.$$

Oil Production and Oil Disasters The production of oil is exogenous and given by

$$o_t^s = a_t^o e_t.$$

This assumption is commonly used in DSGE models of the oil market, given the paucity of data for the oil sector. The permanent component, a_t^o, reflects factors that influence the productive potential of the oil sector, including the evolution of oil reserves and technological progress that increases the ability of the sector to extract oil from current reserves. We include a shock to this permanent component to allow for productivity shocks in the oil sector not related to geopolitical oil supply disruptions. The transitory component reflects temporary changes in the production of oil driven by exogenous geopolitical events. Oil production disasters are modeled as transitory, given evidence that geopolitical supply disruptions historically have not had long-lasting effects on global oil production, as discussed in the calibration section.

The permanent component is cointegrated with productivity in the rest of the economy,

$$a_t^o = \kappa_0 g_t^{\kappa_1}\epsilon_{t-1}^{\kappa_2}a_{t-1}^o \exp(\sigma_{go}\varepsilon_{go,t})$$

[12] A more detailed discussion of normalized CES production functions can be found in Klump et al. (2012).

where $\epsilon_t = a_t/a_t^o$, κ_1 determines the impact response of a growth shock on a_t^o, and κ_2 affects the speed at which a_t^o converges to a_t. This setup allows for a slow response of oil production to productivity growth shocks in the rest of the economy, which is a key feature of the data.[13]

The transitory component of global oil production is given by

$$\ln e_t = \ln \bar{e} - \zeta_e(v_t^e - \bar{\pi}_1^e).$$

The indicator variable v_t^e equals 1 if an oil production disaster occurs and 0 otherwise. The transition matrix for v_t^e is summarized by

$$\Pr(v_{t+1}^e = 1|v_t^e = 1) = \bar{q}^e, \quad \Pr(v_{t+1}^e = 1|v_t^e = 0) = p_t^e,$$

where the probability of an oil disaster follows

$$\ln p_t^e = (1-\rho_p^e)\ln \bar{p}^e + \rho_p^e \ln p_{t-1}^e + \sigma_p^e \varepsilon_{p,t}^e, \quad \varepsilon_{p,t}^e \sim \mathbb{N}(0,1).$$

The size of the disaster is determined by ζ_e, and $\bar{\pi}_1^e = \frac{\bar{p}^e}{1+\bar{p}^e-\bar{q}^e}$ is the unconditional probability of the disaster.

Oil Storage A representative oil storage firm maximizes profits by choosing inventories, s_{t+1}, and how much oil to supply to the final goods firm, o_t. The firm's maximization problem is given by

$$V_t^o = \max_{o_t, s_{t+1}} \; p_t^o o_t + E_t[x_{t+1} V_{t+1}^o]$$

subject to

$$s_{t+1} = (1-\omega)s_t + o_t^s - o_t - \tfrac{\pi}{2}(s_t/a_t)^{-2} a_t,$$

where ω is the cost of storage. Following Gao et al. (2022), there is a penalty, π, that prevents stockouts ($s=0$) from occurring, as they are not observed in the global oil market.

[13] When $\kappa_1 = 1$ and $\kappa_2 = 0$, $a_t^o = a_t$, so the production of oil responds immediately to changes in productivity elsewhere in the economy. This special case corresponds to the assumption made in Gao et al. (2022). Cointegration in DSGE models with oil is rare. One exception is Ready (2018), who models cointegration between oil production and TFP in a setting with long-run risk. Similarly, cointegrated TFP processes have been used in two-country international real business cycle models (e.g., Rabanal et al., 2011).

The first-order condition for the storage firm is given by

$$1 = E_t[x_{t+1} r^s_{t+1}],$$

where

$$r^s_{t+1} \equiv ((1 - \omega + \pi(s_{t+1}/a_{t+1})^{-3}) p^o_{t+1})/p^o_t.$$

Household A representative household maximizes the present discounted value of utility by choosing consumption, c_t, hours worked, n_t, bond holdings, b_{t+1}, and equity shares, s^e_{t+1}, which have unit net supply. The household has Epstein-Zin recursive preferences to distinguish between risk aversion, γ, and the intertemporal elasticity of substitution, ψ (see Epstein and Zin, 1989).

The household's maximization problem is given by

$$J_t = \max_{c_t, n_t, s^e_{t+1}, b_{t+1}} \left((1-\beta) u_t^{1-1/\psi} + \beta (E_t[J_{t+1}^{1-\gamma}])^{\frac{1-1/\psi}{1-\gamma}} \right)^{\frac{1}{1-1/\psi}}$$

subject to

$$u_t = c_t^{\chi} (a_t(1-n_t))^{1-\chi},$$

$$c_t + p^e_t s^e_{t+1} + b_{t+1}/r_t = w_t n_t + (p^e_t + d^e_t) s^e_t + b_t,$$

where β is the discount factor, p^e_t is the equity price, r_t is the risk-free rate, w_t is the wage rate, d^e_t are dividends from firm ownership, and the Frisch elasticity of labor supply $\eta^{\lambda} = \frac{1-n_t}{n_t} \frac{1-(1-1/\psi)\chi}{1/\psi}$.

The first-order conditions for the household are given by

$$\chi w_t (1-n_t) = (1-\chi) c_t,$$

$$1 = E_t[x_{t+1} r_t],$$

$$1 = E_t[x_{t+1} r^e_{t+1}],$$

where

$$r^e_{t+1} \equiv (p^e_{t+1} + d^e_{t+1})/p^e_t,$$

$$x_{t+1} \equiv \beta (u_{t+1}/u_t)^{1-1/\psi} (c_t/c_{t+1}) (J_{t+1}/z_t)^{1/\psi-\gamma},$$

$$z_t \equiv (E_t[J_{t+1}^{1-\gamma}])^{1/(1-\gamma)}.$$

The equity risk premium is defined as

$$r_t^{ex} \equiv r_t^e - r_{t-1}.$$

Market Clearing Following Jermann (1998) and Gourio (2012), both the final goods and storage firms issue bonds to finance their assets, where ϑ determines leverage. Since the Modigliani-Miller theorem holds in our model, the introduction of firm leverage only affects equity returns. There is no effect on household or firm decisions. Aggregate firm dividends are given by

$$d_t^e = d_t^f + d_t^s - \vartheta(E_{t-1}k_t - \tfrac{1}{r_t}E_t k_{t+1}) - \vartheta(E_{t-1}s_t - \tfrac{1}{r_t}E_t s_{t+1}),$$

where $d_t^f = y_t - i_t - p_t^o o_t - w_t n_t$ and $d_t^s = p_t^o o_t$.

Asset market clearing implies that $s_t^e = 1$ and total bond issuance is given by

$$b_t \equiv b_t^f + b_t^s = \vartheta(E_{t-1}k_t + E_{t-1}s_t).$$

Market clearing in the goods market implies

$$c_t + i_t = y_t.$$

Due to the stochastic trend in productivity, we detrend the model by defining $\tilde{x}_t = x_t/a_t$. The detrending process introduces the growth terms $g_t = a_t/a_{t-1}$ and $g_{o,t} = a_t^o/a_{t-1}^o$. Appendix E provides the detrended equilibrium system of equations.

Uncertainty We follow Plante et al. (2018) and Bernstein et al. (2024) and define output uncertainty as the conditional volatility of log output growth, which is given by

$$\mathcal{U}_t^y = \sqrt{E_t[(\ln(y_{t+1}/y_t) - E_t[\ln(y_{t+1}/y_t)])^2]}.$$

Oil price uncertainty, $\mathcal{U}_t^{p^o}$, is analogously defined as the uncertainty surrounding $\ln(p_{t+1}^o/p_t^o)$. This definition is equivalent to the measure we used to compute oil price uncertainty in the data.[14]

[14]The uncertainty surrounding oil price growth is equivalent to the uncertainty surrounding the log oil price because p_t^o is known at time t and cancels from the definition of $\mathcal{U}_t^{p^o}$. An analogous result holds for output uncertainty.

4.2 SOLUTION METHOD Modeling the oil sector considerably increases the computational cost of solving the model compared to a model that only includes macroeconomic risk. Our model has 7 state variables $(k_t, s_t, v_t^g, v_t^e, \ln p_t^g, \ln p_t^e, \epsilon_{t-1})$, 4 of which are related to the oil market. There are 4 continuous and 2 discrete shocks. In total, the state space contains over $300{,}000$ nodes and $40{,}000$ shock realizations for each node in the state space.

The existence of time-varying disaster risk prevents the use of perturbation methods. We therefore employ a fully nonlinear solution method. Specifically, the model is solved using the policy function iteration algorithm described in Richter et al. (2014), which is based on the theoretical work in Coleman (1991). The algorithm minimizes the Euler equation errors on each node in the state space and computes the maximum change in the policy functions. It then iterates until the maximum change is below a specified tolerance. The algorithm is programmed in Fortran and run on the BigTex supercomputer at the Federal Reserve Bank of Dallas. Appendix D describes the solution method in more detail.

4.3 CALIBRATION Each period in the model corresponds to one quarter. Given the paucity of global macroeconomic data, we calibrate the model under the assumption that the world economy resembles the U.S. economy. While this model abstracts from many features of the actual global economy, it provides a useful benchmark and a natural starting point for studying the role of downside risk in the global economy. The parameters shown in Table 1 are informed by moments in the data and the related literature.[15] The moments are computed using data from 1975Q1 to 2019Q4. Appendix B documents our data sources.

The discount factor β is set to 0.994 to match the average real interest rate. The relative risk aversion coefficient, γ, and intertemporal elasticity of substitution are set to 10 and 2, respectively, consistent with Gourio (2013), Croce (2014), Gao et al. (2022), and several other recent studies.[16] The Frisch elasticity of labor supply is set to 2 following Peterman (2016), Basu and Bundick

[15] Estimation using Bayesian methods or the simulated method of moments is not possible due to the high dimensionality of the model. Even when using a supercomputer with thousands of cores, the model takes several hours to solve.

[16] Swanson (2018) shows how to compute risk aversion under recursive preferences with an endogenous labor supply. Under our utility kernel, γ corresponds to risk aversion over consumption and leisure.

Table 1: Model calibration at a quarterly frequency

Parameter	Value	Target
Discount Factor (β)	0.994	$E(r)$
Risk Aversion (γ)	10	Gourio (2013), Croce (2014), Gao et al. (2022)
Intertemporal Elasticity of Substitution (ψ)	2	Gourio (2013), Croce (2014), Gao et al. (2022)
Frisch Labor Supply Elasticity (η^λ)	2	Peterman (2016), Basu and Bundick (2017)
Capital-Oil Elasticity of Substitution (σ)	0.105	$SD(\Delta p^o)$
Capital Depreciation Rate (δ)	0.025	Depreciation on fixed assets and durables
Capital-Oil Share of Production (ξ)	0.4043	Average labor share of income
Investment Adjustment Cost (ν)	2.4	$SD(\Delta i)$
Oil Storage Cost (ω)	0.025	Casassus et al. (2018), Gao et al. (2022)
Average Growth Rate ($\bar{g}$)	1.004	$E(\Delta y)$
Firm Leverage (ϑ)	0.9	$SD(r^{ex})$
Elasticity of Oil Supply to TFP (κ_1)	0	Newell and Prest (2019)
Oil Supply Adjustment Speed to TFP (κ_2)	0.05	Half life of 3.5 years
Growth Shock SD (σ_g)	0.01	$SD(\Delta y)$
Oil Production Growth Shock SD (σ_{go})	0.011	$SD(\Delta o^s)$
Growth Disaster Size (ζ_g)	0.022	$E(r^{ex})$
Probability of Entering Growth Disaster ($\bar{p}_g$)	0.0025	Occurs in expectation every 100 years
Probability of Exiting Growth Disaster ($\bar{q}_g$)	0.9	Gourio (2012)
Growth Disaster Probability Persistence (ρ_{pg})	0.8	$SD(\mathcal{U}_y)$
Growth Disaster Probability SD (σ_{pg})	0.8	$AC(\mathcal{U}_y)$
Oil Production Disaster Size (ζ_e)	0.05	Average peak decline in oil production disasters
Probability of Entering Oil Disaster ($\bar{p}_e$)	0.02	Average frequency of oil production disasters
Probability of Exiting Oil Disaster ($\bar{q}_e$)	0.67	Average duration of oil production disasters
Oil Disaster Probability Persistence (ρ_{pe})	0.9	$SD(\mathcal{U}_{p^o})$
Oil Disaster Probability SD (σ_{pe})	1.4	$AC(\mathcal{U}_{p^o})$

(2017), and many others in the business cycle literature.

The elasticity of substitution between capital and oil, σ, is set to 0.105 to match the volatility of oil price growth. Backus and Crucini (2000) adopt the same functional form of the production function and use a similar value (0.09). The Cobb-Douglas weight on capital services (ξ) is set to match the average labor share of income. The investment adjustment cost parameter, ν, is set to match the volatility of per capita investment growth. The capital depreciation rate, δ, matches the annual average rate of depreciation on private fixed assets and durable goods. The oil storage cost, ω, is set to 0.025 following Casassus et al. (2018) and Gao et al. (2022). As in Basu and Bundick (2017), the leverage parameter, ϑ, is set to 0.9 to help match the volatility of the equity premium.

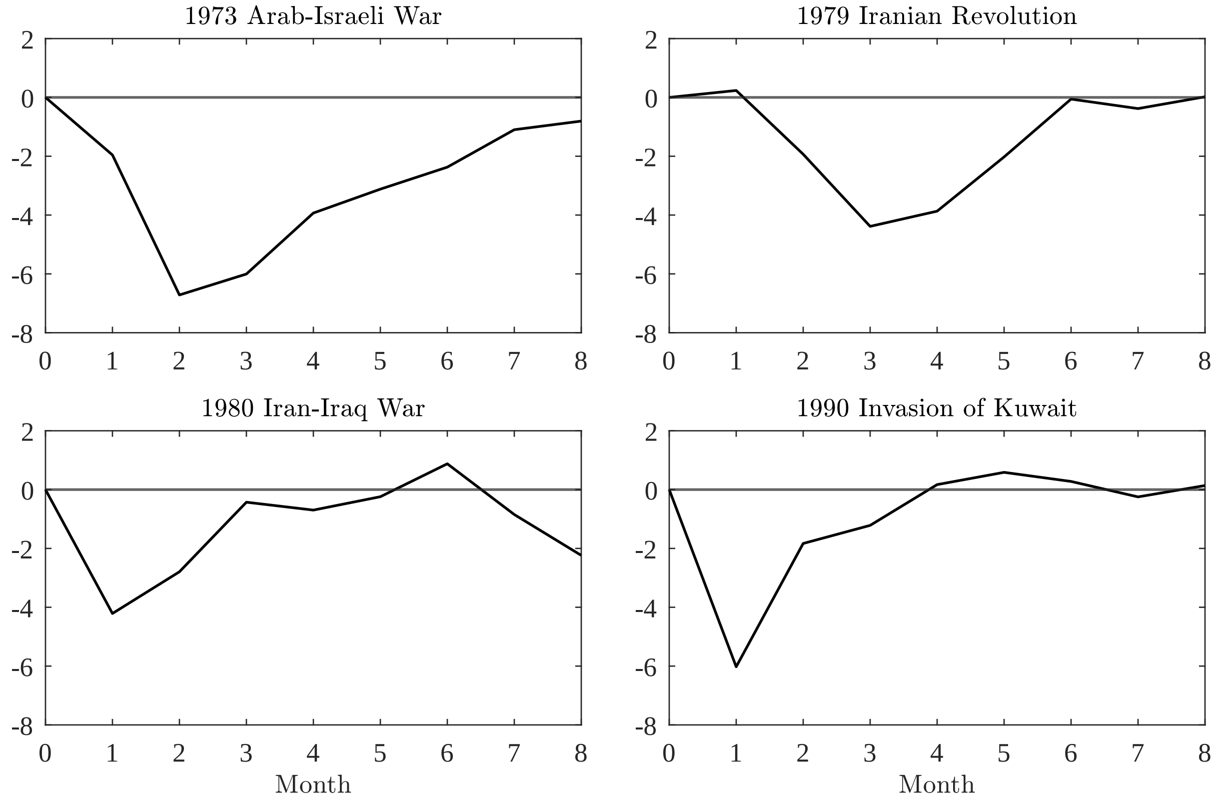
The mean growth rate of productivity, $\bar{g}$, is set to 1.004 to match the average growth rate of per capita real GDP. The standard deviation for the growth shock, σ_g, is set to 0.01 to help match the volatility of real GDP growth. The calibration of the growth disaster parameters is guided by several moments in the data as well as the parameter choices in Gourio (2012). We set the size of the disaster, ζ_g, to 0.022 to match the mean equity premium. The mean probability of entering the disaster state, $\bar{p}_g$, is set to 0.0025, which implies that these disasters happen once every 100 years in expectation. The persistence, ρ_{pg}, and standard deviation, σ_{pg}, of this probability are both set to 0.8 to help match the autocorrelation and volatility of output uncertainty. The fixed probability of exiting a growth disaster, $\bar{q}_g$, is set to 0.9, in line with Gourio (2012). This value implies that growth disasters, on average, last 2.5 years. As shown in Appendix F, the responses to an average growth disaster are very similar to those reported in Gourio (2012), who documents that his responses resemble the empirical estimates in Barro et al. (2013).

The value of κ_1 is set to 0, implying that productivity in the oil sector is unresponsive to changes in productivity in the rest of the economy within the first quarter. This is consistent with the view that oil production in the short run is determined entirely by geological constraints (see Newell and Prest, 2019). We set κ_2 to 0.05, so the half-life of the deviation between a_t^o and a_t is 4 years. The standard deviation of the growth shock to oil production, σ_{go}, is set to 0.011 to match the volatility of global oil production.

The parameters controlling the oil production disasters are based on historical oil production data.[17] Following Hamilton (2013), Figure 3 plots global oil production during major geopolitical events, where production is expressed in percent deviations from the level at the beginning of the event. We set the size of the oil production disaster, ζ_e, to 0.05 to match the average peak decline observed in the data. The mean probability of entering the oil disaster state, $\bar{p}_e$, is set to 0.02 so that disasters occur every 12.5 years in expectation (four major events over the last 50 years). The persistence, ρ_{pe}, and standard deviation, σ_{pe}, of this probability are set to 0.9 and 1.4, respectively,

[17] It may seem that options data could be used to help with the calibration. This is not the case. One challenge is that tail probabilities estimated from equity options as in Barro and Liao (2021) do not help quantify macroeconomic tail risk, but only equity risk. The distinction between financial risk and macroeconomic risk has been emphasized in Gao et al. (2022) and Ludvigson et al. (2021). Likewise, oil disaster probabilities are not recoverable from oil options because these prices reflect both oil and macroeconomic disaster risk in unknown combinations.

Figure 3: Shortfall in global oil production during major geopolitical events



Notes: Reproduced from Hamilton (2013) using updated global oil production data. We exclude the 2002/03 episode because the revised data show no evidence of a material shortfall.

to help match the autocorrelation and volatility of oil price uncertainty. The fixed probability of exiting an oil production disaster, $\bar{q}_e$, is set to 0.67 so that a disaster lasts, on average, for 3 quarters, which corresponds to the longest duration observed in the four episodes in Figure 3.

To compute the model-implied moments, we simulate the model $10{,}000$ times, each with 180 quarters to match the length of the data used to calibrate the model. We calculate the moments of interest in each simulated data set and then compute the average moments across all simulations. Table 2 compares the data and model-implied moments. The model closely matches most of the targeted moments. This includes moments related to the oil market (e.g., the standard deviations of oil price growth and oil production growth, the oil expenditure share, and the oil inventory-to-oil consumption share), real activity (e.g., the standard deviations of output and investment growth), asset prices (e.g., the average risk-free rate and equity risk premium), and uncertainty (e.g., the

Table 2: Data and simulated moments

Moment	Data	Model	Moment	Data	Model
$E(\Delta y)$	0.39	0.39	$SD(\Delta o^s)$	2.01	2.13
$E(s/o)$	0.97	0.97	$SD(\Delta p^o)$	14.39	14.22
$E(p^o o/y)$	0.045	0.046	$SD(r^{ex})$	8.29	3.73
$E(r^{ex})$	2.18	2.03	$SD(\mathcal{U}_y)$	14.51	15.60
$E(r)$	0.22	0.23	$SD(\mathcal{U}_{p^o})$	29.95	28.97
$SD(\Delta y)$	0.74	0.83	$AC(\mathcal{U}_y)$	0.87	0.77
$SD(\Delta i)$	1.95	1.87	$AC(\mathcal{U}_{p^o})$	0.93	0.80
$SD(\Delta s)$	2.30	2.12	$AC(\Delta o^s)$	-0.11	-0.20
$SD(r)$	0.91	0.45	$Corr(\Delta y, \mathcal{U}_y)$	-0.15	-0.38
$AC(\Delta y)$	0.32	0.21	$Corr(\Delta y, \mathcal{U}_{p^o})$	-0.27	-0.35

Notes: Moments above the middle line are targeted while those below it are untargeted. The model is calibrated to data from 1975Q1-2019Q4. $SD(\mathcal{U}_y)$ and $SD(\mathcal{U}_{p^o})$ are normalized by $SD(\Delta y)$ and $SD(\Delta p^o)$, respectively, to be consistent with the normalization in Jurado et al. (2015).

standard deviations and autocorrelations of output uncertainty and oil price uncertainty).[18] Jointly matching all four of these key aspects of the economy gives us confidence that the model provides a good description of oil market, real activity, and uncertainty dynamics.

The model also performs well at matching several untargeted moments shown at the bottom of Table 2. For example, the volatility of oil inventory growth and the autocorrelations of output growth and oil production growth closely match the data. Output and oil price uncertainty are somewhat more countercyclical in the model than in the data, but this could presumably be addressed by adding exogenous volatility shocks. Finally, allowing for macroeconomic risk and geopolitical oil price risk raises the volatility in the risk-free rate and brings it more in line with the data. These results provide further validation of our model.

4.4 DISCUSSION Our model incorporates precautionary savings by households in response to higher oil price uncertainty as well as storage, the two main economic mechanisms that are thought to propagate oil price uncertainty shocks. While we do not model real options arising from irre-

[18]One concern is the oil share calculated using U.S. data may not be representative of the global economy. We also calculated oil shares using supply-use tables from the World Input-Output Database (Timmer et al., 2015). These tables are available for 38 countries, including the U.S., China, Japan, Brazil, India, Indonesia and many countries in Europe. The average across all countries was 0.05, very close to the ergodic mean of the share in our model.

versible investment as in Bernanke (1983), our model features limited substitutability between capital and oil. This feature causes the expected return on investment to decline when the probability of an oil production disaster increases, generating recessionary effects in the model.

Although Bernanke's theoretical analysis is often cited in support of models of oil price volatility shocks, it is not well appreciated that Bernanke was not modeling a monthly or quarterly oil price volatility shock. Rather, he envisioned agents being uncertain about whether the price of oil would permanently move to a higher level or not, which is a different thought experiment. In his model there are two types of capital that differ by their oil efficiency. The irreversibility of the investment decision causes risk averse agents to postpone the acquisition of either type of capital. The difficulty in generalizing this model to general equilibrium is that it requires aggregating different types of capital across many firms.

A closely related model that deals with the aggregation of different types of capital in general equilibrium was proposed by Atkeson and Kehoe (1999). In their putty-clay model there is a continuum of capital goods indexed by their oil efficiency. Existing capital goods use oil in fixed proportions, so, in the short run, there is no substitutability between capital and oil. However, firms may invest in new capital with different oil efficiency in response to changes in the price of oil. Although this point is not the focus of Atkeson and Kehoe (1999), their model implies that higher oil price uncertainty would reduce investment, as discussed in Plante and Traum (2012).

The reason we do not incorporate the putty-clay framework within our model is that two key assumptions made by Atkeson and Kehoe (1999) do not hold in our model. One is that the price of oil is exogenous; the other is that under their assumptions oil consumption does not respond to the price of oil on impact. These assumptions not only allow Atkeson and Kehoe to abstract from storage, but they allow them to aggregate across different types of capital without the need to track the distribution of capital types. The fact that the infinite-dimensional state space of capital stocks in the model can be reduced to a one-dimensional space facilitates the solution of their model.

In contrast, in our model the price of oil is endogenously determined. Suppose, for example, that there is an oil supply shock. In that case, we must add storage to the model because otherwise equilibrium in the oil market is unattainable. If oil consumption is predetermined and hence unresponsive to the oil price fluctuations caused by the oil supply shock, oil inventories must absorb any imbalances in the oil market each period. It can be shown that, as a result, the oil inventory moments of the simulated model data differ substantially from the oil inventory moments in the actual data. It may seem that this problem could be addressed by dropping the assumption that oil consumption is unresponsive to the price of oil, but this would render the capital stock intractable, which is why we do not consider the putty-clay framework in our model. However, our model with disaster risk generates investment and output responses that are qualitatively consistent with those in models of irreversible investment. The reason is that in our model risk averse agents are reluctant to invest given the limited substitutability between capital and oil.

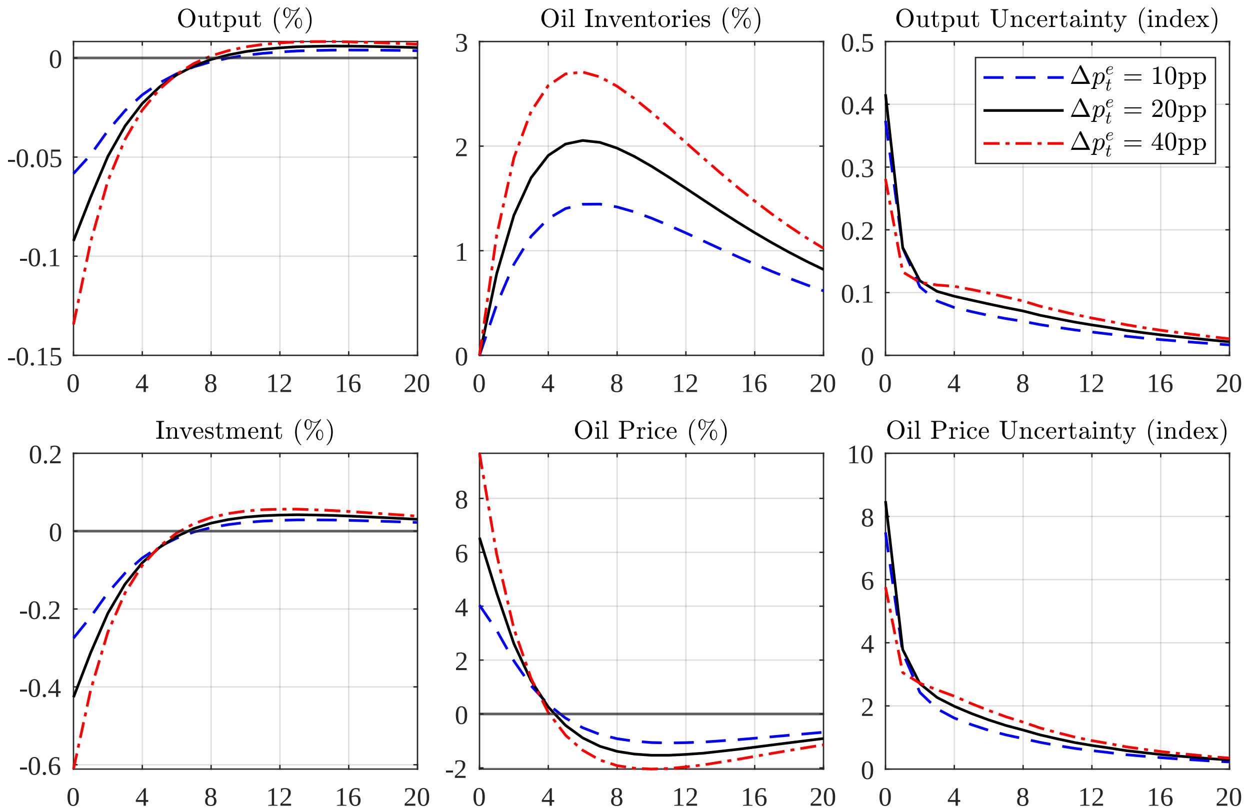
5 WHAT IS THE ROLE OF UNCERTAINTY SHOCKS?

As discussed in Section 3, economists' intuition about the impact of oil price uncertainty shocks continues to be based on insights from partial equilibrium models or from general equilibrium models with exogenous oil price volatility shocks, no fluctuations in macroeconomic uncertainty, and two-sided risk. This section examines the role of uncertainty shocks within the context of a general equilibrium model with endogenous time-varying uncertainty about the price of oil and output driven by macroeconomic and oil production disasters.

This model provides a useful benchmark for what we would expect the relationship between oil price uncertainty and output uncertainty to be in the data. First, it is capable of generating fluctuations in oil price uncertainty that are qualitatively similar to those in the data. Second, output uncertainty and oil price uncertainty are not independent. The model helps us understand to what extent their relationship is driven by exogenous shifts in macroeconomic risk, exogenous shifts in geopolitical risk in oil markets, or by other shocks.

5.1 TRANSMISSION OF UNCERTAINTY SHOCKS In practice, economic agents will witness disasters only infrequently. Nevertheless, disasters matter for economic behavior because there is

Figure 4: Responses to alternative oil production disaster probability shocks



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized.

a probability that they may be realized in the future. As we highlight in this section, changes in the probability of a disaster, which generate fluctuations in uncertainty, may create large responses in the oil market and the macroeconomy even when no disasters actually occur.

Oil Disaster Probability Figure 4 shows the responses of key model variables when the exogenous oil disaster probability is increased by 10, 20, and 40 percentage points (pp), respectively. Higher odds of an oil production disaster generate stronger precautionary storage demand, reflected in a persistent build-up of oil inventories. This raises the price of oil, with the initial increase ranging from about 4% for a 10pp shock to the disaster probability to about 10% for a 40pp shock.

The probability shock reduces investment, with the effect ranging from a 0.27% drop for a 10pp shock to 0.6% for a 40 pp shock. The negative effect on investment arises for two distinct reasons. First, an oil production disaster, if it were to occur, would reduce the return to capital, since oil and capital are complements in production. Thus, the higher probability of such a disaster lowers the expected return from investing in capital. Second, the return to capital today declines because higher precautionary demand for oil inventories raises the price of oil. Together, these two effects push down output, but the overall magnitude is modest since the investment share in output is small.

Higher odds of an oil production disaster raise both output uncertainty and oil price uncertainty, but the effects on oil price uncertainty are much larger. For example, a 10pp increase in the probability of an oil disaster raises the output uncertainty index only by 0.4, but the oil price uncertainty index by 7.5. Thus, the oil disaster probability shock looks in some ways like an exogenous oil price uncertainty shock. However, as discussed later, the downside risk inherent in the oil production disaster leads to very different responses compared to a stochastic volatility shock to oil production growth.

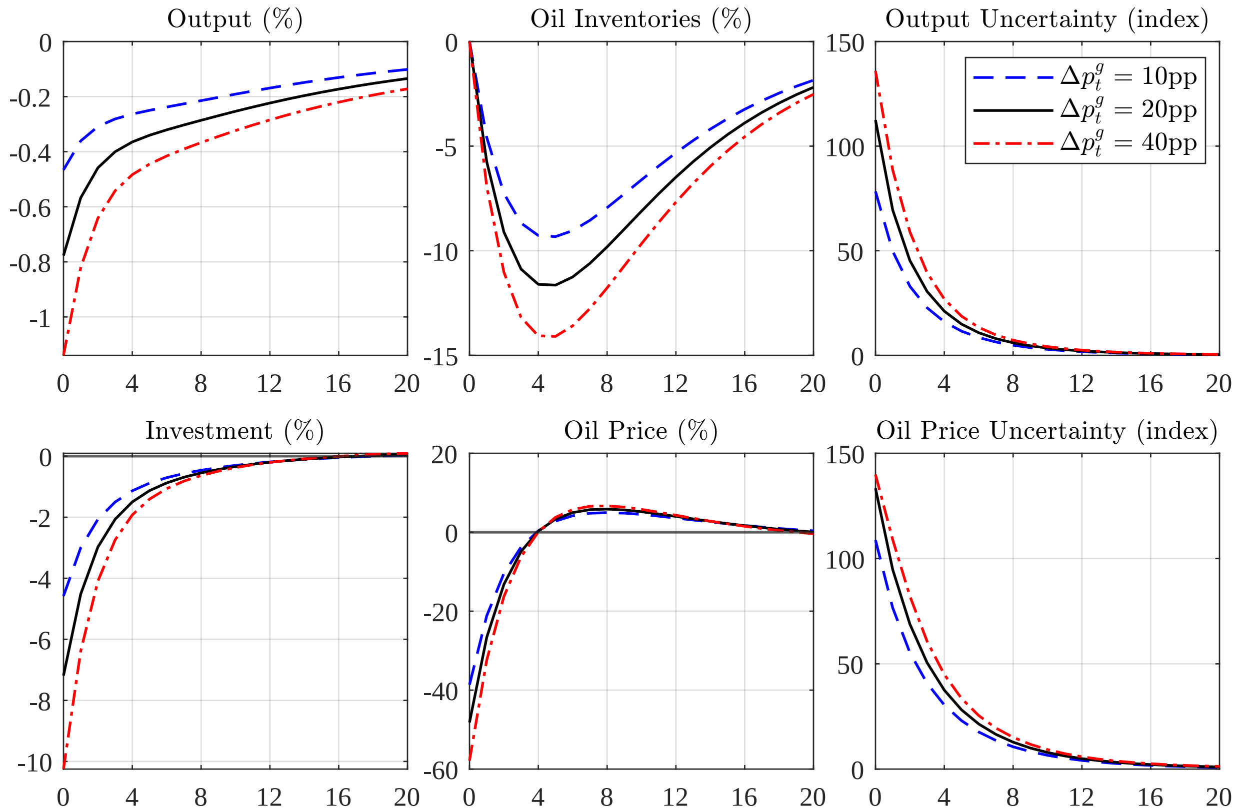
The model shows that the recessionary effects of the probability shock are reflected in output immediately, but are short-lived. The responses do not change proportionately with the shock size. For example, the responses of output and the price of oil to a 40pp increase in the oil disaster probability are only about 2 times larger than when the probability rises by 10pp. This result highlights that exogenous variation in uncertainty transmits to the macroeconomy nonlinearly.

Raising the disaster probability beyond a certain point lowers oil price uncertainty because the agents in the model perceive the disaster as increasingly likely. At the same time, the effect of the disaster probability shock on the oil price and real activity strengthens and eventually converges to the effects that occur when an average oil production disaster is realized. As shown in Appendix F, an average oil disaster causes a 16% increase in the price of oil and a 0.18% decline in output. However, unlike an oil disaster probability shock, inventories sharply decline as oil supply is cut.

Growth Disaster Probability A growth disaster acts like a negative demand shock in the oil market by reducing real activity and lowering oil demand. This plays a key role in understanding how the oil market responds to an increased probability of an output growth disaster.

Figure 5 shows the responses when the exogenous disaster probability increases by 10, 20, and 40pp, respectively. An increase in the probability of a growth disaster has substantial, albeit short-

Figure 5: Responses to alternative growth disaster probability shocks



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized.

lived, effects on the price of oil. For example, a 10pp increase in the probability causes the price of oil to decline by 39% on impact. There are two related but somewhat distinct mechanisms at play. First, as in Gourio (2012), the higher probability directly reduces the expected return to capital, which lowers oil demand today since capital and oil are complements. Second, lower current and expected oil demand also reduces the expected return from holding oil inventories. As a result, oil currently held in storage is sold off, pushing down the oil price even further.

Although the reduction in the price of oil is beneficial for the economy, the net effect of this probability shock on output is negative. In fact, the decline in output is much larger than from the oil disaster probability shock of the same magnitude. This is because the growth probability shock transmits directly to output rather than through the share of oil in output, which is small. In addition, the response is much more persistent than the response to the oil disaster probability shock.

In related work, Gourio (2012) showed that an increase in the probability of a growth disaster causes the uncertainty about equity prices to rise. Our results show that the same shock also has a major effect on output uncertainty and oil price uncertainty. If the price of oil and oil price uncertainty were exogenous, this interaction between the uncertainty measures would not occur.

As in Figure 4, the responses do not scale proportionately with the increase in the growth disaster probability. For example, a 10pp increase leads to a 39% decline in the price of oil, whereas the price of oil declines by 58% when the probability rises by 40pp. This is true for the other variables as well, once again highlighting the nonlinearity in the transmission of uncertainty.

The key difference between the two disaster probability shocks is that the growth disaster probability shock has substantial effects on both uncertainty variables, whereas the oil disaster probability shock does not. This suggests that the comovement between oil price uncertainty and output uncertainty tends to reflect shifts in macroeconomic risk rather than geopolitical risk.

External validation of the oil market responses An important question is whether the responses of the real price of oil and of oil inventories reported in Figures 4 and 5 (and the corresponding responses associated with the realization of a disaster shown in Appendix F) align with earlier empirical evidence. A natural benchmark are the impulse responses reported in Zhou (2020) based on the workhorse structural VAR model of the global oil market developed in Kilian and Murphy (2014). These response estimates are consistent with those implied by our DSGE model.

The responses to a positive shock to the oil production disaster probability may be interpreted as an example of a positive storage demand shock in the Kilian-Murphy model, which is expected to raise oil inventories and the price of oil, consistent with the responses in Figure 4. Likewise, the responses to an increase in the growth disaster probability represent an example of a negative storage demand shock that lowers oil inventories and the price of oil, consistent with the responses in Figure 5. Both shocks involve anticipation and hence affect the oil market through storage.

The realization of an oil production disaster (Appendix F, Figure 2), in contrast, is best thought of as a negative flow supply shock in the Kilian-Murphy model that lowers inventories and raises the price of oil, consistent with the evidence in Zhou (2020). Finally, the realization of a growth

Table 3: Decomposition of key volatilities

Moment	Data	Model		
		Baseline	No Output Disaster Risk	No Output Disaster Risk or Oil Production Disaster Risk
$SD(\Delta y)$	0.74	0.83	0.66	0.66
$SD(\Delta i)$	1.95	1.87	1.18	1.15
$SD(\Delta o^s)$	2.01	2.13	2.12	1.12
$SD(\Delta p^o)$	14.39	14.22	6.79	5.99
$SD(\mathcal{U}_y)$	14.51	15.60	0.17	0.07
$SD(\mathcal{U}_{p^o})$	29.95	28.97	5.06	2.17

Notes: The models without disaster risk remove both the probability shock and the disaster state. $SD(\mathcal{U}_y)$ and $SD(\mathcal{U}_{p^o})$ are normalized by $SD(\Delta y)$ and $SD(\Delta p^o)$ in the baseline model, respectively, to be consistent with Jurado et al. (2015).

disaster (Appendix F, Figure 3) instead resembles a negative flow demand shock in the Kilian-Murphy framework associated with lower oil prices and inventories, consistent with the evidence in Zhou (2020). Thus, in all cases our DSGE model replicates the sign of the oil price and inventory responses found in the structural VAR literature. Of course, the persistence of the responses need not match, as the DSGE model focuses on specific examples of storage demand, flow demand and flow supply shocks rather typical shocks of this type.[19]

5.2 HOW MUCH VOLATILITY IS DUE TO OUTPUT RISK AND GEOPOLITICAL RISK?

Table 3 shows that the model generally does an excellent job at capturing the volatility in the data. Dropping the output disaster risk from the DSGE model substantially lowers the ability of the model to explain the volatility in the data. The resulting model not only substantially understates the standard deviation of the two uncertainty series, but it also understates most other data moments.

Dropping both output and oil production disasters from the model further lowers the volatilities. In particular, it removes almost all variability in the two uncertainty measures and some of the

[19] Studying the evolution of oil inventories and the oil price during geopolitical disasters would not be informative about the realism of the DSGE model because the anticipation of an oil production disaster causes inventories to move in the opposite direction from it realization. Moreover, the behavior of oil inventories and prices during geopolitical disasters may also reflect past and current macroeconomic shocks. Thus, the realism of the responses in the DSGE model can only be evaluated based on the conditional moments in the data, which requires a structural VAR model.

variability in oil price growth and oil production growth but has little additional effect on the volatility of macroeconomic aggregates.

There are two key takeaways from these results. First, output disaster risk is a major driver of fluctuations in oil price uncertainty, highlighting that oil price uncertainty is not exogenous as is often assumed in the literature. Second, oil production disaster risk is not a major driver of fluctuations in macro aggregates or output uncertainty, suggesting that oil price uncertainty does not play a major role in driving business cycles.

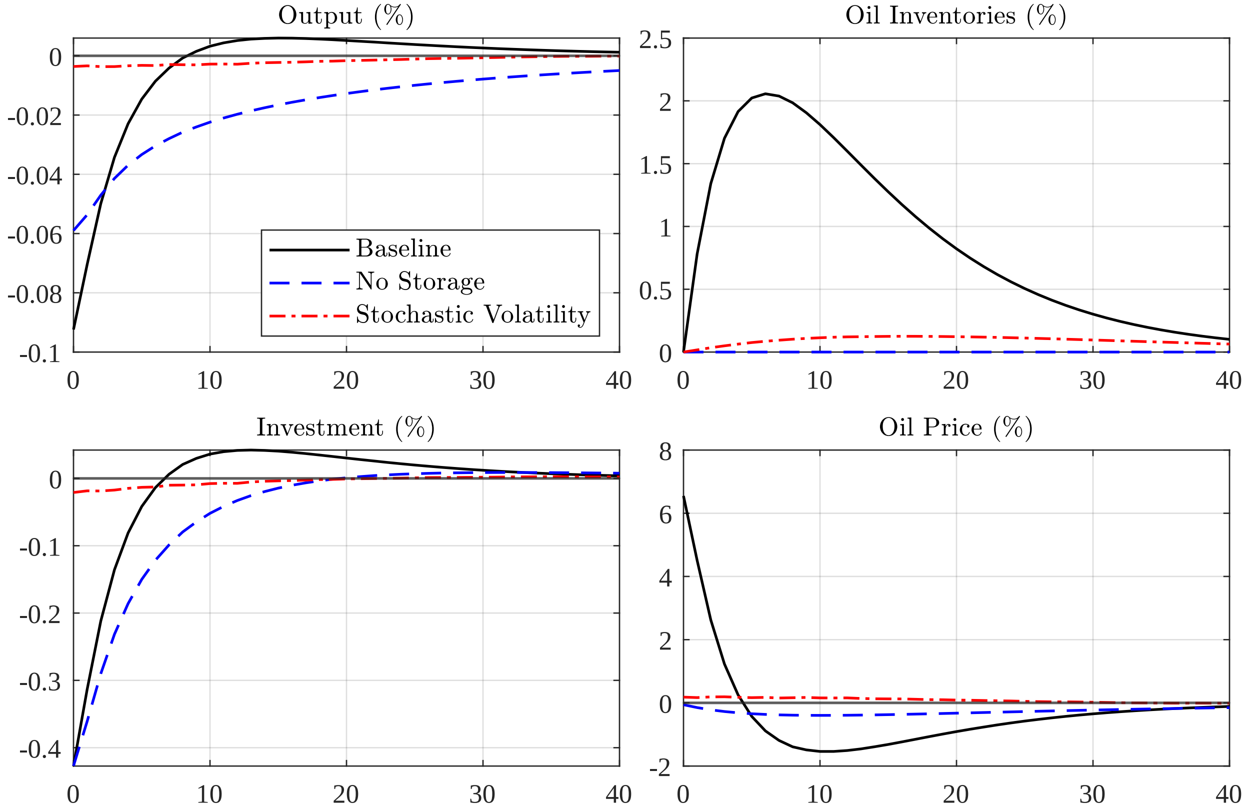
5.3 ALTERNATIVE MODEL SPECIFICATIONS In this section, we highlight key features of our model by considering alternative specifications. We first illustrate the central role of oil storage. We then contrast our model with earlier models incorporating stochastic volatility shocks.

Role of storage There are important movements in oil inventories whenever the probability of a disaster increases. These movements affect the price of oil and, therefore, the evolution of macroeconomic aggregates. In this section, we investigate how important storage is for those responses by comparing the baseline results to those from a model without storage.

Figure 6 shows the responses for the oil disaster probability shock. The key difference is that the price of oil declines slightly in the model without storage, whereas it increases substantially in the baseline model. In the absence of storage, the response of the oil price is driven entirely by the expectation of lower output, which reduces the demand for oil and modestly lowers its price. Given the muted response of the price of oil, the impact effect on output is also reduced.

Figure 7 shows that storage also plays a key role in the propagation of a growth disaster probability shock. In the model with storage, a higher probability of a disaster leads to a reduction in oil inventories due to the greater likelihood of a recession. This causes a substantial decline in the price of oil, which does not occur in the no-storage model. Since a lower price of oil offsets some of the negative effects of this shock on the macroeconomy, the impact effect on output is larger when the model does not contain storage. Overall, our results demonstrate that storage is a key ingredient for understanding the effects of uncertainty in both the oil market and the macroeconomy.

Figure 6: Responses to oil production disaster probability and stochastic volatility shocks



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized. The stochastic volatility shock has been normalized to match the impact response of oil price uncertainty in the baseline model. The baseline and no storage disaster probability shock is 10pp.

Role of downside risk Stochastic volatility (SV) is an alternative way of generating time-varying oil price uncertainty that has been used in previous studies (e.g., Başkaya et al., 2013; Gao et al., 2022; Plante and Traum, 2012). In this section, we compare the results from the baseline model to those from a model where uncertainty is generated by SV. Specifically, we introduce an exogenous volatility shock into productivity growth and oil production growth,

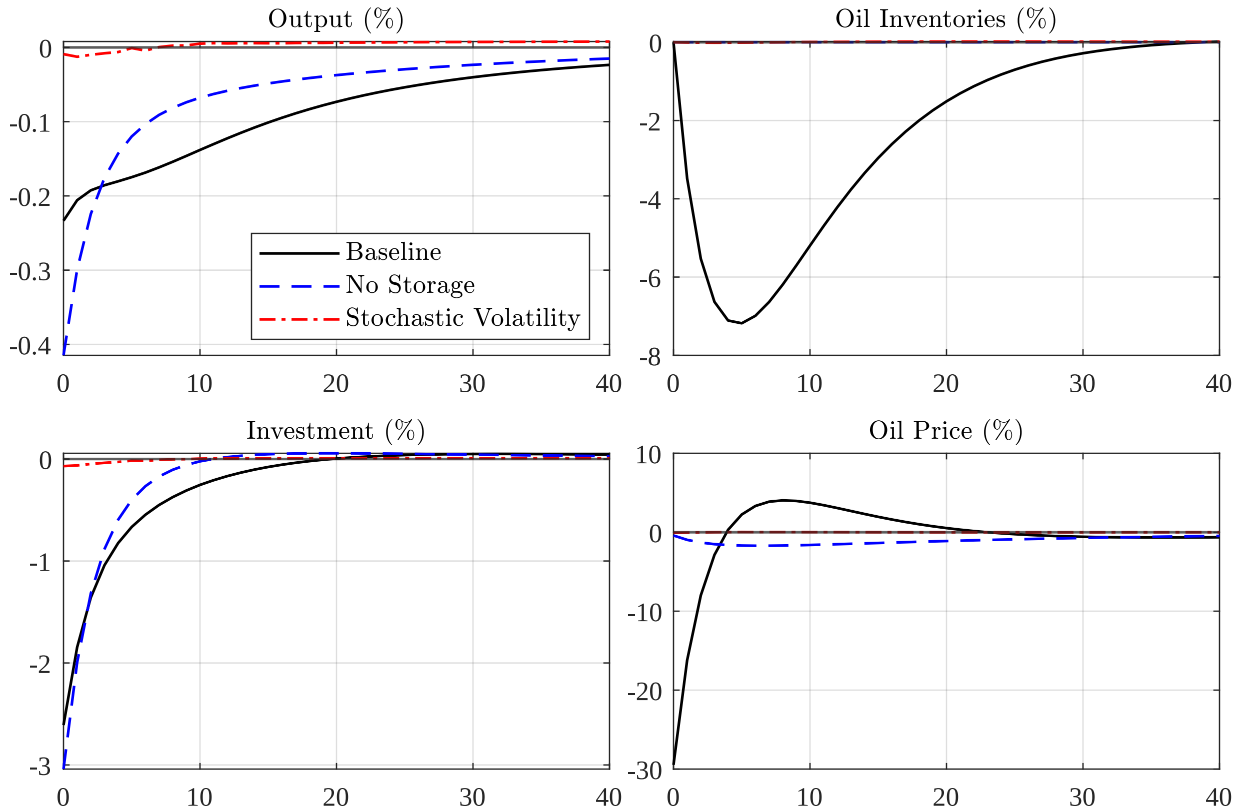
$$\ln g_t = \ln \bar{g} + \sigma_{g,t-1}\varepsilon_{g,t},$$

$$\ln g_{o,t} = \ln \kappa_0 + \kappa_1 \ln g_t + \kappa_2 \ln \epsilon_{t-1} + \sigma_{go,t-1}\varepsilon_{go,t},$$

$$\ln \sigma_{g,t} = (1-\rho_{sv}^g)\ln \bar{\sigma}_g + \rho_{sv}^g \ln \sigma_{g,t-1} + \sigma_{sv}^g \varepsilon_{sv,t}^g,$$

$$\ln \sigma_{go,t} = (1-\rho_{sv}^{go})\ln \bar{\sigma}_{go} + \rho_{sv}^{go} \ln \sigma_{go,t-1} + \sigma_{sv}^{go} \varepsilon_{sv,t}^{go},$$

Figure 7: Responses to growth disaster probability and stochastic volatility shocks



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized. The stochastic volatility shock has been normalized to match the impact response of output uncertainty in the baseline model. The baseline and no storage disaster probability shock is 5pp.

where all shocks are standard normally distributed.[20] The parameters of the level processes are unchanged. The persistence of both SV processes, ρ^g_{sv} and ρ^e_{sv}, are equal to the persistence of the disaster probability processes. The standard deviation of the growth SV shock, σ^g_{sv}, is set to 0.09 to match the volatility of output growth uncertainty. Analogously, the standard deviation of the oil production SV shock, σ^{go}_{sv}, is set to 0.145 to match the volatility of oil price uncertainty.

Figure 6 compares the responses to an SV shock in oil production, $\varepsilon^{go}_{sv,t}$, to the responses to our baseline oil disaster probability shock, $\varepsilon^{e}_{p,t}$. The $\varepsilon^{go}_{sv,t}$ shock is set so the SV specification generates the same impact effect on oil price uncertainty as the oil disaster probability shock. Qualitatively,

[20]Stochastic volatility has also been used to model exogenous uncertainty shocks in a number of other settings including fiscal policy (Fernández-Villaverde et al., 2015), monetary policy (Mumtaz and Zanetti, 2013), household preferences (Basu and Bundick, 2017), and the global interest rate (Fernández-Villaverde et al., 2011).

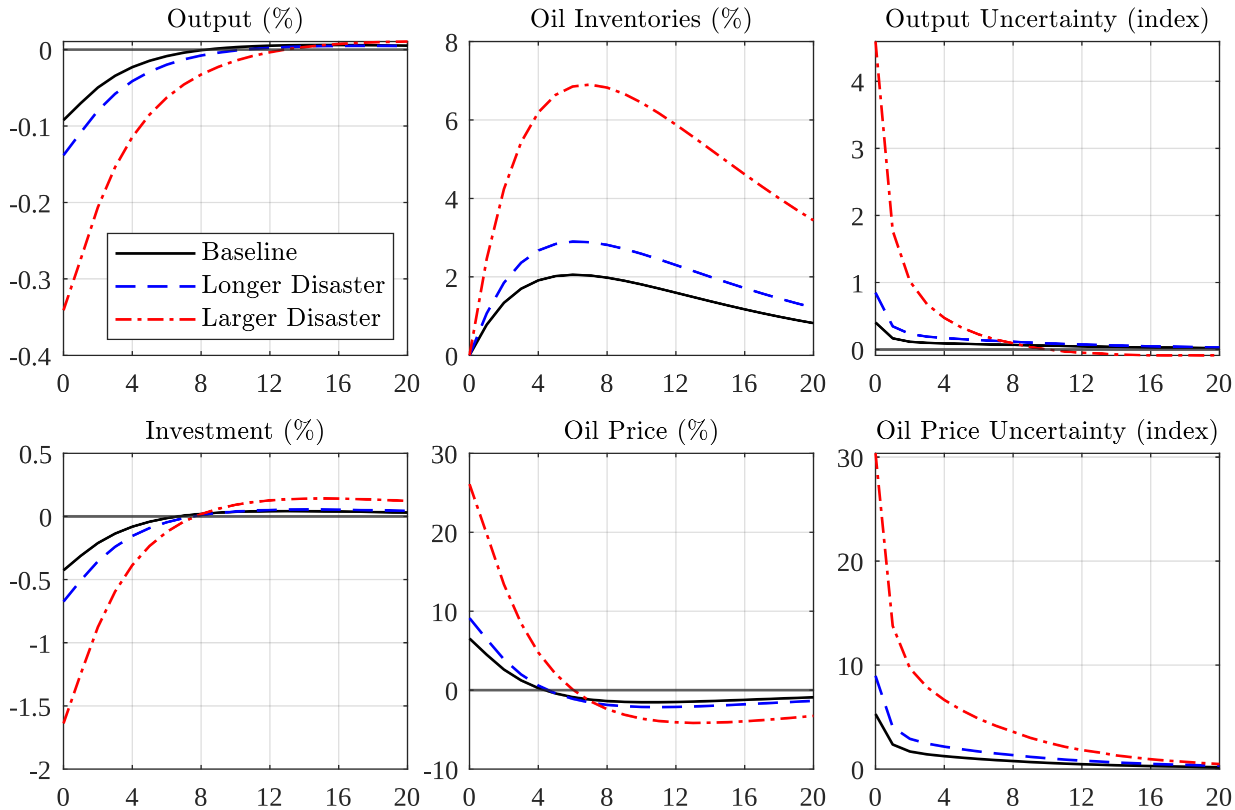
these shocks move the model variables in the same direction, but there are quantitatively significant differences. While the SV shock naturally generates sizable fluctuations in oil price uncertainty, it has little effect on the macroeconomy and the oil market.

The key difference between the two modeling choices is that an oil disaster introduces a source of downside risk into the economy because it makes a sharp drop in oil production more likely. As a result, when the probability of a disaster increases, it not only increases uncertainty but also shifts the conditional mean of economic outcomes. This generates a stronger precautionary demand motive, which pushes up the price of oil and lowers output. The SV shock, on the other hand, is akin to a mean-preserving spread. It generates a sizable increase in uncertainty but has little effect on the conditional mean. Hence, the responses of the price of oil and output are muted. A similar result holds when replacing the growth probability shock with a SV shock on productivity growth, as shown in Figure 7. We conclude that SV shocks are unable to capture the effects of increases in uncertainty associated with major geopolitical events that affect the oil market.[21]

5.4 ALTERNATIVE OIL DISASTER SPECIFICATIONS The surge in oil price uncertainty observed after the invasion of Kuwait in August 1990 far exceeded the increase in oil price uncertainty implied by our baseline model, which is calibrated to match the average magnitude and duration of past geopolitically driven oil production disasters. This suggests that the oil market in 1990 was concerned about a much larger or longer lasting disaster than the average realized oil production disaster observed in the data. Figure 8 explores this question by considering alternative specifications of the oil production disaster. We first consider a disaster with the same 5% magnitude as in the baseline model, but with an expected duration of 10 quarters rather than 3 quarters. We then, alternatively, consider a much larger oil production disaster of 20% of global oil production with the same expected duration as in the baseline model. A 20% shortfall would have been

[21] Similar to our responses for the SV specification, Gao et al. (2022) find small impacts of oil production volatility shocks in their baseline model. They show that the responses are amplified when markups are assumed to be time-varying such that the markup falls with oil consumption. The responses are even larger when level and volatility shocks to oil production are also assumed to be negatively correlated. The empirical support for these assumptions is not clear. For example, time-varying markups are a standard feature of micro-founded New Keynesian models. Plante and Traum (2014) examine such a model where oil is an intermediate input and find that SV shocks to the price of oil have a negligible effect on the macroeconomy.

Figure 8: Responses to an oil production disaster probability shock under different disasters



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized. The disaster probability shock is 20pp for all three specifications.

the approximate share of world oil production at risk if Iraq had succeeded in conquering not only Kuwait in 1990, but also Saudi Arabia and its smaller neighbors along the Persian Gulf such as Qatar, Bahrain, and the UAE. It also corresponds to the share of world oil production at risk from Iranian retaliation in the event of an Israeli attack on Iranian oil export facilities in 2024.

While making the oil production disaster longer lasting only modestly raises the effects on the global economy and the uncertainty measures compared to the baseline, making the oil production disaster larger increases the effect on oil price uncertainty six-fold. This brings the response much more in line with the observed spike in oil price uncertainty in 1990 (see Figure 2). At the same time, the responses of the price of oil and macroeconomic aggregates roughly quadruple in magnitude. The increase in the price of oil rises from 6.5% on impact to 26% and the reduction in output rises from 0.09% to 0.34%. As the disaster probability increases, these responses increase and converge to what happens if the disaster is realized, which is shown in Appendix F. For example, with a 40pp (60pp) probability shock, the price of oil rises by 37% (44%) and output declines by 0.49% (0.60%). If the disaster is realized, the price of oil rises by 54% and output falls by 0.63%.

The specification of the oil disaster also affects the ability of oil production disaster risk to explain variation in oil price uncertainty. While oil production disaster risk accounts for only 17% of this variability in the baseline model, as shown in Table 3, this share rises to 23% when the disaster is longer lasting and to 65% when the magnitude of the disaster is increased. We conclude that geopolitically driven oil disasters play a more important role when agents expect, at least sometimes, a larger oil production disaster than observed on average in the historical data. Such expectations would be consistent with a 20% geopolitically driven shortfall in global oil production being so rare that it is never observed in the historical data. Changing the magnitude of the oil disaster, however, does not alter our finding that a large portion of the variability in oil price uncertainty is driven by macroeconomic uncertainty.

6 RELATIONSHIP TO THE EXISTING LITERATURE

We are not the first to study the transmission of oil price uncertainty shocks within a DSGE model. For example, Başkaya et al. (2013) analyze the business cycle implications of oil price uncertainty based on a stylized oil-importing small open economy. One important difference is that oil price uncertainty is exogenous in their model. In contrast, our analysis shows that oil price uncertainty in general depends on level shocks as well as macroeconomic uncertainty shocks. Allowing for both macroeconomic and oil price uncertainty is important when assessing their respective roles in explaining economic fluctuations, as illustrated in Section 5.2. Another important difference is their use of SV shocks. Our results in Section 5.3 show that models with SV are unable to capture the responses to macroeconomic and oil production disaster probability shocks.

Our DSGE model shares some features with the theoretical model in Gao et al. (2022) in that both models allow the price of oil to be endogenously determined and incorporate uncertainty shocks. One key difference is that their model features SV shocks to oil production and productivity growth rather than downside risk. Another difference is that they do not examine the responses of oil price uncertainty to the level shocks in their model. Nor do they explore the relationship between oil price uncertainty and macroeconomic uncertainty.

The study related most closely to ours is perhaps Olovsson (2019) with the important difference that, while his model allows for oil storage and oil production disasters, it does not allow the disaster probability to vary over time, nor does it include macroeconomic disasters. These two features are crucial for understanding the economic effects of geopolitical risk. In addition, the focus of his paper is not on uncertainty.

Our DSGE model also differs from the theoretical model in Ready (2018) who does not study how the economy responds to shifts in the likelihood of a major temporary drop in oil production driven by geopolitical events, but instead examines how discrete shifts in the uncertainty about long-run oil supplies affect asset prices and the economy in a model with long-run risk.[22]

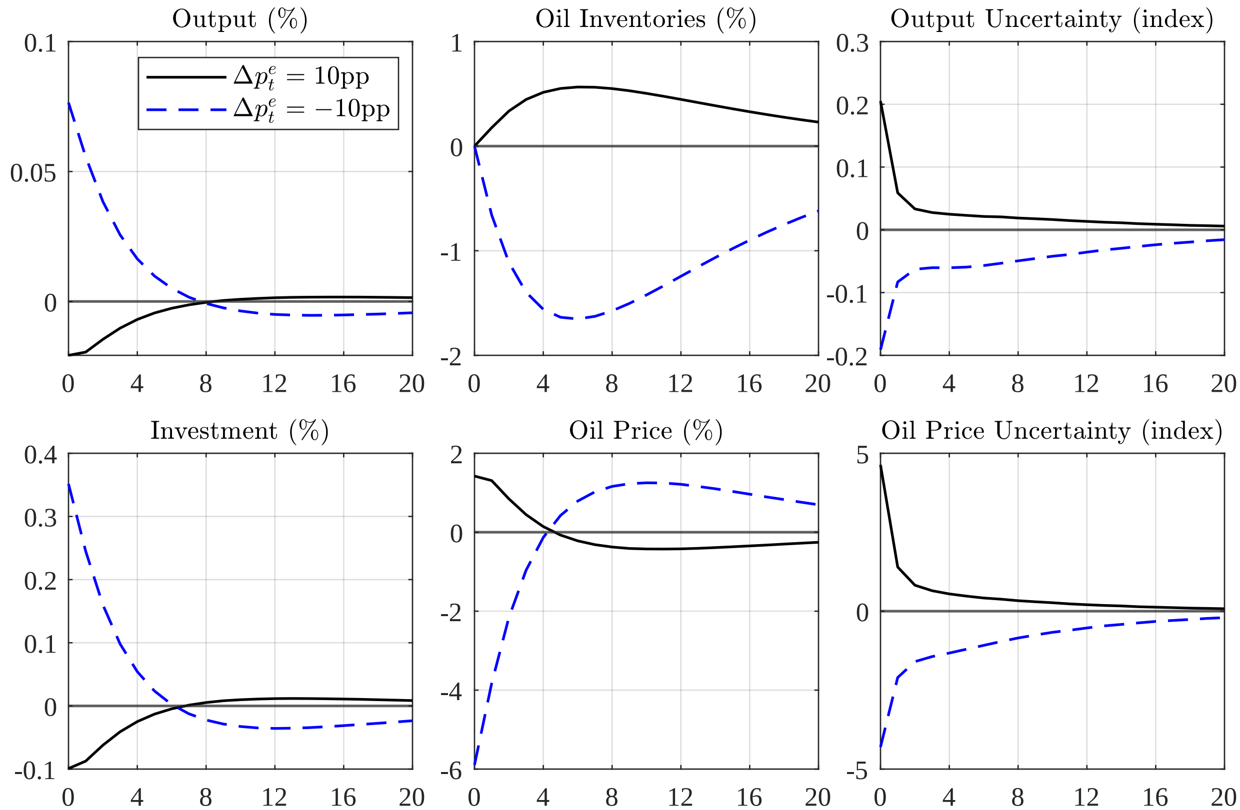
Finally, what sets our work apart from all these earlier studies is that we address the implications of the endogeneity of oil price uncertainty for the identification of oil price uncertainty shocks in empirical work. This question, which we turn to next, has not been addressed in prior work.

7 Implications for Empirical Work

The model in Section 4 highlights that oil price uncertainty endogenously responds not only to exogenous uncertainty about future oil production driven by geopolitical events, but also to exogenous uncertainty about the future path of the economy. Thus, geopolitically driven oil price uncertainty shocks differ in general from shocks to observed oil price uncertainty, as measured by the method of Jurado et al. (2015) or the OVX oil volatility index. This result is consistent with practitioners' understanding that uncertainty about the oil price reflects not only uncertainty about future oil production, but also uncertainty about future oil consumption driven by macroeconomic uncertainty, financial uncertainty, and policy uncertainty. For example, market commentators in recent years have routinely highlighted the role of uncertainty about the prospects of the Chinese

[22] In related work, Hamann et al. (2023) examine the effects of sovereign default risk in oil-producing economies.

Figure 9: Responses to positive and negative oil production disaster probability shocks



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized.

economy, the resolution of the Covid-19 pandemic, and whether the U.S. economy is about to enter a recession in assessing the uncertainty about the price of oil. Perhaps less obviously, the model also shows that oil price uncertainty responds to level shocks in the macroeconomy, as shown in the responses to a growth disaster in Appendix F. These results invalidate the premise of exogenous oil price uncertainty shocks and cast doubt on the ability of standard empirical models to correctly identify exogenous oil price uncertainty shocks.

The endogeneity of oil price uncertainty shocks is not the only concern with these models. For example, VAR models with GARCH errors, as in Elder and Serletis (2010), have two additional shortcomings. First, they postulate that every level shock to the price of oil is also an oil price uncertainty shock. In our model, level and uncertainty shocks affect oil price uncertainty differently. Second, they assume that positive and negative oil price shocks both increase oil price uncertainty, which is inconsistent with our model. Figure 9 illustrates this point by comparing the responses to a ± 10pp disaster probability shock.[23] A decrease in the probability of an oil disaster reduces the price of oil and oil price uncertainty on impact, while an increase in this probability raises the oil price and oil price uncertainty. The same result holds for a growth disaster probability shock, as shown in Appendix F.

Models that break the link between level and uncertainty shocks such as the VAR model with SV in Jo (2014) have their own limitations. Our analysis implies that empirical measures of oil price uncertainty shocks and shocks to the level of the price of oil are not independent, as assumed in VAR models with SV. The reason is that oil price uncertainty is endogenous and may be driven by the same shocks as the price of oil. For example, an increase in the probability of a growth disaster not only raises oil price uncertainty, but also causes storage demand to increase, raising the real price of oil.[24] In addition, the assumption that the effects of a rise and decline in oil price uncertainty on output are symmetric is violated in our model.

The insight that oil price uncertainty is simultaneously determined with macroeconomic aggregates applies not only to GARCH and SV models but also to recursively identified linear VAR models that order oil price uncertainty first in the spirit of Bloom (2009), such as Gao et al. (2022).[25] Thus, the seemingly robust empirical evidence from linear and nonlinear VAR models that oil price uncertainty shocks substantially lower real activity must be viewed with caution.

8 CONCLUDING REMARKS

There has been growing interest in the impact of shifts in geopolitical risk in global commodity markets, in particular in the market for crude oil. In this paper, we introduced a theoretical model of the global economy that is designed to examine how this risk affects oil price uncertainty and

[23] The simulations are initialized at a 15% oil disaster probability to permit a positive and negative shock. The state vector equals the average of periods in the ergodic distribution that are within 1pp of the initial disaster probability.

[24] Moreover, as shown in Section 5, while an increase in oil price uncertainty may be alternatively generated by an SV shock to oil production, only a disaster probability shock can generate meaningful recessionary effects. Thus, one would not expect large recessionary effects of shocks to oil price uncertainty when estimating VAR models with SV.

[25] Exploring alternative recursive orderings does not address this concern, as shown in Kilian et al. (2024).

the macroeconomy. Unlike previous studies, we modeled geopolitical risk as downside risk to oil production and allowed oil price and macroeconomic uncertainty to be determined endogenously. Our results show that shocks to the probability of a major shortfall in global oil production driven by geopolitical events only have modest effects on the oil market and real activity and are not a major driver of macroeconomic fluctuations.

Our analysis highlighted the importance of jointly modeling macroeconomic and geopolitical risk. We showed that oil price uncertainty responds to level shocks in the macroeconomy and to macroeconomic uncertainty shocks, in addition to geopolitically driven oil price uncertainty shocks. Shocks to the probability of growth disasters are not only recessionary, but they also play a major role in the determination of oil price uncertainty, which helps explain why oil price uncertainty has historically been associated with reductions in real activity. In our model, more than half of the observed oil price uncertainty tends to be driven by the economy. This fact, along with other implications of our model discussed in the paper, calls into question standard empirical models of the transmission of oil price uncertainty shocks that provide seemingly robust evidence supporting the conventional wisdom that oil price uncertainty plays a major role in driving the business cycle.

These findings suggest that economists and policymakers need to rethink the role of geopolitical oil price risk in the global economy and be cognizant of the interplay between oil price uncertainty, macroeconomic uncertainty, and the state of the economy. Notwithstanding the attention geopolitical events in oil markets have attracted, we conclude that geopolitical oil price risk is unlikely to generate sizable recessionary effects. Even when considering a geopolitically driven disaster involving a 20% drop in global oil production, which far exceeds the magnitude of historically observed oil production shortfalls, it takes a large increase in the probability of this disaster or its actual realization to cause a sizable recessionary impact.

REFERENCES

ABIAD, A. AND I. A. QURESHI (2023): “The Macroeconomic Effects of Oil Price Uncertainty,” *Energy Economics*, 125.

AGUIAR-CONRARIA, L. AND Y. WEN (2007): “Understanding the Large Negative Impact of Oil Shocks,” *Journal of Money, Credit and Banking*, 39, 925–944.

ALFARO, I., N. BLOOM, AND X. LIN (2024): "The Finance Uncertainty Multiplier," *Journal of Political Economy*, 132, 577–615.
ALQUIST, R. AND L. KILIAN (2010): "What Do We Learn From the Price of Crude Oil Futures?" *Journal of Applied Econometrics*, 25, 539–573.
ALQUIST, R., L. KILIAN, AND R. J. VIGFUSSON (2013): "Forecasting the Price of Oil," in *Handbook of Economic Forecasting*, ed. by G. Elliott, C. Granger, and A. Timmermann, North-Holland, vol. 2, 427–507.
ATKESON, A. AND P. J. KEHOE (1999): "Models of Energy Use: Putty-Putty versus Putty-Clay," *American Economic Review*, 89, 1028–1043.
BACKUS, D. K. AND M. J. CRUCINI (2000): "Oil Prices and the Terms of Trade," *Journal of International Economics*, 50, 185–213.
BAŞKAYA, Y. S., T. HÜLAGÜ, AND H. KÜÇÜK (2013): "Oil Price Uncertainty in a Small Open Economy," *IMF Economic Review*, 61, 168–198.
BAKER, S. R., N. BLOOM, AND S. J. DAVIS (2016): "Measuring Economic Policy Uncertainty," *Quarterly Journal of Economics*, 131, 1593–1636.
BARRO, R., E. NAKAMURA, J. STEINSSON, AND J. URSÚA (2013): "Crises and Recoveries in an Empirical Model of Consumption Disasters," *American Economic Journal: Macroeconomics*, 5, 35–74.
BARRO, R. J. AND G. Y. LIAO (2021): "Rare Disaster Probability and Options Pricing," *Journal of Financial Economics*, 139, 750–769.
BARRO, R. J. AND J. F. URSÚA (2012): "Rare Macroeconomic Disasters," *Annual Review of Economics*, 4, 83–109.
BARSKY, R. B. AND L. KILIAN (2002): "Do We Really Know That Oil Caused the Great Stagflation? A Monetary Alternative," in *NBER Macroeconomics Annual 2001, Volume 16*, ed. by M. Eichenbaum, E. Hurst, and V. Ramey, University of Chicago Press, 137–198.
BASU, S. AND B. BUNDICK (2017): "Uncertainty Shocks in a Model of Effective Demand," *Econometrica*, 85, 937–958.
BAUMEISTER, C. AND L. KILIAN (2016a): "Lower Oil Prices and the U.S. Economy: Is This Time Different?" *Brookings Papers on Economic Activity*, 287–357.
——— (2016b): "Understanding the Decline in the Price of Oil since June 2014," *Journal of the Association of Environmental and Resource Economists*, 3, 131–158.
BERGER, D., I. DEW-BECKER, AND S. GIGLIO (2020): "Uncertainty Shocks as Second-Moment News Shocks," *Review of Economic Studies*, 87, 40–76.
BERNANKE, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *The Quarterly Journal of Economics*, 98, 85–106.
BERNANKE, B. S., M. GERTLER, AND M. WATSON (1997): "Systematic Monetary Policy and the Effects of Oil Price Shocks," *Brookings Papers on Economic Activity*, 28, 91–157.
BERNSTEIN, J., M. PLANTE, A. W. RICHTER, AND N. A. THROCKMORTON (2024): "A Simple Explanation of Countercyclical Uncertainty," *American Economic Journal: Macroeconomics*, 16, 143–171.
BIANCHI, F., C. L. ILUT, AND M. SCHNEIDER (2018): "Uncertainty Shocks, Asset Supply and Pricing over the Business Cycle," *Review of Economic Studies*, 85, 810–854.
BLOOM, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685.
——— (2014): "Fluctuations in Uncertainty," *Journal of Economic Perspectives*, 28, 153–176.
BLOOM, N., M. FLOETOTTO, N. JAIMOVICH, I. SAPORTA-EKSTEN, AND S. J. TERRY (2018): "Really Uncertain Business Cycles," *Econometrica*, 86, 1031–1065.

BORN, B. AND J. PFEIFER (2021): "Uncertainty Driven Business Cycles: Assessing the Markup Channel," *Quantitative Economics*, 12, 587–623.

BRAUN, R. (2023): "The Importance of Supply and Demand for Oil Prices: Evidence from Non-Gaussianity," *Quantitative Economics*, 14, 1163–1198.

CALDARA, D. AND M. IACOVIELLO (2022): "Measuring Geopolitical Risk," *American Economic Review*, 112, 1194–1225.

CASASSUS, J., P. COLLIN-DUFRESNE, AND B. R. ROUTLEDGE (2018): "Equilibrium Commodity Prices with Irreversible Investment and Non-linear Technologies," *Journal of Banking & Finance*, 95, 128–147.

COLEMAN, II, W. J. (1991): "Equilibrium in a Production Economy with an Income Tax," *Econometrica*, 59, 1091–1104.

CROCE, M. M. (2014): "Long-Run Productivity Risk: A New Hope for Production-Based Asset Pricing?" *Journal of Monetary Economics*, 66, 13–31.

CROSS, J. L., B. H. NGUYEN, AND T. D. TRAN (2022): "The Role of Precautionary and Speculative Demand in the Global Market for Crude Oil," *Journal of Applied Econometrics*, 37, 882–895.

DAVIS, S. J. AND J. HALTIWANGER (2001): "Sectoral Job Creation and Destruction Responses to Oil Price Changes," *Journal of Monetary Economics*, 48, 465–512.

DE GROOT, O., A. RICHTER, AND N. THROCKMORTON (2018): "Uncertainty shocks in a model of effective demand: Comment," *Econometrica*, 86, 1513–1526.

DIEBOLD, F. X. AND L. KILIAN (2001): "Measuring Predictability: Theory and Macroeconomic Applications," *Journal of Applied Econometrics*, 16, 657–669.

DRAKOS, K. AND P. T. KONSTANTINOU (2013): "Investment Decisions in Manufacturing: Assessing the Effects of Real Oil Prices and Their Uncertainty," *Journal of Applied Econometrics*, 28, 151–165.

EDELSTEIN, P. AND L. KILIAN (2009): "How Sensitive are Consumer Expenditures to Retail Energy Prices?" *Journal of Monetary Economics*, 56, 766–779.

ELDER, J. AND A. SERLETIS (2010): "Oil Price Uncertainty," *Journal of Money, Credit and Banking*, 42, 1137–1159.

EPSTEIN, L. G. AND S. E. ZIN (1989): "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework," *Econometrica*, 57, 937–69.

FARHI, E. AND X. GABAIX (2016): "Rare Disasters and Exchange Rates," *Quarterly Journal of Economics*, 131, 1–52.

FERDERER, P. J. (1996): "Oil Price Volatility and the Macroeconomy," *Journal of Macroeconomics*, 18, 1–26.

FERNÁNDEZ-VILLAVERDE, J., P. GUERRÓN-QUINTANA, K. KUESTER, AND J. F. RUBIO-RAMÍREZ (2015): "Fiscal Volatility Shocks and Economic Activity," *American Economic Review*, 105, 3352–84.

FERNÁNDEZ-VILLAVERDE, J., P. GUERRÓN-QUINTANA, J. F. RUBIO-RAMÍREZ, AND M. URIBE (2011): "Risk Matters: The Real Effects of Volatility Shocks," *American Economic Review*, 101, 2530–61.

FINN, M. G. (2000): "Perfect Competition and the Effects of Energy Price Increases on Economic Activity," *Journal of Money, Credit and Banking*, 32, 400–416.

GAO, L., S. HITZEMANN, I. SHALIASTOVICH, AND L. XU (2022): "Oil Volatility Risk," *Journal of Financial Economics*, 144, 456–491.

GOURIO, F. (2012): "Disaster Risk and Business Cycles," *American Economic Review*, 102, 2734–2766.

——— (2013): "Credit Risk and Disaster Risk," *American Economic Journal: Macroeconomics*, 5, 1–34.

GOURIO, F., M. SIEMER, AND A. VERDELHAN (2013): "International Risk Cycles," *Journal of International Economics*, 89, 471–484.

GUO, H. AND K. L. KLIESEN (2005): "Oil Price Volatility and U.S. Macroeconomic Activity," *Federal Reserve Bank of St. Louis Review*, 87, 669–684.

HAMANN, F., J. C. MENDEZ-VIZCAINO, E. G. MENDOZA, AND P. RESTREPO-ECHAVARRIA (2023): "Natural Resources and Sovereign Risk in Emerging Economies: A Curse and a Blessing," NBER Working Paper 31058.

HAMILTON, J. D. (2013): "Historical Oil Shocks," in *Routledge Handbook of Major Events in Economic History*, Routledge, 239–265.

HOOKER, M. A. (1996): "What Happened to the Oil Price-Macroeconomy Relationship?" *Journal of Monetary Economics*, 38, 195–213.

——— (2002): "Are Oil Shocks Inflationary? Asymmetric and Nonlinear Specifications versus Changes in Regime," *Journal of Money, Credit and Banking*, 34, 540–561.

JERMANN, U. J. (1998): "Asset Pricing in Production Economies," *Journal of Monetary Economics*, 41, 257–275.

JO, S. (2014): "The Effects of Oil Price Uncertainty on Global Real Economic Activity," *Journal of Money, Credit and Banking*, 46, 1113–1135.

JURADO, K., S. C. LUDVIGSON, AND S. NG (2015): "Measuring Uncertainty," *American Economic Review*, 105, 1177–1216.

KELLOGG, R. (2014): "The Effect of Uncertainty on Investment: Evidence from Texas Oil Drilling," *American Economic Review*, 104, 1698–1734.

KILIAN, L. (2009): "Not All Oil Price Shocks Are Alike: Disentangling Demand and Supply Shocks in the Crude Oil Market," *American Economic Review*, 99, 1053–69.

KILIAN, L. AND D. P. MURPHY (2014): "The Role Of Inventories And Speculative Trading In The Global Market For Crude Oil," *Journal of Applied Econometrics*, 29, 454–478.

KILIAN, L., M. D. PLANTE, AND A. W. RICHTER (2024): "Macroeconomic Responses to Uncertainty Shocks: The Perils of Recursive Orderings," Manuscript, Federal Reserve Bank of Dallas.

KILIAN, L. AND R. J. VIGFUSSON (2011): "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?" *Quantitative Economics*, 2, 419–453.

KIM, H. (2022): "Inequality, Disaster risk, and the Great Recession," *Review of Economic Dynamics*, 45, 187–216.

KIM, I.-M. AND P. LOUNGANI (1992): "The Role of Energy in Real Business Cycle Models," *Journal of Monetary Economics*, 29, 173–189.

KLUMP, R., P. MCADAM, AND A. WILLMAN (2012): "The Normalized CES Production Function: Theory and Empirics," *Journal of Economic Surveys*, 26, 769–799.

LEDUC, S. AND Z. LIU (2016): "Uncertainty Shocks are Aggregate Demand Shocks," *Journal of Monetary Economics*, 82, 20–35.

LEDUC, S. AND K. SILL (2004): "A Quantitative Analysis of Oil-Price Shocks, Systematic Monetary Policy, and Economic Downturns," *Journal of Monetary Economics*, 51, 781–808.

LEE, K. AND S. NI (2002): "On the Dynamic Effects of Oil Price Shocks: A Study Using Industry Level Data," *Journal of Monetary Economics*, 49, 823–852.

LEE, K., S. NI, AND R. A. RATTI (1995): "Oil Shocks and the Macroeconomy: The Role of Price Variability," *The Energy Journal*, 16, 39–56.

LUDVIGSON, S. C., S. MA, AND S. NG (2021): "Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?" *American Economic Journal: Marcoeconomics*, 13, 369–410.

MORK, K. A. (1989): "Oil and Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results," *Journal of Political Economy*, 97, 740–744.

MUMTAZ, H. AND F. ZANETTI (2013): "The Impact of the Volatility of Monetary Policy Shocks," *Journal of Money, Credit and Banking*, 45, 535–558.

NEWELL, R. G. AND B. C. PREST (2019): "The Unconventional Oil Supply Boom: Aggregate Price Response from Microdata," *Energy Journal*, 40, 1–30.

OLOVSSON, C. (2019): "Oil Prices in a General Equilibrium Model with Precautionary Demand for Oil," *Review of Economic Dynamics*, 32, 1–17.

PETERMAN, W. B. (2016): "Reconciling Micro and Macro Estimates of the Frisch Labor Supply Elasticity," *Economic Inquiry*, 54, 100–120.

PINDYCK, R. S. (1991): "Irreversibility, Uncertainty, and Investment," *Journal of Economic Literature*, 29, 1110–1148.

PLANTE, M., A. W. RICHTER, AND N. A. THROCKMORTON (2018): "The Zero Lower Bound and Endogenous Uncertainty," *Economic Journal*, 128, 1730–1757.

PLANTE, M. AND N. TRAUM (2012): "Time-Varying Oil Price Volatility and Macroeconomic Aggregates," Federal Reserve Bank of Dallas Working Paper 1201.

——— (2014): "Time-Varying Oil Price Volatility and Macroeconomic Aggregates," Manuscript, HEC Montréal.

RABANAL, P., J. F. RUBIO-RAMÍ REZ, AND V. TUESTA (2011): "Cointegrated TFP Processes and International Business Cycles," *Journal of Monetary Economics*, 58, 156–171.

RAMEY, V. A. AND D. J. VINE (2010): "Oil, Automobiles, and the US Economy: How Much Have Things Really Changed?" in *NBER Macroeconomics Annual 2010*, ed. by D. Acemoglu and M. Woodford, University of Chicago Press, vol. 25, 333–368.

READY, R. C. (2018): "Oil Consumption, Economic Growth, and Oil Futures: The Impact of Long-Run Oil Supply Uncertainty on Asset Prices," *Journal of Monetary Economics*, 94, 1–26.

RICHTER, A. W., N. A. THROCKMORTON, AND T. B. WALKER (2014): "Accuracy, Speed and Robustness of Policy Function Iteration," *Computational Economics*, 44, 445–476.

ROTEMBERG, J. J. AND M. WOODFORD (1996): "Imperfect Competition and the Effects of Energy Price Increases on Economic Activity," *Journal of Money, Credit and Banking*, 28, 550–577.

SHEN, W. (2015): "News, Disaster Risk, and Time-Varying Uncertainty," *Journal of Economic Dynamics and Control*, 51, 459–479.

SWANSON, E. (2018): "Risk Aversion, Risk Premia, and the Labor Margin with Generalized Recursive Preferences," *Review of Economic Dynamics*, 28, 290–321.

TIMMER, M. P., E. DIETZENBACHER, B. LOS, R. STEHRER, AND G. J. VRIES (2015): "An Illustrated User Guide to the World Input Output Database: The Case of Global Automotive Production," *Review of International Economics*, 23, 575–605.

WACHTER, J. A. (2013): "Can Time-Varying Risk of Rare Disasters Explain Aggregate Stock Market Volatility?" *Journal of Finance*, 68, 987–1035.

ZHOU, X. (2020): "Refining the Workhorse Oil Market Model," *Journal of Applied Econometrics*, 35, 130–140.

Online Appendix: Geopolitical Oil Price Risk and Economic Fluctuations*

Lutz Kilian† Michael D. Plante‡ Alexander W. Richter§

November 6, 2024

ABSTRACT

This appendix describes the methodology for constructing a time series of oil price uncertainty, the data sources and transformations, and the solution method for the DSGE model. It plots a time series of the real price of oil, presents responses to a growth and oil production disaster, and compares the responses to a positive and negative growth disaster probability shock.

*The views expressed in this paper are our own and do not necessarily reflect the views of the Federal Reserve Bank of Dallas or the Federal Reserve System.

†Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201, and CEPR (lkilian2019@gmail.com).
‡Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201 (michael.plante@dal.frb.org).
§Federal Reserve Bank of Dallas, 2200 N Pearl Street, Dallas, TX 75201 (alex.richter@dal.frb.org).

A MEASURING UNCERTAINTY

Our method of constructing quarterly measures of uncertainty builds on Jurado et al. (2015). We first summarize the key steps of the estimation process before discussing the data used in the estimation.

A.1 METHODOLOGY Let $\mathbf{Y}_t = (y_{1,t}, \ldots, y_{N_y,t})'$ be a vector of data containing N_y variables. Our objective is to estimate the 1-quarter ahead uncertainty about select elements of $\mathbf{Y}_t$, defined as

$$\mathcal{U}_t^j \equiv \sqrt{E[(y_{j,t+1} - E[y_{j,t+1}|I_t])^2|I_t]},$$

where the expectation is taken with respect to the information set I_t and j refers to the variable of interest. There are four steps:

1. Generate forecast errors for $y_{j,t+1}$ using a forecasting model that includes lags of the variable y_j, estimated factors extracted from a panel of predictor variables, $\hat{\mathbf{F}}_t$, and a set of additional predictors contained in a vector $\mathbf{W}_t$.
2. Fit autoregressive models for the factors in $\hat{\mathbf{F}}_t$ and the variables in $\mathbf{W}_t$ and generate residuals for each variable.
3. Estimate a stochastic volatility model for each residual.
4. Calculate $\mathcal{U}_t^j$.

Factors Let $\mathbf{X}_t = (X_{1,t}, \ldots, X_{N_x,t})'$ be a vector of predictors that are available for forecasting. These data are transformed to be stationary. It is assumed that the transformed variables have an approximate factor structure,

$$X_{i,t} = \Lambda_i^{F'} \mathbf{F}_t + e_{i,t}^X,$$

where $\mathbf{F}_t$ is a $r_F \times 1$ vector of latent factors, $\Lambda_i^{F'}$ is a $1 \times r_F$ vector of loadings for variable i and the idiosyncratic errors are given by $e_{i,t}^X$. The estimated factors, denoted as $\hat{\mathbf{F}}_t$, are estimated using principal components and the number of factors is selected using the criterion of Bai and Ng (2002). Each of the factors is assumed to follow an autoregressive process with two lags,

$$F_t = \Phi^F(L) F_{t-1} + v_t^F,$$
$$v_t^F = \sigma_t^F \epsilon_t^F, \quad \epsilon_t^F \sim \mathbb{N}(0,1),$$
$$\ln(\sigma_t^F)^2 = \alpha^F + \beta^F \ln(\sigma_{t-1}^F)^2 + \tau^F \eta_t^F, \quad \eta_t^F \sim \mathbb{N}(0,1),$$

where $\Phi^F(L)$ is a lag polynomial. As with the other lag order choices made below, our results are robust to reasonable variation in the lag order.

Additional predictors The $r_W \times 1$ vector $\mathbf{W}_t$ includes the squared values of the first factor in $\hat{F}_t$ and a set of N_G factors estimated using principal components on the squared values of the variables in $\mathbf{X}_t$. Each variable in $\mathbf{W}_t$ is assumed to follow an autoregressive process with two lags,

$$W_t = \Phi^W(L)W_{t-1} + v_t^W,$$
$$v_t^W = \sigma_t^W \epsilon_t^W, \quad \epsilon_t^W \sim \mathbb{N}(0,1),$$
$$\ln(\sigma_t^W)^2 = \alpha^W + \beta^W \ln(\sigma_{t-1}^W)^2 + \tau^W \eta_t^W, \quad \eta_t^W \sim \mathbb{N}(0,1),$$

where $\Phi^W(L)$ is a lag polynomial.

Forecasting Model A forecast for $y_{j,t+1}$ is produced with the factor-augmented forecasting model,

$$y_{j,t+1} = \phi_j^Y(L)y_{j,t} + \gamma_j^F(L)\hat{\mathbf{F}}_t + \gamma_j^W(L)\mathbf{W}_t + \nu_{j,t+1}^Y,$$
$$\nu_t^y = \sigma_t^y \epsilon_t^y, \quad \epsilon_t^y \sim \mathbb{N}(0,1)$$
$$\ln(\sigma_t^y)^2 = \alpha^y + \beta^y \ln(\sigma_{t-1}^y)^2 + \tau^y \eta_t^y, \quad \eta_t^y \sim \mathbb{N}(0,1),$$

where $\phi_j^Y(L)$, $\gamma_j^F(L)$, and $\gamma_j^W(L)$ are lag polynomials of orders 2, 1, and 1, respectively. As in Jurado et al. (2015, footnote 10), a hard threshold is applied to remove any variables from the forecasting model that do not have incremental predictive power.

Uncertainty Define $\mathbf{Z}_t \equiv (\hat{\mathbf{F}}_t', \mathbf{W}_t')'$ as a vector that collects the estimated factors and the additional predictors contained in $\mathbf{W}_t$. Then let $\mathcal{Z}_t \equiv (\mathbf{Z}_t', \ldots, \mathbf{Z}_{t-q+1}')'$ and $Y_{j,t} = (y_{j,t}, \ldots, y_{j,t-q+1})'$, where $q = 2$. The FAVAR model can be written in companion form as

$$\begin{pmatrix} \mathcal{Z}_t \\ Y_{j,t} \end{pmatrix} = \begin{pmatrix} \Phi^{\mathcal{Z}} & 0 \\ \Lambda_j' & \Phi_j^Y \end{pmatrix} \begin{pmatrix} \mathcal{Z}_{t-1} \\ Y_{j,t-1} \end{pmatrix} + \begin{pmatrix} \mathcal{V}_t^{\mathcal{Z}} \\ \mathcal{V}_{j,t}^Y \end{pmatrix} \Longleftrightarrow \mathcal{Y}_{j,t} = \Phi_j^{\mathcal{Y}} \mathcal{Y}_{j,t-1} + \mathcal{V}_{j,t}^{\mathcal{Y}}.$$

The forecast error variance is

$$\Omega_{j,t}^{\mathcal{Y}}(1) \equiv E_t[(\mathcal{Y}_{j,t+1} - E_t\mathcal{Y}_{j,t+1})(\mathcal{Y}_{j,t+1} - E_t\mathcal{Y}_{j,t+1})'],$$

where $E_t\mathcal{Y}_{j,t+1} = \Phi_j^{\mathcal{Y}}\mathcal{Y}_{j,t}$. The forecast error variances can be calculated as

$$\Omega_{j,t}^{\mathcal{Y}}(1) = E_t[\mathcal{V}_{j,t+1}^{\mathcal{Y}} \mathcal{V}_{j,t+1}^{\mathcal{Y}\prime}].$$

The uncertainty of $y_{j,t+1}$ is

$$\mathcal{U}_t^j = \sqrt{1_j' \Omega_{j,t}^{\mathcal{Y}}(1) 1_j},$$

where 1 is a selection vector and j refers to the growth rate of real GDP and the growth rate of the inflation-adjusted U.S. refiners' acquisition cost of imported crude oil, respectively.

A.2 Data

Our dataset includes most of the financial and macroeconomic variables listed in the data appendix of Ludvigson et al. (2021) plus U.S. real GDP and the inflation-adjusted U.S. refiners' acquisition cost of imported crude oil.

The macroeconomic variables are from the April 2024 vintage of the FRED-MD database with the following modifications.

- We linearly interpolate the missing values of $UMCSENTx$ that occur through 1977.
- We set the missing value of $CP3Mx$ for 4/1/2020 to its value on 3/1/2020.
- We set the missing value of $COMPAPFFx$ for 4/1/2020, to its value on 3/1/2020.

Monthly data are averaged by quarter and transformed to stationarity using the code in the FRED-MD database. Both real GDP and the real price of oil are log-differenced. The data set starts in 1974Q1. The sample begins in 1974Q2, because we lose one observation due to differencing.

The financial variables are obtained from FRED-MD, CRSP and the Fama-French database. Returns are aggregated by summing the monthly values by quarter.

B Data Sources

We use the following time-series provided by Haver Analytics:

1. **Consumer Price Index for All Urban Consumers**: Not seasonally Adjusted, Monthly, Index (PCUN@USECON)
2. **World Production of Crude Oil Including Lease Condensate**
   Not Seasonally Adjusted, Thousands of Barrels per Day
   (Monthly, AWOACAUF@ENERGY; Quarterly, BWOACAUF@ENERGY)
3. **United States: Petroleum Products Expenditures**
   Annual, Millions of Dollars (ZUSPATCV@USENERGY)
4. **US Crude Oil Imported Acquisition Cost by Refiners**
   Not Seasonally Adjusted, Quarterly, Dollars per Barrel (CUSIQABF@USENERGY)
5. **Civilian Noninstitutional Population: 16 Years & Over**
   Not Seasonally Adjusted, Quarterly, Thousands (LN16N@USECON)
6. **Gross Domestic Product: Implicit Price Deflator**
   Seasonally Adjusted, Quarterly, 2012=100 (DGDP@USNA)
7. **Gross Domestic Product**
   Seasonally Adjusted, Quarterly, Billions of Dollars (GDP@USECON)
8. **Gross Domestic Product**
   Annual, Millions of Dollars (GDPY@USNA)

9. **Personal Consumption Expenditures: Nondurable Goods**
   Seasonally Adjusted, Quarterly, Billions of Dollars (CN@USECON)
10. **Personal Consumption Expenditures: Services**
    Seasonally Adjusted, Quarterly, Billions of Dollars (CS@USECON)
11. **Personal Consumption Expenditures: Durable Goods**
    Seasonally Adjusted, Quarterly, Billions of Dollars (CD@USECON)
12. **Private Fixed Investment**
    Seasonally Adjusted, Quarterly, Billions of Dollars (F@USECON)
13. **Total Economy: Labor share**
    Seasonally Adjusted, Quarterly, Percent (LXEBL@USNA)
14. **Net Stock: Private Fixed Assets**, Annual, Billions of Dollars (EPT@CAPSTOCK)
15. **Net Stock: Durable Goods**, Annual, Billions of Dollars (EDT@CAPSTOCK)
16. **Depreciation: Private Fixed Assets**, Annual, Billions of Dollars (KPT@CAPSTOCK)
17. **Depreciation: Durable Goods**, Annual, Billions of Dollars (KDT@CAPSTOCK)
18. **CBOE Crude Oil Volatility Index (OVX)**, Daily, Index (SPOVX@DAILY)

We also use the following data sources:

1. **FRED-MD**, Monthly Databases for Macroeconomic Research. The data is available at https://research.stlouisfed.org/econ/mccracken/fred-databases (McCracken, 2024). Under Monthly Data, we use the April 2024 vintage.
2. **Fama-French**, Database. The data is available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
   (Fama and French, 2024).
3. **WRDS**, Stock Market Indexes. The data is available at https://wrds-www.wharton.upenn.edu (Wharton Research Data Services, 2024).
4. **Geopolitical Risk Index**, Historical series (GPRH). The data is available at https://www.matteoiacoviello.com/gpr.htm (Caldara and Iacoviello, 2024).
5. **Global Oil Inventories** Monthly, Millions of Barrels per Day (Inv_t) from Kilian (2022).

We apply the following data transformations:

1. **Per Capita Real Output**: $Y_t = 10^9 \times GDP_t/((DGDP_t/100)(1000 \times LN16N_t))$.
2. **Per Capita Real Consumption**: $C_t = 10^9(CN_t+CS_t)/((DGDP_t/100)(1000\times LN16N_t))$.
3. **Per Capita Real Investment**: $I_t = 10^9(F_t + CD_t)/((DGDP_t/100)(1000 \times LN16N_t))$.

4. **Depreciation Rate**: $\delta = (1 + \frac{1}{T/4}\sum_{t=1}^{T/4}(KPT_t + KDT_t)/(EPT_{t-1} + EDT_{t-1}))^{1/4} - 1$.
5. **Capital Services Share**: $\xi = 1 - \frac{1}{T}\sum_{t=1}^{T} LXEBL/100$.
6. **Real Price of Oil**: $p_t^o = CUSIQABF_t/(DGDP_t/100)$.
7. **Expenditure Share of Oil**: $ZUSPATCV_t/GDPY_t$.
8. **Oil Consumption**: $o_t =$ Days per Month $\times\, AWOACAUF_t/1000 - (INV_t - INV_{t-1})$.
9. **Inventory-Oil Consumption Share**: $INV_t/\sum_{j=t-2}^{t} o_t$ for $t = 3, 6, \ldots, 3T$.
10. **CPI Inflation Rate**: $\pi_t^{cpi} = 100 \times (PCUN_t/PCUN_{t-1} - 1)$.
11. **Asset Returns**: We use two time series from the Fama-French data library:

    - Net nominal risk-free rate, monthly, percent (RF)
    - Net nominal excess market return, monthly, percent ($MKTmRF$)

    Define the market return as

    $$RM_t \equiv MKTmRF_t + RF_t.$$

    The gross quarterly analogues of the Fama-French series and CPI inflation are given by

    $$RF_t^Q \equiv \prod_{j=t-2}^{t}(1 + RF_j/100),\ RM_t^Q \equiv \prod_{j=t-2}^{t}(1 + RM_j/100),\ \pi_t^Q \equiv \prod_{j=t-2}^{t}(1 + \pi_j^{cpi}/100)$$

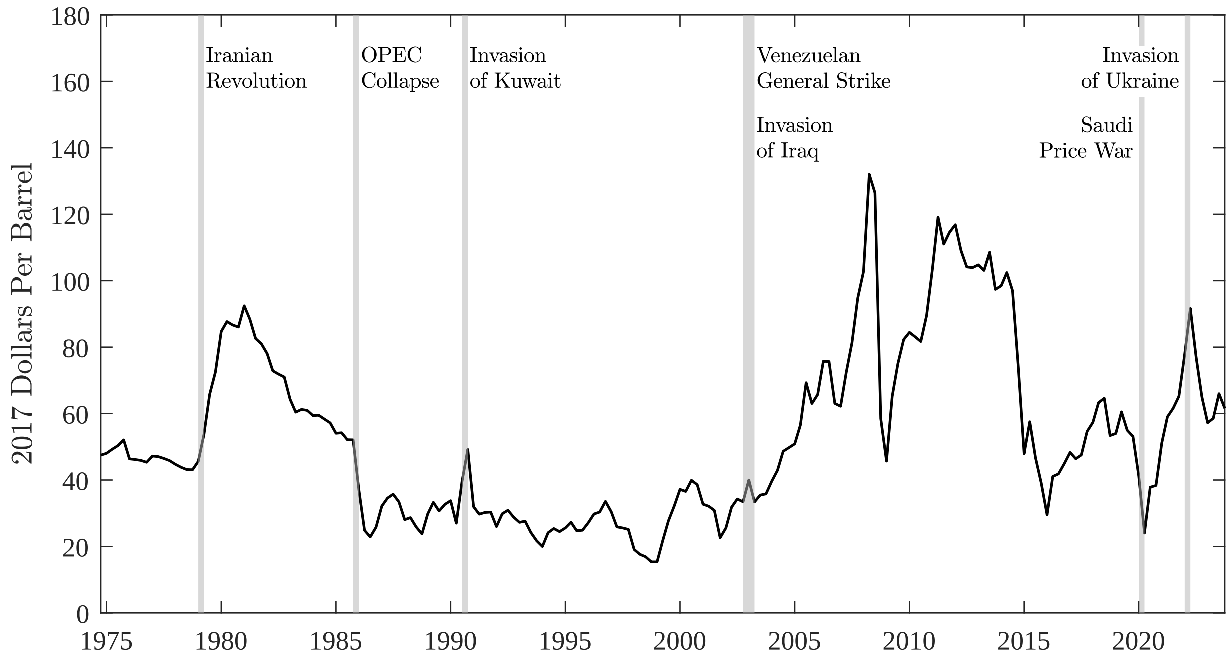
    for $t = 3, 6, \ldots, 3T$, so the quarterly real risk-free rate and equity premium are

    $$r_t = 100 \times (RF_t^Q/\pi_t^Q - 1),\ r_t^{ex} = 100 \times (RM_t^Q/\pi_t^Q - 1) - r_t.$$

All empirical targets are computed using quarterly data, except the expenditure share of oil which is based on annual data.

C Oil Market Data

Figure 1: Real U.S. refiners' acquisition cost crude oil imports, 1974Q4-2023Q4



D Solution Method

The equilibrium system of the DSGE model is summarized by $E[g(\mathbf{x}_{t+1}, \mathbf{x}_t, \varepsilon_{t+1})|\mathbf{z}_t, \vartheta] = 0$, where g is a vector-valued function, $\mathbf{x}_t$ is the vector of model variables, ε_t is the vector of shocks, $\mathbf{z}_t = [k_t, s_t, v_t^g, v_t^e, \ln p_t^g, \ln p_t^e, \epsilon_t]$ is the vector of states, and ϑ is the vector of parameters.

We discretize the continuous shocks, $\{\varepsilon_g, \varepsilon_{go}, \varepsilon_p^g, \varepsilon_p^e\}$ using the Markov chain in Rouwenhorst (1995). The bounds of the six continuous state variables are chosen so there is minimal extrapolation over 99% of the ergodic distribution. Specifically, the bounds on capital, k_t, range from -15% to $+10\%$, the bounds on storage, s_t, range from -50% to $+50\%$, and the bounds on the error correction term, ϵ_t, range from -30% to $+15\%$ of the deterministic steady state. The bounds on the probability of a growth disaster, p_t^g, are set to $[0.00005, 0.8]$, while the bounds on the probability of an oil production disaster, p_t^e, are set to $[0.0000025, 0.8]$. Both are converted to logs, consistent with the specifications of the processes. We discretize k_t, s_t, and ϵ_t each into 7 points, and $\ln p_t^g$ and $\ln p_t^g$ into 15 points given the nonlinearity in the transmission of the probability shocks. All of the grids for the continuous states are evenly spaced. There are also binary indicators for whether the economy is in a growth disaster or an oil production disaster, creating 4 outcomes. The product of the points in each dimension, D, is the total number of nodes in the state space ($D = 308{,}700$).

The realization of $\mathbf{z}_t$ on node d is denoted $\mathbf{z}_t(d)$. The Rouwenhorst method provides integration nodes for the continuous shocks, $[\varepsilon_{g,t+1}(m), \varepsilon_{go,t+1}(m), \varepsilon^g_{p,t+1}(m), \varepsilon^e_{p,t+1}(m)]$. The transition matrices for the discrete states determine the integration weights for their future realizations, $[v^g_{t+1}(m), v^e_{t+1}(m)]$. The weight for a particular realization of the continuous and discrete shocks is $\phi(m)$, where $m \in \{1, \ldots, M\}$ and M is the product of the number of realizations of each shock. The two disaster probability shocks, ε^g_p and ε^e_p, have the same number of realizations as the corresponding state variable (15). Each growth shock, ε_g and ε_{go}, has 7 possible realizations. Each discrete state has two possible outcomes. Thus, $M = 44{,}100$ possible shock realizations.

The vector of policy functions and the realization on node d are denoted by $\mathbf{pf}_t$ and $\mathbf{pf}_t(d)$, where $\mathbf{pf}_t \equiv [n(\mathbf{z}_t), o(\mathbf{z}_t), J(\mathbf{z}_t), p^e(\mathbf{z}_t), r(\mathbf{z}_t)]$. The following steps outline our algorithm:

1. Use the Sims (2002) `gensys` algorithm to solve the log-linear model without any disasters or time-varying probabilities. Then map the solution for the policy functions to the discretized state space, copying the solution on the dimensions that were excluded from the linear model. This provides an initial conjecture, $\mathbf{pf}_0$, for the nonlinear algorithm.
2. On iteration $j \in \{1, 2, \ldots\}$ and each node $d \in \{1, \ldots, D\}$, use Chris Sims' `csolve` to find the $\mathbf{pf}_t(d)$ that satisfies $E[g(\cdot)|\mathbf{z}_t(d), \vartheta] \approx 0$. Guess $\mathbf{pf}_t(d) = \mathbf{pf}_{j-1}(d)$. Then
   (a) Solve for all variables dated at time t, given $\mathbf{pf}_t(d)$ and $\mathbf{z}_t(d)$.
   (b) Linearly interpolate the policy functions, $\mathbf{pf}_{j-1}$, at the updated state variables, $\mathbf{z}_{t+1}(m)$, to obtain $\mathbf{pf}_{t+1}(m)$ on every integration node, $m \in \{1, \ldots, M\}$.
   (c) Given $\{\mathbf{pf}_{t+1}(m)\}_{m=1}^M$, solve for the other elements of $\mathbf{s}_{t+1}(m)$ and compute
   $$E[g(\mathbf{x}_{t+1}, \mathbf{x}_t(d), \varepsilon_{t+1})|\mathbf{z}_t(d), \vartheta] \approx \textstyle\sum_{m=1}^M \phi(m) g(\mathbf{x}_{t+1}(m), \mathbf{x}_t(d), \varepsilon_{t+1}(m)).$$
   When `csolve` has converged, set $\mathbf{pf}_j(d) = \mathbf{pf}_t(d)$.
3. Repeat step 2 until $\text{maxdist}_j < 10^{-4}$, where $\text{maxdist}_j \equiv \max\{|(\mathbf{pf}_j - \mathbf{pf}_{j-1})/\mathbf{pf}_{j-1}|\}$. When that criterion is satisfied, the algorithm has converged to an approximate solution.

E DETRENDED EQUILIBRIUM

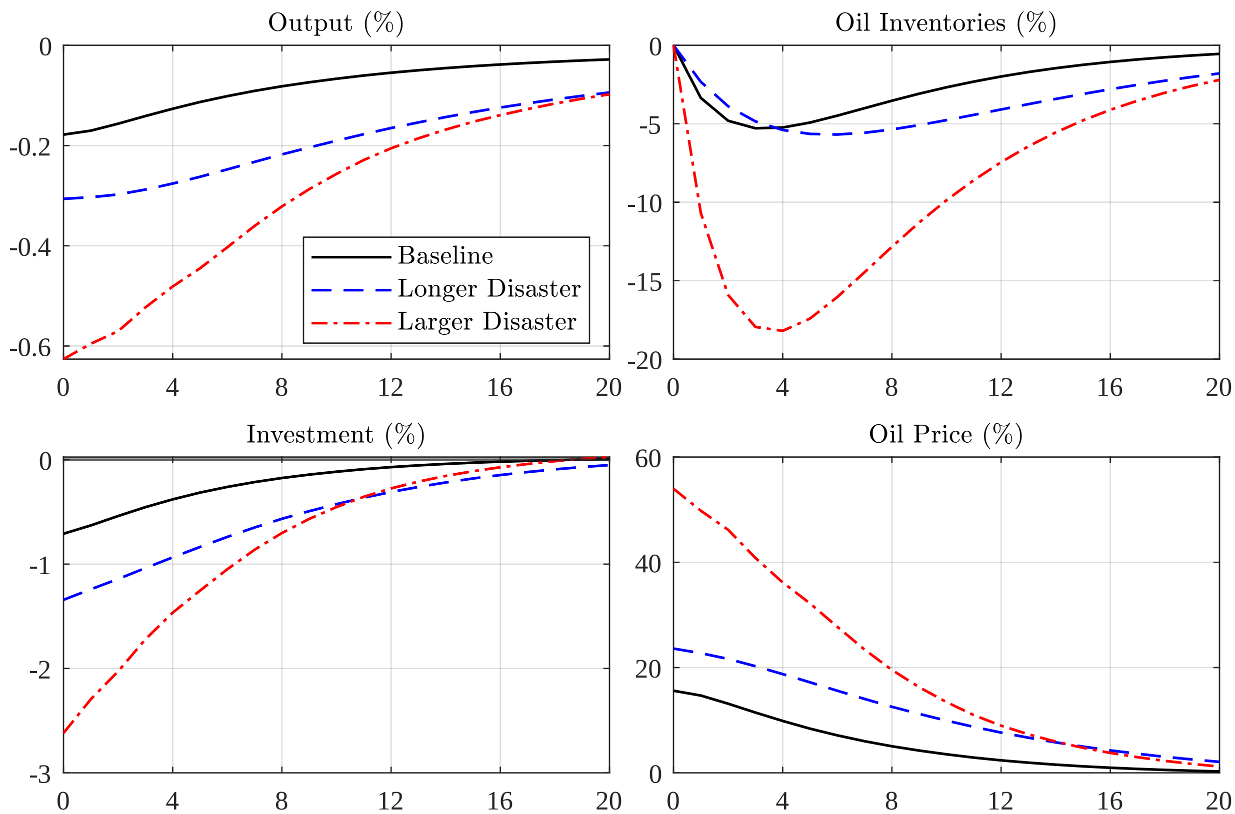
We detrend the model by defining $\tilde{x}_t = x_t/a_t$. The equilibrium system of equations is given by

$$\tilde{w}_t = (1-\xi)\tilde{y}_t/n_t$$
$$p_t^o = \xi\alpha\frac{(\tilde{o}_t/o_0)^{1-1/\sigma}}{(1-\alpha)(\tilde{k}_t/k_0)^{1-1/\sigma}+\alpha(\tilde{o}_t/o_0)^{1-1/\sigma}}\frac{\tilde{y}_t}{\tilde{o}_t}$$
$$E_t[x_{t+1}r_{t+1}^i] = 1$$
$$r_t^i = e^{-\zeta v_t}\frac{1}{p_{t-1}^k}(r_t^k + (1-\delta+a_1+\tfrac{a_2}{\nu-1}(\tilde{\imath}_t/\tilde{k}_t)^{1-1/\nu})p_t^k)$$
$$p_t^k = \tfrac{1}{a_2}(\tilde{\imath}_t/\tilde{k}_t)^{1/\nu}$$
$$r_t^k = \xi(1-\alpha)\frac{(\tilde{k}_t/k_0)^{1-1/\sigma}}{(1-\alpha)(\tilde{k}_t/k_0)^{1-1/\sigma}+\alpha(\tilde{o}_t/o_0)^{1-1/\sigma}}\frac{\tilde{y}_t}{\tilde{k}_t}$$
$$E_t[x_{t+1}r_{t+1}^s] = 1$$
$$r_t^s = \frac{1}{p_{t-1}^o}(1-\omega+\pi\tilde{s}_t^{-3})p_t^o$$
$$\chi\tilde{w}_t\ell_t = (1-\chi)\tilde{c}_t$$
$$x_t = (\beta/g_t^\gamma)(\tilde{u}_t/\tilde{u}_{t-1})^{1-1/\psi}(\tilde{c}_{t-1}/\tilde{c}_t)(\tilde{J}_t/\tilde{z}_{t-1})^{1/\psi-\gamma}$$
$$\tilde{u}_t = \tilde{c}_t^\chi\ell_t^{1-\chi}$$
$$\tilde{z}_t = (E_t[(g_{t+1}J_{t+1})^{1-\gamma}])^{1/(1-\gamma)}$$
$$\tilde{J}_t = \left((1-\beta)\tilde{u}_t^{1-1/\psi}+\beta\tilde{z}_t^{1-1/\psi}\right)^{\frac{1}{1-1/\psi}}$$
$$\tilde{y}_t = y_0 n_t^{1-\xi}\left((1-\alpha)(\tilde{k}_t/k_0)^{1-1/\sigma}+\alpha(\tilde{o}_t/o_0)^{1-1/\sigma}\right)^{\xi/(1-1/\sigma)}$$
$$g_{t+1}\tilde{k}_{t+1} = e^{-\zeta_g v_{t+1}^g}(1-\delta+a_1+\tfrac{a_2}{1-1/\nu}(\tilde{\imath}_t/\tilde{k}_t)^{1-1/\nu})\tilde{k}_t$$
$$g_{t+1}\tilde{s}_{t+1} = (1-\omega)\tilde{s}_t + \tilde{o}_t^s - \tilde{o}_t - \tfrac{\pi}{2}\tilde{s}_t^{-2}$$
$$\tilde{o}_t^s = e_t/\epsilon_t$$
$$\tilde{c}_t + \tilde{\imath}_t = \tilde{y}_t$$
$$n_t + \ell_t = 1$$
$$\ln g_{o,t} = \ln\kappa_0 + \kappa_1\ln g_t + \kappa_2\ln\epsilon_{t-1} + \sigma_{go}\varepsilon_{go,t}$$
$$\ln\epsilon_t = \ln g_t - \ln g_{o,t} + \ln\epsilon_{t-1}$$
$$\ln g_t = \ln\bar{g} + \sigma_g\varepsilon_{g,t} - \zeta_g(v_t^g - \bar{\pi}_1^g)$$
$$\ln e_t = \ln\bar{e} - \zeta_e(v_t^e - \bar{\pi}_1^e)$$
$$Pr(v_{t+1}^g = 1|v_t^g = 1) = \bar{q}^g, \quad Pr(v_{t+1}^g = 1|v_t^g = 0) = p_t^g$$
$$Pr(v_{t+1}^e = 1|v_t^e = 1) = \bar{q}^e, \quad Pr(v_{t+1}^g = 1|v_t^g = 0) = p_t^e$$
$$\ln p_t^g = (1-\rho_p^g)\ln\bar{p}^g + \rho_p^g\ln p_{t-1}^g + \sigma_p^g\varepsilon_{p,t}^g$$
$$\ln p_t^e = (1-\rho_p^e)\ln\bar{p}^e + \rho_p^e\ln p_{t-1}^e + \sigma_p^e\varepsilon_{p,t}^e$$
$$E_t[x_{t+1}r_t] = 1$$
$$1 = E_t[x_{t+1}r_{t+1}^e]$$
$$r_t^e = g_t(\tilde{p}_t^e + \tilde{d}_t^e)/\tilde{p}_{t-1}^e$$
$$\tilde{d}_t^e = \xi\tilde{y}_t - \tilde{\imath}_t - \vartheta_f(E_{t-1}\tilde{k}_t - \tfrac{1}{r_t}E_t[g_{t+1}\tilde{k}_{t+1}]) - \vartheta_s(E_{t-1}\tilde{s}_t - \tfrac{1}{r_t}E_t[g_{t+1}\tilde{s}_{t+1}])$$

F ADDITIONAL RESULTS

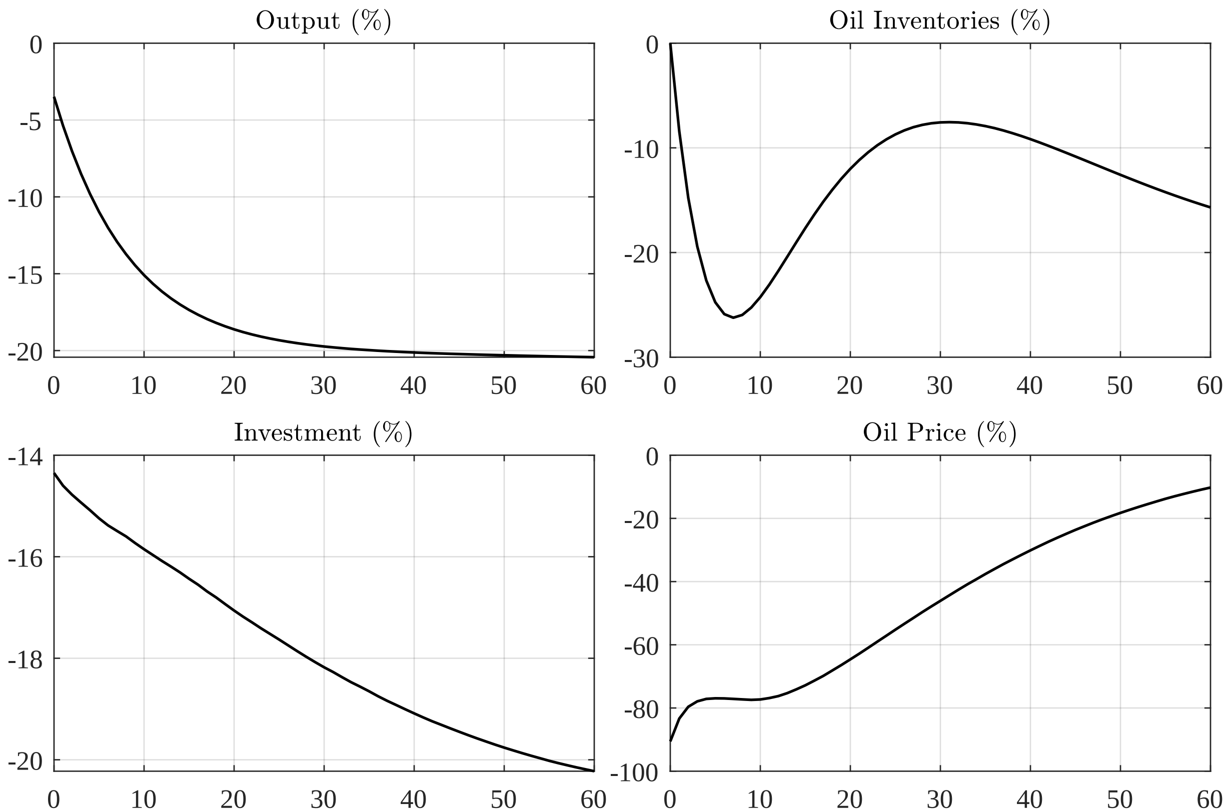
Figures 2 and 3 show how the economy responds to an oil production and growth disaster realization, respectively. The disaster occurs in the initial period and then follows its expected path. Figure 4 shows the responses to a ±5pp growth disaster probability shock. The simulations are initialized at a 15% growth disaster probability to permit a positive and negative shock.

Figure 2: Responses to an oil production disaster realization



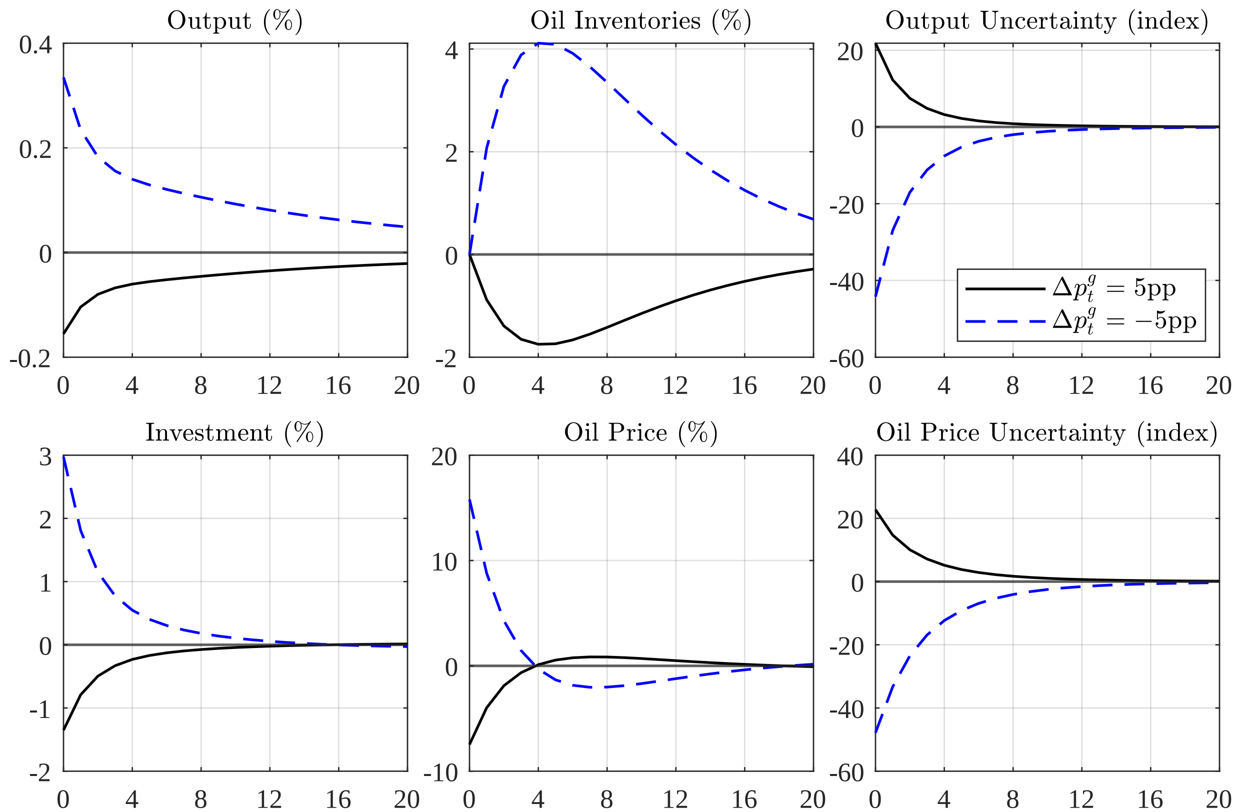
Notes: Responses in deviations from the baseline.

Figure 3: Responses to a growth disaster realization



Notes: Responses in deviations from the baseline.

Figure 4: Responses to positive and negative growth disaster probability shocks



Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized.

REFERENCES

BAI, J. AND S. NG (2002): “Determining the Number of Factors in Approximate Factor Models,” *Econometrica*, 70, 191–221.

CALDARA, D. AND M. IACOVIELLO (2024): “Historical Geopolitical Risk Index [dataset],” Accessed May 20, 2024.

FAMA, E. F. AND K. R. FRENCH (2024): “Data Library [dataset],” Accessed May 7, 2024.

JURADO, K., S. C. LUDVIGSON, AND S. NG (2015): “Measuring Uncertainty,” *American Economic Review*, 105, 1177–1216.

KILIAN, L. (2022): “Facts and Fiction in Oil Market Modeling,” *Energy Economics*, 110.

LUDVIGSON, S. C., S. MA, AND S. NG (2021): “Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?” *American Economic Journal: Marcoeconomics*, 13, 369–410.

MCCRACKEN, M. W. (2024): “Monthly and Quarterly Databases for Macroeconomic Research [dataset],” Accessed May 7, 2024.

ROUWENHORST, K. G. (1995): “Asset Pricing Implications of Equilibrium Business Cycle Models,” in *Frontiers of Business Cycle Research*, ed. by T. F. Cooley, Princeton, NJ: Princeton University Press, 294–330.

SIMS, C. A. (2002): “Solving Linear Rational Expectations Models,” *Computational Economics*, 20, 1–20.

WHARTON RESEARCH DATA SERVICES (2024): “Stock Market Indexes [dataset],” Accessed May 7, 2024.