Geopolitical Oil Price Risk and Economic Fluctuations*

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ABSTRACT

Market participants and policymakers are concerned about major oil production shortfalls driven by geopolitical events. Even when such events never materialize, unanticipated increases in the probability of a production shortfall may generate a surge in the price of oil and oil price uncertainty. We provide the first systematic account of the quantitative importance of time-varying geopolitical risk to oil production for the global economy. We show that a 20 percentage point increase in the probability of a 5% shortfall in oil production causes a 0.12% reduction in global output. When considering a 20% shortfall, the drop in output quadruples.

Keywords: Geopolitical risk, macroeconomic risk, time-varying uncertainty, rare disasters, oil, endogeneity, probability shocks, economic fluctuations, precautionary savings, inventories
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1 INTRODUCTION

Time-varying 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, in recent years many market analysts have listed risks to oil supplies as one of the top geopolitical risks, reflecting concerns about OPEC quota decisions, global access to Russian oil, and a potential widening of the conflict between Israel and Iran, among others.

These concerns were reinforced by the Twelve-Day War between Iran and Israel in June 2025. As the probability of a severe disruption of maritime traffic through the Strait of Hormuz briefly surged to 60% in mid-June, the Brent price of oil peaked at $80 per barrel and oil price uncertainty, as measured by implied volatility, surged.[1] Even though the Strait of Hormuz never closed, the oil market reacted strongly to this shift in the probability of a major geopolitically driven shortfall of oil supplies. The market reaction reflected the fact that a closure of the Strait would have put close to 20% of global oil production at risk. Goldman Sachs warned that such an event would push the price of oil to $110 per barrel and reduce global growth by 0.3 percentage points.[2] Other investment banks and the IMF reached a similar conclusion.

Despite the obvious interest among policymakers and market participants in the effects of fluctuations in the probability of a major geopolitically driven oil supply disruption on the global economy, this question has not been addressed in the academic literature to date.[3] Existing work

[1] The probability is from Polymarket (https://polymarket.com/event/will-iran-close-the-strait-of-hormuz-in-2025).

[2] See Goldman Sachs "Assessing the Economic Impacts of the War in the Middle East," June 23, 2025.

[3] The work most closely related to ours is Olovsson (2019). While Olovsson's model also allows for stochastic oil production disasters, his model is annual and only allows for a two-point *iid* distribution over the disaster probability. Thus, the model is not designed to understand the implications of continuously evolving disaster probabilities, as observed in the data. Additionally, his main focus is on understanding the general equilibrium implications of oil storage without addressing the endogeneity of oil price and macroeconomic uncertainty.

on the role of oil price uncertainty makes simplifying assumptions that prevent one from analyzing events such as the surge in geopolitical oil production risk in 2025. For example, studies employing stochastic volatility shocks to the price of oil assume that oil price uncertainty is exogenous and that the risk in the model is two-sided. This first assumption is implausible, as our paper illustrates, and the second assumption prevents one from thinking about time-varying geopolitical oil production risk.

We develop a model of the global economy in which geopolitical risk in the oil market arises from the possibility of rare oil production disasters driven by geopolitical events. Our model includes risk averse agents, an oil production sector, oil storage, and limited substitutability between oil and capital. The price of oil is determined endogenously.[4] Oil production disasters are of stochastic length and occur with a time-varying probability. The baseline size and duration of these disasters—a 5% drop in global oil production that lasts 3 quarters on average—is set to match the behavior of global oil production during major geopolitical events in the oil market over the past 50 years, such as the Arab-Israeli War in 1973, the Iranian Revolution in 1979, and the invasion of Kuwait in 1990. We also explore the possibility that agents might be concerned about larger oil production disasters than observed historically. The model allows us to assess the effects of an increase in the probability of a major geopolitical oil supply disruption, addressing a key question often faced by policymakers and market participants.

Our analysis recognizes that, while downside geopolitical risk to oil production 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 also cause surges in oil price uncertainty. Thus, the model allows for the endogenous determination of both macroeconomic and oil price uncertainty, in contrast with previous work. Following Gourio (2012), macroeconomic disasters are modeled as sharp declines in economic growth and may be viewed as the result of an economic crisis such as the Great Depression or the Financial Crisis of 2008.

[4]Since the model is global, we abstract from oil imports and exports and international capital flows. 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. This reflects data limitations and the need to keep our highly nonlinear model computationally tractable.

We show that shocks to the probability of an oil production disaster cause a simultaneous surge in oil price uncertainty and in the price of oil, much like what occurred in June 2025 during the Iran-Israel War. These shocks cause oil inventories to be accumulated before the disaster is realized, as storage demand increases. In addition, they lower aggregate investment and aggregate output. How large these macroeconomic effects are depends on the magnitude of the probability shock as well as the magnitude of the potential oil production disaster. We show that a 20 percentage point increase in the probability of a 5% shortfall in global oil production causes a 0.12% reduction in output. When considering a 20% shortfall, which roughly corresponds to the cessation of oil supplies from the Persian Gulf, the drop in output quadruples.

Our model also allows us to consider how the oil market responds to macroeconomic disaster risk. We show that the responses of output uncertainty and oil price uncertainty to a shock to the probability of a macroeconomic disaster are an order of magnitude larger than the responses to a shock to the probability of an oil production disaster of the same magnitude. More than half of the observed oil price uncertainty tends to be driven by the macroeconomy, which helps explain why higher oil price uncertainty has historically been associated with lower real activity. This result highlights that this association should not be interpreted as a causal link.

Modeling downside risk is crucial. While increases in oil price uncertainty may alternatively be explained by stochastic volatility shocks to oil production growth, these shocks have little effect on the economy because they do not generate risk tilted to the downside. Likewise, the ability to store oil plays a central role. Without storage, the responses of the price of oil and real activity to higher oil production risk tend to be muted, suggesting that models without storage will fail to capture the full effects of shifts in oil production risk. Oil storage also matters for the responses to macroeconomic disaster probability shocks, underscoring the importance of jointly modeling oil production disasters and macroeconomic disasters.

Our analysis not only helps gauge the effects of geopolitical oil price risk, but it also has important implications for empirical work on the effects of oil price uncertainty shocks. We show that level and uncertainty shocks are not the same, as implicitly assumed in VAR-GARCH models, and

that 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. Only if oil price uncertainty evolves independently of other shocks in the economy is there a direct causal link from oil price uncertainty shocks to macro 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.

Related Literature Our work relates to several strands of the literature. First, it complements a 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; Jurado et al., 2015; Leduc and Liu, 2016; Ludvigson et al., 2021) by uncovering the underlying sources of time-varying uncertainty, building on Gourio (2012). This allows us to study the interaction between macroeconomic and oil price uncertainty and to make more precise statements about the role of geopolitical oil production risk in the global economy.

Second, our analysis contributes to the literature that uses micro-founded models to examine the relationship between oil price uncertainty and the economy. Notable contributions include Başkaya et al. (2013), Gao et al. (2022), and Olovsson (2019). These studies rely on simplifications such as stochastic volatility shocks or *iid* distributed disaster risk, and all of them abstract from macroeconomic risk.[5] In contrast, we examine this question within a general equilibrium model with endogenous oil price and macroeconomic uncertainty. Our analysis accounts for the fact that geopolitical oil price risk is time-varying and inherently one-sided. This allows us to quantify the effects of shocks to the probability of an oil production disaster driven by geopolitical events.

Third, our analysis is relevant for a large empirical literature making the case that oil price uncertainty shocks are recessionary (e.g., Bernanke, 1983; Drakos and Konstantinou, 2013; El-

[5]Our model also differs from the general equilibrium model in Ready (2018) who 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, rather than addressing how the economy responds to shifts in the likelihood of a major temporary drop in oil production driven by geopolitical events.

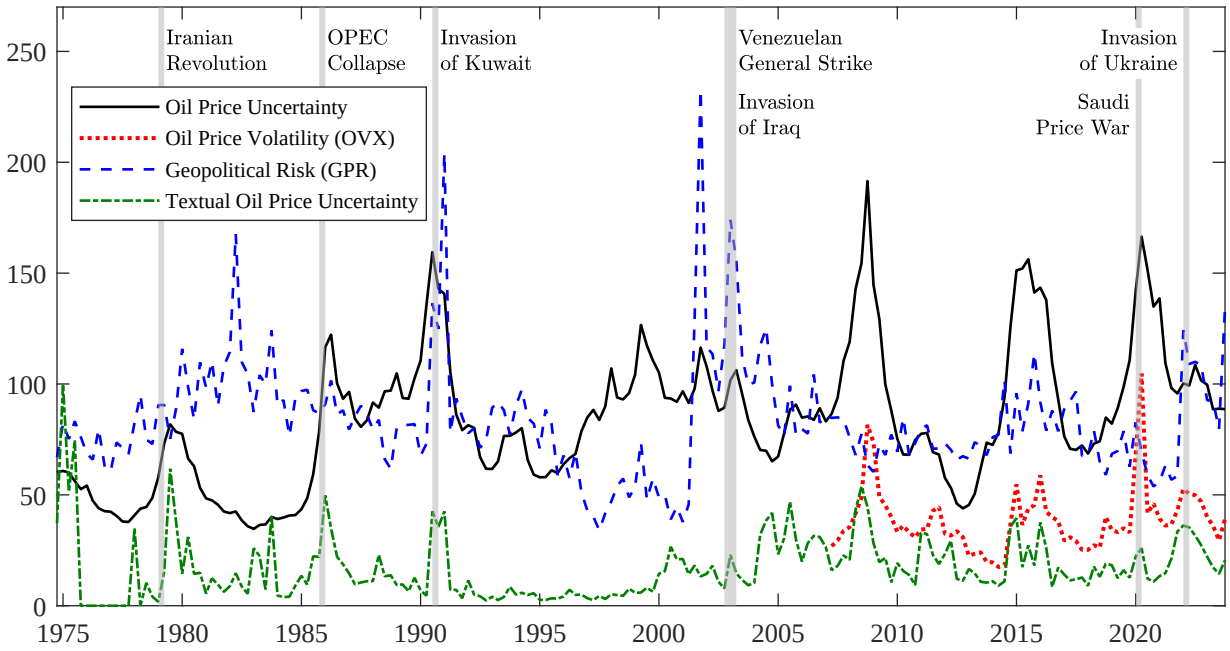
der and Serletis, 2010; Ferderer, 1996; Gao et al., 2022; Guo and Kliesen, 2005; Jo, 2014) and affect oil production and storage (e.g., Cross et al., 2022; Kellogg, 2014). We find that oil price uncertainty responds to macroeconomic level and uncertainty shocks. This fact complicates the identification of oil price uncertainty shocks and has important implications for empirical work seeking to establish the macroeconomic effects of shocks to oil price uncertainty.

Outline The remainder of the paper is organized as follows. In Section 2, 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. Section 3 reviews why oil price uncertainty matters for the economy. Section 4 introduces a calibrated model of the global economy that elucidates the determination of oil price uncertainty and macroeconomic uncertainty. In Section 5, we study the effects of shocks to the probability of oil production and macroeconomic disasters on the economy and their ability to explain economic fluctuations. Our analysis 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 model. Section 6 discusses implications of our analysis for empirical work on the effects of oil price uncertainty shocks. The concluding remarks are in Section 7.

2 MEASURING OIL PRICE UNCERTAINTY

There has been growing interest in the impact of shifts in geopolitical risk in the oil market 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 spike in uncertainty in March 2022 driven by concerns that Russia might refuse to sell oil to Europe after the invasion of Ukraine. Other recent sources of oil price uncertainty have included concerns 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.

Figure 1: Empirical measures of oil price uncertainty, 1974Q4-2023Q4



Notes: 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 geopolitical risk (GPR) series in Caldara and Iacoviello (2022).

The focus of our paper is to develop a deeper 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 can raise oil price uncertainty, not all surges in oil price uncertainty are driven by geopolitical events.

Figure 1 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. 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.[6] As is standard, the real price of oil is defined as the U.S. refiners' acquisition cost for oil imports deflated by the implicit GDP deflator (see Appendix E). 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.[7] 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, 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.

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

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

[7]Our analysis 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 domestic price effectively 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 U.S. price is not a good proxy for the global price of oil after 1974. These problems are compounded in the pre-1974 era. The nominal price of oil prior to 1974 was stable for extended periods except for discrete jumps, reflecting the regulation of the U.S. oil market. As stressed in Hamilton (1985, p. 99), the striking stability of the nominal price of crude oil between the 1950s and the early 1970s "can be attributed to state regulatory commissions' policy of defending posted prices." 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).

geopolitical uncertainty coincided with increased 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.[8] Figure 1 also shows that our data-based index of oil price uncertainty and the OVX index differ systematically from the text-based oil price uncertainty index proposed in Abiad and Qureshi (2023) based on the methodology in Baker et al. (2016). The correlation of the text-based oil price uncertainty index with the OVX index, when that index is available, is only 0.56. This suggests that text-based measures fail to capture changes in oil price uncertainty as perceived by financial markets. Moreover, the correlation with our index is only 0.32 when extending the sample back to 1975. This is not surprising because nothing in the construction of the text-based index ensures that it captures changes in the degree of uncertainty over time, as opposed to merely changes in press coverage. Finally, 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 direction of the changes in these indices often differs, and the correlation between the indices is close to zero.

3 WHY 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 (e.g., Barsky and Kilian, 2002). This explanation is consistent with micro-founded models of the

[8] 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.

transmission of oil price shocks that predict that rising oil prices 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).[9]

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 favored this interpretation. A leading explanation of the nonlinearity required to explain the large effect of positive oil price shocks and the negligible effect of negative oil price shocks, is that a 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.[10]

The literature has emphasized three mechanisms that explain why fluctuations in oil price uncertainty matter for the real economy. In this paper, we propose a theoretical model that incorporates these insights. The key feature of this model is that increases in both the price of oil and oil price uncertainty arise endogenously in response to increased geopolitical oil production risk.

3.1 REAL OPTIONS THEORY

Theories of investment under uncertainty and real options predict that rising uncertainty about, for example, the price of oil will depress current investment. Theoretical foundations for such real options in firm-level investment decisions have been developed by

[9]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.

[10]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).

Bernanke (1983), among others, in a partial equilibrium setting.[11] For example, 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 output declines. Uncertainty for this purpose may be measured by the expected conditional volatility of the real price of oil over the relevant investment horizon. The same reasoning applies to purchases of energy-intensive consumer durables such as cars (see Edelstein and Kilian, 2009).

There are several caveats to the application of real options theory to the price of oil. First, the quantitative importance of the cash flow channel depends on how important the 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, this framework implicitly takes the price of oil as exogenously given. This simplifying assumption does not hold in practice, complicating the analysis. The concern is that we may

[11] Bernanke (1983) is concerned with the unanticipated formation of an energy exporter cartel such as OPEC as his leading example. It has been understood in the literature that the same framework can be applied to other exogenous events including a shock to geopolitically driven oil price uncertainty (e.g., Elder and Serletis, 2010). While Bernanke's analysis is presented in a central planning context, he stresses that there is no difficulty in replicating his results in a competitive decentralized decision-making environment. For related discussion of the effects of uncertainty shocks more generally see Pindyck (1991) and Bloom (2014).

attribute to oil price uncertainty the effects of macroeconomic uncertainty, which is more likely to affect the cash flow from the investment. Finally, as discussed in Section 4.4, it is 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 second 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. 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. General equilibrium models incorporating oil storage have been presented in Olovsson (2019) and Gao et al. (2022).

4 A MODEL OF GEOPOLITICAL RISK

In this section, we introduce a model of the global economy designed to elucidate the determinants of oil price uncertainty and to examine the implications of geopolitical oil production risk.

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 good. The distinguishing feature of the model is that it includes downside risk to both oil production and the macroeconomy. 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 Depression or the Great 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.[12] Time-variation in the probability of oil production and macroeconomic disasters induces exogenous variation in oil price and macroeconomic uncertainty. 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 faced by agents is not two-sided. Rather it involves a sharp reduction in oil production. Rare oil production 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.

Productivity and Macroeconomic Disasters Productivity growth $g_t = a_t/a_{t-1}$ 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 macroeconomic disaster occurs and 0 otherwise. The transition matrix for v_t^g is summarized by

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

[12] 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. (2025).

where the probability of a macroeconomic disaster follows

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

which ensures that p_t^g is bounded between 0 and 1. The size of the disaster is ζ_g, and $\bar{\pi}_1^g$ is the unconditional probability of the disaster, which is evaluated by simulation. Details about how the ergodic probability is computed can be found in Appendix C.

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 its investment (i_t), capital (k_{t+1}), labor (n_t), and oil (o_t) inputs. Following the seminal work of 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.[13]

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

$$r_{t+1}^i \equiv e^{-\zeta_g v_{g,t+1}}(r_{t+1}^k + (1-\delta+\mu_1+\tfrac{\mu_2}{\nu-1}(i_{t+1}/k_{t+1})^{1-1/\nu})p_{t+1}^k)/p_t^k,$$

$$r_t^k \equiv \xi(1-\alpha)\frac{(k_t/k_0)^{1-1/\sigma}}{(1-\alpha)(k_t/k_0)^{1-1/\sigma}+\alpha(o_t/o_0)^{1-1/\sigma}} \frac{y_t}{k_t},$$

$$p_t^k \equiv \tfrac{1}{1-\phi'(i_t/k_t)} = \tfrac{1}{\mu_2}(\tfrac{i_t}{k_t})^{1/\nu}.$$

Oil Production and Oil Production Disasters The production of oil is given by $o_t^s = a_t^o e_t$. 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. We also allow a_t^o to depend on the state of the economy since productivity in oil production is assumed to be cointegrated with productivity in the rest of the economy. This allows oil production to respond to changes in oil demand. 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.

[13] A more detailed discussion of normalized CES production functions can be found in Klump et al. (2012). Some more recent studies, such as Başkaya et al. (2013), Hassler et al. (2021), Olovsson (2019), and Ready (2018), favor a specification of the production function that treats oil as complementary to a capital-labor bundle. Our substantive conclusions are robust to this alternative functional form, as shown in Appendix F.

The permanent component of oil production is given by

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

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.[14]

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 ζ_e, and $\bar{\pi}_1^e$ is the unconditional probability of the disaster, which is evaluated by simulation in the same way as the ergodic probability for the macroeconomic 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

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

[14] 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 is rare in general equilibrium models with oil. 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).

where ω is the cost of storage. Following Gao et al. (2022), the law of motion for s_t includes a penalty function that prevents stockouts, as they are not observed in the global oil market. The penalty function ensures $s_t > 0$, removing the need for a non-negativity constraint. The advantage of this approach is that it captures the fact that inventories rarely get close to zero in the data.

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

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

where

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

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

$$r^e_{t+1} \equiv (p^e_{t+1} + d^e_{t+1})/p^e_t,$$
$$x_{t+1} \equiv \beta(u_{t+1}/u_t)^{1-1/\psi}(c_t/c_{t+1})(J_{t+1}/z_t)^{1/\psi-\gamma},$$
$$z_t \equiv (E_t[J^{1-\gamma}_{t+1}])^{1/(1-\gamma)}.$$

The equity risk premium is defined as

$$r^{ex}_t \equiv r^e_t - r_{t-1}.$$

Market Clearing Following Jermann (1998) and Gourio (2012), the final goods firm issues debt to finance its expected asset holdings, 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

$$d^e_t = d^f_t + d^s_t - \vartheta(E_{t-1}k_t - \tfrac{1}{r_t}E_t k_{t+1}),$$

where $d^f_t = y_t - i_t - p^o_t o_t - w_t n_t$ and $d^s_t = p^o_t o_t$. Asset market clearing implies that $s^e_t = 1$ and total bond issuance is given by $b_t = \vartheta E_{t-1}k_t$. 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 $\tilde{x}_t \equiv x_t/a_t$. The detrending process introduces the growth terms $g_t = a_t/a_{t-1}$ and $g_{o,t} = a^o_t/a^o_{t-1}$. Appendix D 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

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

Oil price uncertainty, $\mathcal{U}^{p_o}_t$, is analogously defined as the uncertainty surrounding $\ln(p^o_{t+1}/p^o_t)$. This definition is equivalent to the measure we used to compute oil price uncertainty in the data.[15]

[15]The uncertainty surrounding oil price growth is equivalent to the uncertainty surrounding the log oil price because p^o_t is known at time t and cancels from the definition of $\mathcal{U}^{p_o}_t$. 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 shocks 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 size of the model is at the limit of what is computationally feasible. In particular, versions of this model that allow for different blocks of countries would be computationally intractable.

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 was programmed in Fortran and run on the BigTex supercomputer at the Federal Reserve Bank of Dallas. Appendix C describes the solution method in more detail.

4.3 CALIBRATION Each period in the model is one quarter. The parameters shown in Table 1 are informed by moments in the data and the related literature. For some parameters, we rely on U.S. data to inform our calibration given the paucity of global data. The moments are computed using data from 1975Q1 to 2019Q4. Excluding the more recent data ensures that the calibration is not unduly influenced by the COVID-19 pandemic. Appendix B provides our data sources.[16]

The discount factor β is set to 0.997 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.[17] The Frisch elasticity, which is pinned down by the steady-state labor supply, is set to 2 following

[16]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, evaluating the model at a given parameterization takes many hours to solve.

[17]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)	0.997	$E(r)$
Risk Aversion (γ)	10	Gao et al. (2022), Croce (2014)
Intertemporal Substitution Elasticity (ψ)	2	Gao et al. (2022), Croce (2014)
Frisch Labor Supply Elasticity (η^{λ})	2	Peterman (2016), Basu-Bundick (2017)
Capital-Oil Elasticity of Substitution (σ)	0.105	$SD(\Delta p^o)$
Capital Depreciation Rate (δ)	0.025	Depreciation on fixed assets, durables
Capital-Oil Share of Production (ξ)	0.4043	Avg. labor share of income
Investment Adjustment Cost (ν)	3.3	$SD(\Delta i)$
Oil Storage Cost (ω)	0.025	Casassus et al. (2018), Gao et al. (2022)
Oil Production Weight (α)	0.134	$E[o/y]$
Oil Inventory Stockout Cost (τ)	0.00001	$E[s/o]$
Average Growth Rate ($\bar{g}$)	1.0039	$E(\Delta y)$
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)	0.0095	$SD(\Delta y)$
Oil Production Growth Shock SD (σ_{go})	0.011	$SD(\Delta o^s)$
Macro Disaster Size (ζ_g)	0.018	$E(r^{ex})$
Prob. of Entering Macro Disaster ($\bar{p}_g$)	0.005	Occurs in expectation every 50 years
Prob. of Exiting Macro Disaster ($\bar{q}_g$)	0.9	Gourio (2012)
Macro Disaster Prob. Persistence (ρ_{pg})	0.8	$AC(\mathcal{U}_y)$
Macro Disaster Prob. Shock SD (σ_{pg})	0.9	$SD(\mathcal{U}_y)$
Oil Production Disaster Size (ζ_e)	0.05	Avg. peak decline in oil prod. disasters
Prob. of Entering Oil Disaster ($\bar{p}_e$)	0.02	Avg. frequency of oil prod. disasters
Prob. of Exiting Oil Disaster ($\bar{q}_e$)	0.67	Avg. duration of oil prod. disasters
Oil Disaster Prob. Persistence (ρ_{pe})	0.9	$AC(\mathcal{U}_{p^o})$
Oil Disaster Prob. Shock SD (σ_{pe})	1.4	$SD(\mathcal{U}_{p^o})$

Peterman (2016), Basu and Bundick (2017), and many others in the business cycle literature.

The weight on oil in the production function α is set to 0.134 to match the average oil expenditure share in the data. Similarly, the parameter τ controlling the size of the oil inventory stockout cost is set to match the average inventory share of oil consumption. 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

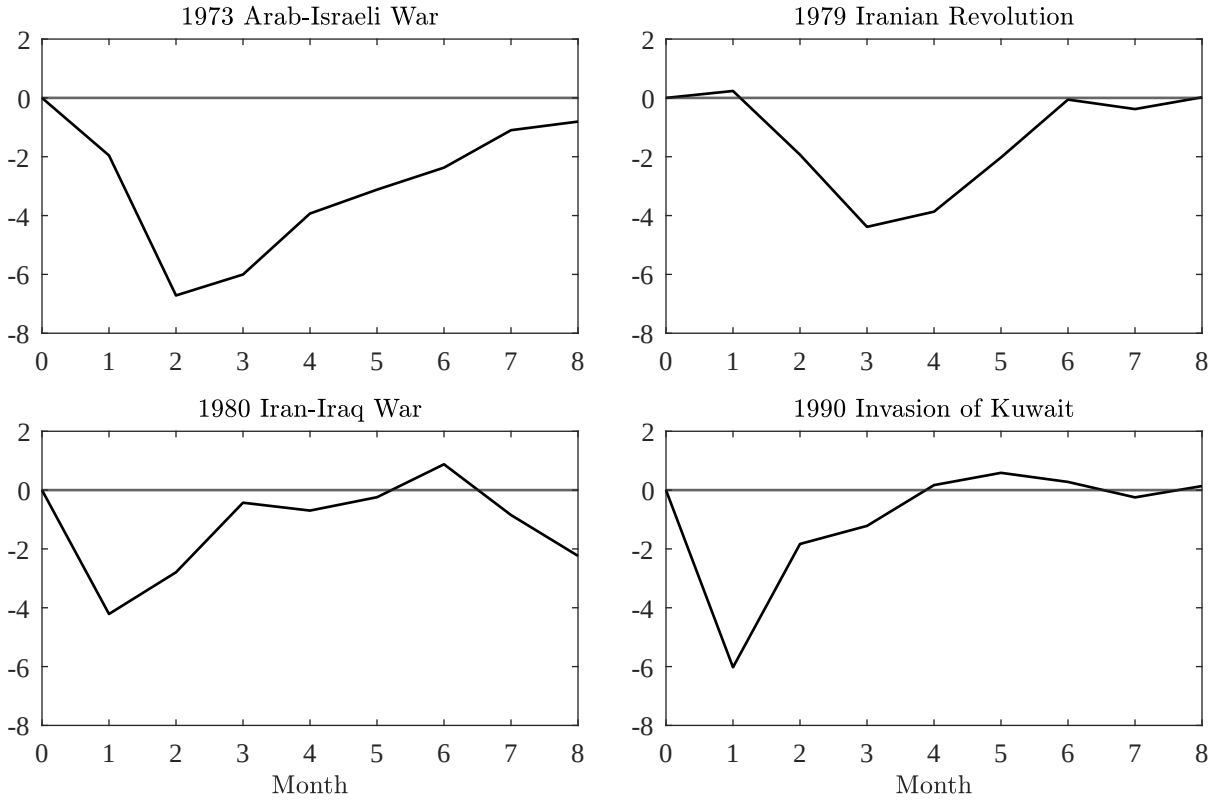
on private fixed assets and durable goods. The oil storage cost, ω, is set to 0.025 following Casassus et al. (2018) and Gao et al. (2022). As in Basu and Bundick (2017), the leverage parameter, ϑ, is set to 0.9 to help match the volatility of the equity premium.

The mean growth rate of productivity, $\bar{g}$, is set to 1.0039 to match the average growth rate of per capita real GDP. The standard deviation for the growth shock, σ_g, is set to 0.0095 to help match the volatility of real GDP growth. The calibration of the macroeconomic 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 0.018 to match the mean equity premium. The mean probability of entering the disaster state, $\bar{p}_g$, is set to 0.005, which implies that these disasters happen once every 50 years in expectation given that there were two major events over the last 100 years. The persistence, ρ_{pg}, and standard deviation, σ_{pg}, of this probability are set to 0.8 and 0.9, respectively, to help match the autocorrelation and volatility of output uncertainty. The fixed probability of exiting a macroeconomic disaster, $\bar{q}_g$, is set to 0.9, in line with Gourio (2012). This value implies that macroeconomic disasters, on average, last 2.5 years. As shown in Appendix F, the responses to an average macroeconomic 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 and technological constraints (see, e.g., 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. Following Hamilton (2013), Figure 2 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 in the data. The mean probability of entering the oil disaster state, $\bar{p}_e$, is set to 0.02 so that disasters

Figure 2: 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.

occur every 12.5 years in expectation, given that there were 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, 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 2.[18]

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.

[18]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.

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	2.14
$E(s/o)$	0.97	0.97	$SD(\Delta p^o)$	14.39	14.29
$E(p^o o/y)$	0.045	0.046	$SD(r^{ex})$	8.29	5.51
$E(r^{ex})$	2.18	2.09	$SD(\mathcal{U}_y)$	14.51	15.61
$E(r)$	0.22	0.20	$SD(\mathcal{U}_{p^o})$	29.95	30.49
$SD(\Delta y)$	0.74	0.87	$AC(\mathcal{U}_y)$	0.87	0.81
$SD(\Delta i)$	1.95	1.92	$AC(\mathcal{U}_{p^o})$	0.93	0.82
$SD(\Delta s)$	2.30	2.23	$AC(\Delta y)$	0.32	0.28
$SD(r)$	0.91	0.37	$AC(\Delta o^s)$	-0.11	-0.20
$Corr(\Delta y, \mathcal{U}_y)$	-0.15	-0.48	$AC(\Delta p^o)$	0.19	0.00
$Corr(\Delta y, \mathcal{U}_{p^o})$	-0.27	-0.44	$AC(p^o)$	0.95	0.94

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 Jurado et al. (2015). The standard deviations and rates are percents.

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 standard deviations and autocorrelations of output uncertainty and oil price uncertainty). 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.[19]

The model also performs well at matching several untargeted moments shown at the bottom of Table 2. These results provide further validation of our model. 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.

[19]One potential 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 average share in our model.

The model also reproduces the near random-walk behavior of the price of oil. Finally, allowing for disaster risk raises the volatility in the risk-free rate, which has traditionally been difficult to match in real business cycle models.

4.4 DISCUSSION Our model embodies all three main transmission channels of oil price uncertainty emphasized in the literature, as reviewed in Section 3. It directly incorporates precautionary savings by households in response to higher oil price uncertainty as well as oil storage. In addition, 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 that resemble those hypothesized by Bernanke and other researchers.

Although Bernanke's theoretical analysis is often cited in support of models of oil price volatility shocks, it is not well appreciated that Bernanke's framework does not allow for monthly or quarterly energy price volatility shocks. Rather, he envisioned agents being uncertain about whether the price of energy 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 energy 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 allow Atkeson and Kehoe to not only abstract from storage, but also to aggregate across different types of capital without tracking the distribution of capital types. The fact that the infinite-dimensional state space of capital stocks in their 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.

To illustrate this point, Appendix G evaluates the Atkeson-Kehoe (AK) putty-clay model with exogenous oil prices, augmented to include a stochastic volatility shock to the price of oil. We compare the responses of consumption and investment to an oil price uncertainty shock in this model to the corresponding responses in an alternative model that is identical except that the putty-clay structure has been replaced by the CES production function from our baseline model. We illustrate that the closer σ is to zero, the better the responses implied by the CES production function approximate the responses implied by the Leontief structure embodied in the AK model. For $\sigma = 0.1$, which corresponds to the value used in our baseline model with endogenous oil prices, the approximation is quite good. It is in this sense that our baseline model captures the essence of the results in Bernanke (1983) and Atkeson and Kehoe (1999), while remaining tractable in general

equilibrium even when the oil price is endogenous.

5 THE EFFECTS OF TIME-VARYING DISASTER RISK

The model provides a useful benchmark for what we would expect the relationship between oil price uncertainty and output uncertainty to be in the data. It is capable of generating fluctuations in oil price uncertainty that are qualitatively similar to those in the data, and it does not force output uncertainty and oil price uncertainty to be 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. It also sheds light on the impact of geopolitical oil price risk on the global economy.

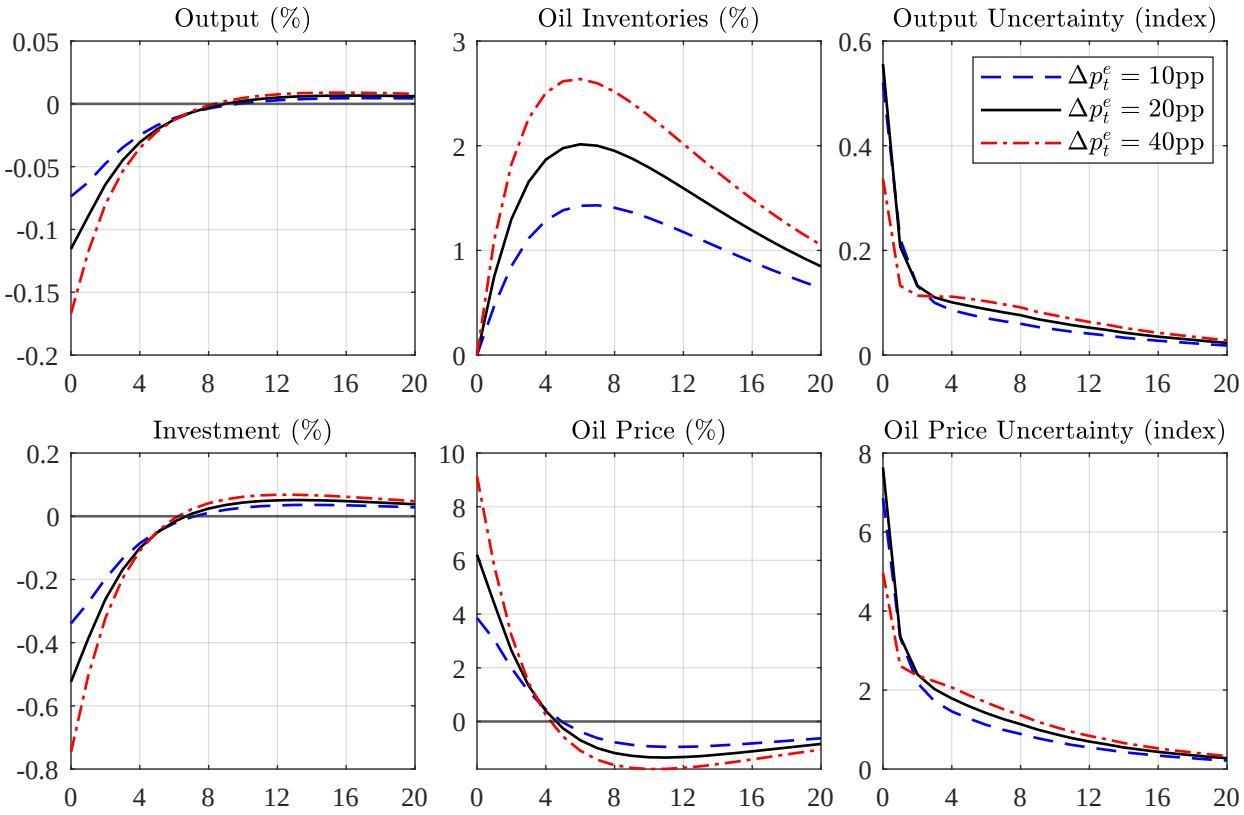
5.1 TRANSMISSION OF DISASTER PROBABILITY SHOCKS

Economic agents will witness disasters only infrequently. Nevertheless, disasters matter for economic behavior because there is a probability that they may be realized in the future. For example, the Twelve-Day War between Iran and Israel in June 2025 triggered concerns that the Strait of Hormuz might be closed, disrupting oil exports. As we highlight in this section, changes in the probability of such disasters will cause the oil market and the macroeconomy to move even when no disasters actually occur.[20]

Oil Disaster Probability Figure 3 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 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 9% for a 40pp shock.

[20] A positive shock to the probability of a geopolitically driven oil production shortfall lowers expected oil production and raises the uncertainty about the future price of oil. Such shocks differ from news about expected oil production or expected oil consumption, as discussed in the previous literature (see Kilian and Murphy, 2014). For example, Arezki et al. (2017) estimate the domestic macroeconomic impact of large oil discoveries rather than the impact on the global economy of a shift in the probability of such a discovery. Moreover, they are not concerned with geopolitical risk nor do they examine the response of the price of oil or of the uncertainty about the price of oil. Likewise, the literature on the impact of OPEC announcements on oil price expectations is not concerned with uncertainty nor does it focus on the anticipation of rare geopolitical oil supply disruptions (e.g., Känzig, 2021; Kilian, 2024).

Figure 3: Responses to alternative oil production disaster probability shocks



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

The probability shock reduces investment, with the effect ranging from a 0.34% drop for a 10pp shock to 0.75% 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 anticipatory demand for oil inventories raises the price of oil. Together, these two effects push down output, but the overall magnitude is modest.

Higher odds of an oil production disaster raise 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 0.34, but the oil price uncertainty index by 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.

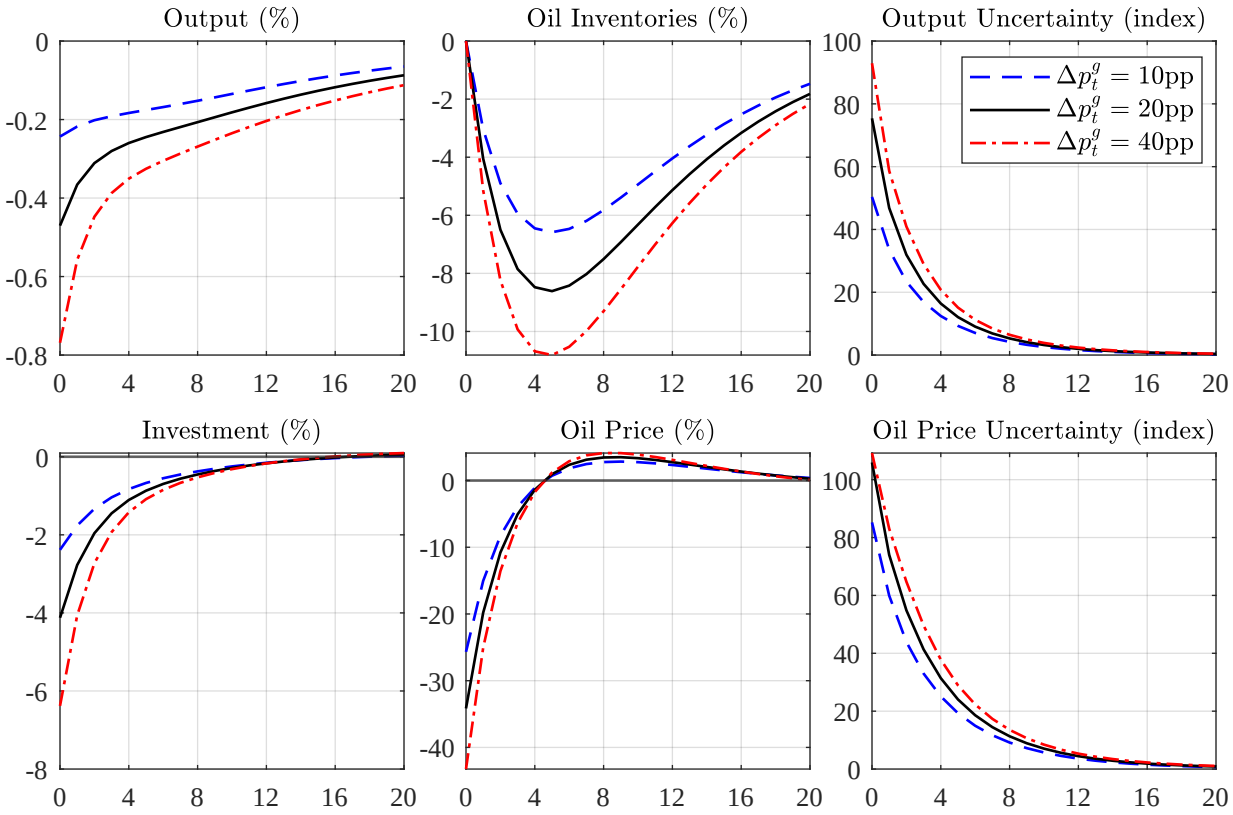
The model shows that the recessionary effects of the probability shock are reflected in output immediately, but are short-lived. The responses do not change proportionately with the shock size. For example, the responses of output and the price of oil to a 40pp increase in the oil disaster probability 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.

Macroeconomic Disaster Probability A macroeconomic disaster such as the Financial Crisis of 2008 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 a macroeconomic disaster. Figure 4 shows the responses when the growth disaster probability exogenously increases by 10, 20, and 40pp, respectively. All three shocks have substantial, albeit short-lived, effects on the price of oil. For example, a 10pp increase in the probability causes the price of oil to decline by 26% 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 reduce 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 an oil disaster probability shock of the same magnitude. This is because the disaster probability shock transmits directly to output rather than through the share of oil in output, which is small. In addition, the response is more persistent than the response to an oil disaster probability shock.

In related work, Gourio (2012) showed that an increase in the probability of a macroeconomic 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.

Figure 4: Responses to alternative macroeconomic disaster probability shocks



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

As in Figure 3, the responses do not scale proportionately with the increase in the macroeconomic disaster probability. For example, a 10pp increase leads to a 26% decline in the price of oil, whereas the price of oil declines by 43% 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 macroeconomic 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.[21]

[21] Studying the evolution of oil inventories and the oil price during geopolitical disasters would not be informative about the realism of our model because the anticipation of an oil production disaster causes inventories to move in the opposite direction from its 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 our model can only be evaluated based on the conditional moments in the data, which requires a nonlinear structural econometric model consistent with the structure of our model. No such model exists in the literature.

Table 3: Decomposition of key volatilities

Moment	Data	Baseline Model	No Macro Disaster Risk	No Macro Disaster Risk or Oil Production Disaster Risk
$SD(\Delta y)$	0.74	0.87	0.65	0.65
$SD(\Delta i)$	1.95	1.92	1.27	1.24
$SD(\Delta o^s)$	2.01	2.14	2.12	1.12
$SD(\Delta p^o)$	14.39	14.29	6.30	5.63
$SD(\mathcal{U}_y)$	14.51	15.61	0.30	0.14
$SD(\mathcal{U}_{p^o})$	29.95	30.49	4.97	2.02

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).

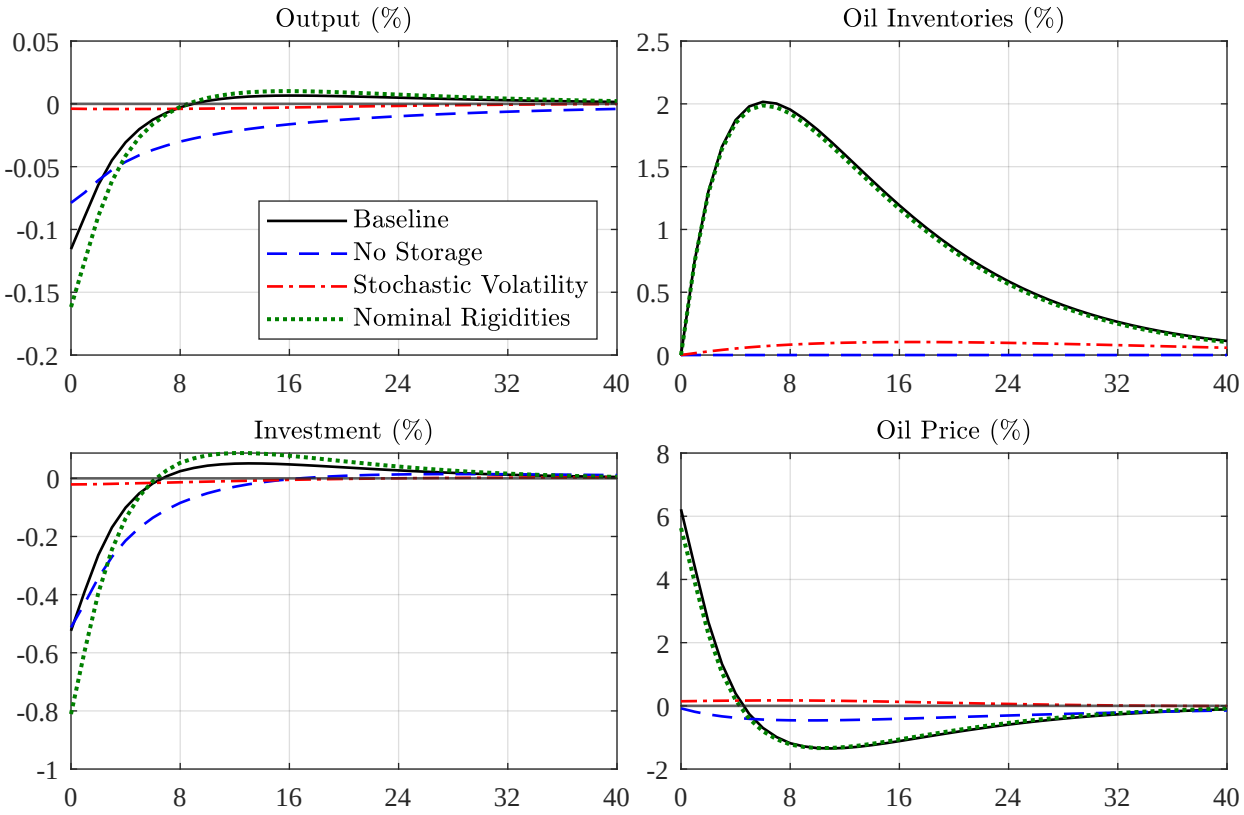
5.2 HOW MUCH VOLATILITY IS DUE TO MACROECONOMIC RISK AND GEOPOLITICAL RISK?

Table 3 shows that the model generally does an excellent job at capturing the volatility in the data. Dropping macroeconomic disaster risk from the 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 volatilities. Removing both macroeconomic 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 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, macroeconomic 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. We also

Figure 5: Responses to oil production disaster probability and stochastic volatility shocks



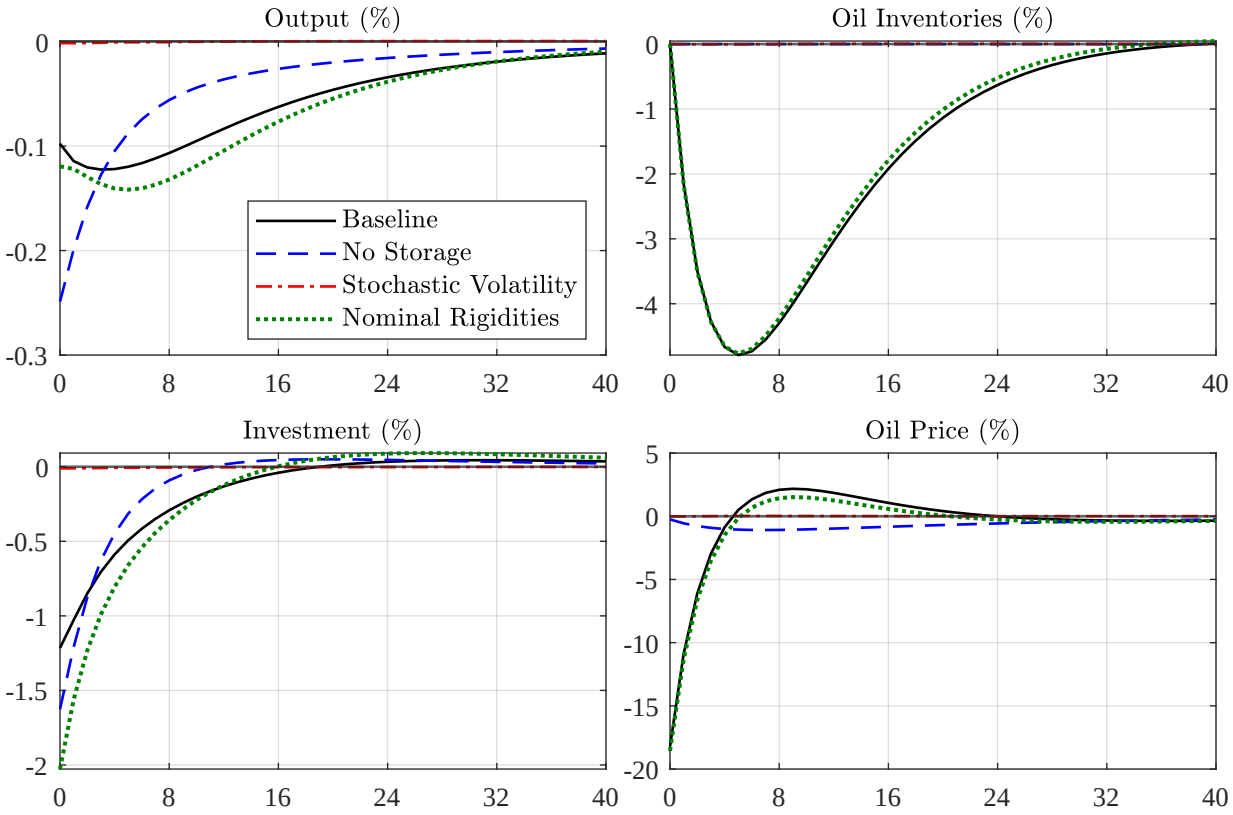
Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized. The stochastic volatility shock has been normalized to match the impact response of oil price uncertainty in the baseline model. All disaster probability shocks are 20pp.

show that the introduction of nominal rigidities does not affect the substance of our results and explore the implications of allowing households to directly consume oil and of a higher average oil expenditure share.

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 5 shows the responses for the oil disaster probability shock. The key difference is that the price of oil slightly declines on impact 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

Figure 6: 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. All disaster probability shocks are 5pp.

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 6 shows that storage also plays a key role in the propagation of a macroeconomic 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.

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,

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

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

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

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

where all shocks are standard normally distributed.[22] 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 0.095 to match the volatility of output 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 5 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, 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

[22] 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).

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 disaster probability shock with a SV shock on productivity growth, as shown in Figure 6. 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.[23]

Nominal Rigidities The literature has emphasized that sticky prices and monopolistic competition are potentially important amplifiers of uncertainty shocks (e.g., Basu and Bundick, 2017; Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015; Leduc and Liu, 2016). To explore how these features affect our results, we add a New Keynesian block to our baseline model. This extension replaces the expressions for the factor prices and the goods market clearing condition with

$$
\begin{aligned}
w_t &= (1-\xi) mc_t y_t / n_t, \\
p_t^o &= \xi \alpha mc_t \frac{(o_t/o_0)^{1-1/\sigma}}{(1-\alpha)(k_t/k_0)^{1-1/\sigma} + \alpha (o_t/o_0)^{1-1/\sigma}} \frac{y_t}{o_t}, \\
r_t^k &= \xi (1-\alpha) mc_t \frac{(k_t/k_0)^{1-1/\sigma}}{(1-\alpha)(k_t/k_0)^{1-1/\sigma} + \alpha (o_t/o_0)^{1-1/\sigma}} \frac{y_t}{k_t}, \\
c_t + i_t &= \left(1 - \tfrac{\varphi}{2}\left(\tfrac{\pi_t}{\bar{\pi}} - 1\right)^2\right) y_t,
\end{aligned}
$$

where mc_t is marginal cost, π_t is the gross inflation rate, and φ scales the price adjustment cost. It also adds a Phillips curve, an Euler equation for the nominal bond, and a Taylor rule given by

$$
\begin{aligned}
\varphi\left(\frac{\pi_t}{\bar{\pi}} - 1\right)\frac{\pi_t}{\bar{\pi}} &= 1 - \theta + \theta mc_t + \varphi E_t\left[x_{t,t+1}\left(\frac{\pi_{t+1}}{\bar{\pi}} - 1\right)\frac{y_{t+1}}{y_t}\frac{\pi_{t+1}}{\bar{\pi}}\right], \\
1 &= E_t[x_{t+1} r_t^n / \pi_{t+1}], \\
r_t^n &= \bar{r}^n (\pi_t/\bar{\pi})^{\phi_\pi},
\end{aligned}
$$

[23] 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. When modeling time-varying markups using more conventional assumptions, as is standard in New Keynesian models, the effects are much smaller. For example, 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.

where r_t^n is the gross nominal interest rate, θ is the elasticity of substitution between intermediate goods, and ϕ_π is the monetary response to inflation. We set the additional parameters to conventional values in the literature. Specifically, we set $\theta = 6$ to achieve a 20% steady-state markup, $\varphi = 80$ so prices adjust about once a year in a (linear) Calvo setting, $\phi_\pi = 1.5$ in line with a standard Taylor rule, and $\bar{\pi} = 1.005$ consistent with a 2% annual inflation target.

As shown in Figures 5 and 6, the presence of nominal rigidities slightly amplifies the responses of investment and output to both types of disaster probability shocks. In particular, a 20pp oil disaster shock lowers investment by 0.52% and output by 0.12% in our baseline model, compared to 0.81% and 0.16% in the model with nominal rigidities. While these differences confirm the insights from the literature, they do not alter our finding that 20pp oil disaster probability shocks in the baseline model have modest effects on the macroeconomy.

Oil Share and Household Oil Consumption It may seem that our analysis understates the importance of oil production risk because oil was presumably more important for the economy in the 1970s than it is today. However, there is no evidence that the average oil share, as measured in this paper, was substantially higher in the 1970s than we assumed. For example, the actual U.S. oil share was near 6% in the mid-1970s compared with our average share of 4.5%.

This is not to say that there have not been fluctuations in this share about its average value. For example, the U.S. oil share in the early 1980s briefly reached an all-time maximum of 8%, while dropping below 3% in 1998 and 2020. Such fluctuations are largely driven by variation in the price of oil. When the price of oil is unusually high or low, so is the oil share. Our calibrated model replicates this pattern. It reproduces shares between 4% and 8% in the baseline specification.

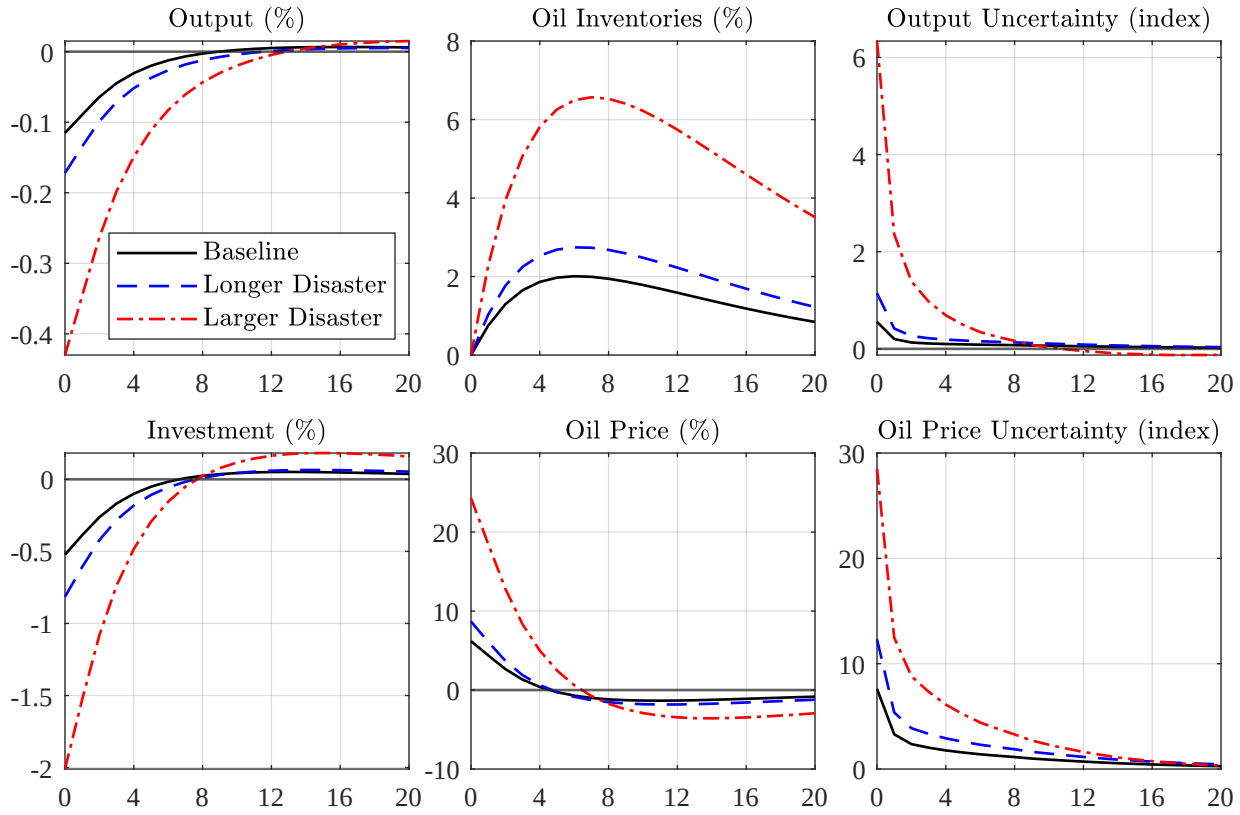
Nevertheless, it is of interest to know how sensitive our key findings are to a higher average oil share. In Appendix F, we consider an unrealistically high average oil share of 8%. We find that in this case the effect of a 20pp shock to the probability of an oil production disaster on output is only 0.05 percentage points larger than in the baseline model and there is little change in the oil price response. It also remains true that oil production disaster risk is not an important determinant of macroeconomic volatility.

Another potential concern is that our baseline model does not allow oil to be consumed directly by households. In the model, households only purchase consumer goods produced with oil as an intermediate input. This concern, however, is alleviated by the fact that the primary effect of allowing for oil to be consumed directly involves the transfer of income from oil importing countries to oil exporting countries, as households consume imported crude oil in the form of fuels (e.g., Baumeister et al., 2018; Edelstein and Kilian, 2009). As consumer spending on other goods declines in the oil-importing economy, the economy contracts unless the petrodollars are recycled. Since our global model is a closed economy, there is no income transfer by construction, obviating this concern. Additional analysis in Appendix F that allows oil to directly enter the utility function confirms that this change does not materially affect our findings.

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 7 explores this question by considering alternative specifications of the oil production disaster, given a 20pp probability shock. 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 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.

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

Figure 7: Responses to an oil production disaster probability shock under different disasters

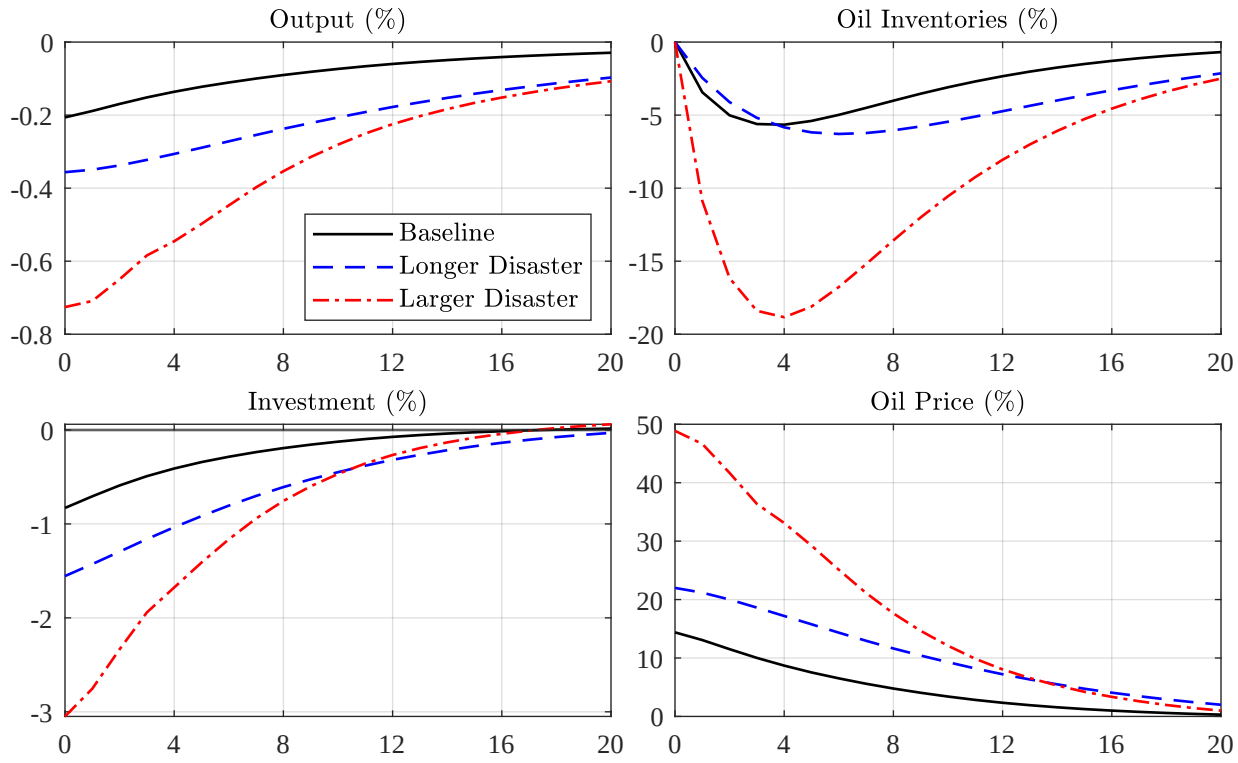


Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized. The disaster probability shock is 20pp for all three specifications.

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 1). 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% on impact to 24%, and the reduction in output rises from 0.12% to 0.43%.

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 16% of this variability in the baseline model, as shown in Table 3, this share rises to 22% when the disaster is longer lasting and to 69% 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.

Figure 8: Responses to an oil production disaster realization



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.

5.5 OIL DISASTER REALIZATION So far, we reported the responses to oil production and macroeconomic disaster probability shocks, conditional on no disasters being realized. It is of independent interest to assess the impact of the realization of such disasters. As the probability of an oil production disaster increases, the economic effects converge to those that occur when a disaster is realized, except for oil inventories. The latter response changes sign when the production shortfall is realized, as storage firms respond to the temporarily higher price of oil.

Figure 8 shows responses under the baseline calibration (5% drop in global oil production that is expected to last for 3 quarters) and when allowing for a longer disaster (10 quarters on average) or a larger disaster (20% drop in global oil production). In the baseline model, we find that output declines by 0.21% on impact, but the effects nearly double when allowing the disaster to last longer and reach -0.73% on impact when increasing the magnitude of the shortfall to 20% of global oil

production. In the latter case, the oil price jumps by nearly 50% on impact compared to only 14% in the baseline model. This evidence is consistent with the view that oil production disasters may have substantial effects on the economy and on the price of oil. Our model helps quantify what these effects are based on a formal model, complementing assessments published by investment banks.[24]

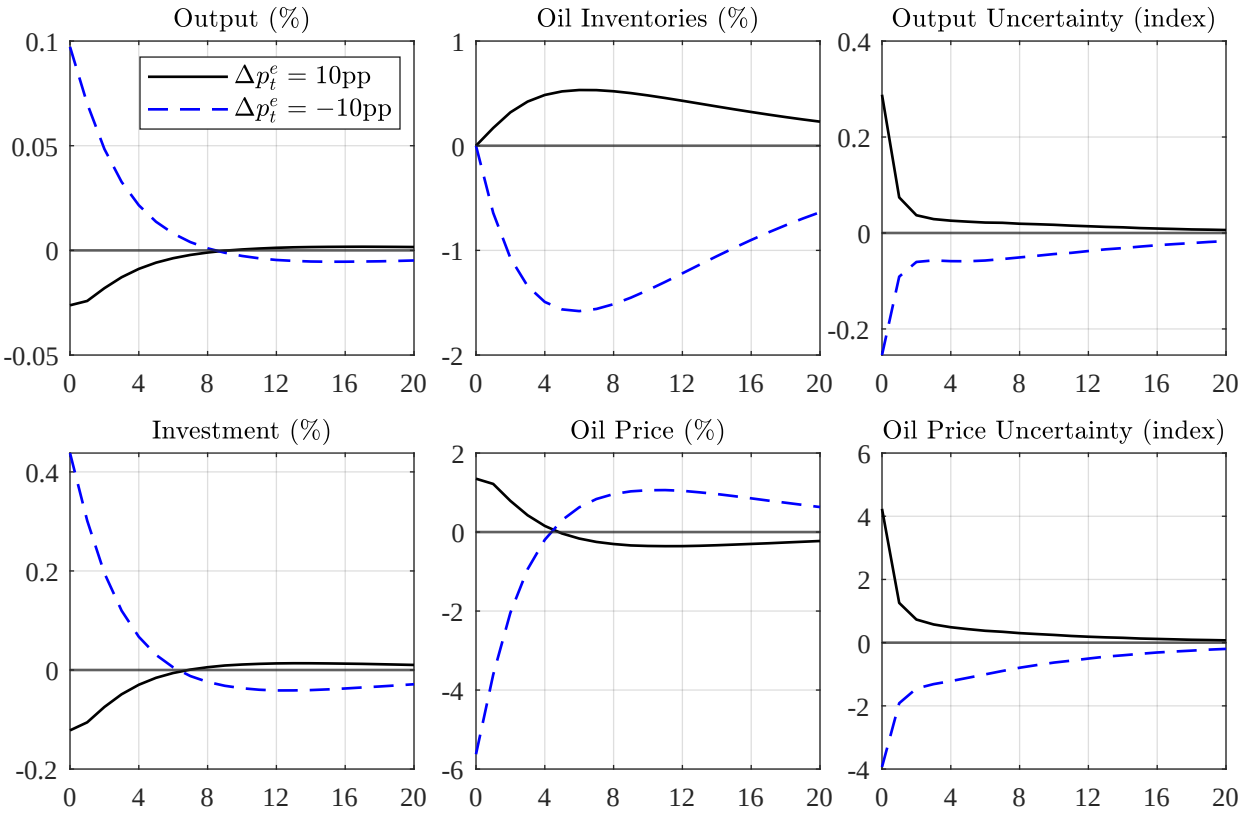
6 IMPLICATIONS FOR EMPIRICAL WORK

Our analysis 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, financial, and policy uncertainty. For example, market commentators have routinely highlighted the role of uncertainty about the prospects of the Chinese economy or the U.S. economy for 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. 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), 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. Elder and Serletis also impose the restriction 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

[24]The corresponding results for the realization of the macroeconomic disaster are provided in Appendix F.

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.

probability shock.[25] 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 macroeconomic disaster probability shock, as shown in Appendix F.

Alternative models that break the link between level and uncertainty shocks such as the VAR model with SV in Jo (2014) instead postulate that oil price uncertainty shocks and shocks to the level of the price of oil are independent. However, our analysis shows 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 macroeconomic disaster not only raises oil price uncertainty, but also causes

[25]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.

storage demand to increase, raising the real price of oil.[26]

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 as in Gao et al. (2022). Exploring alternative recursive orderings does not address this concern, as shown in Kilian et al. (2025). 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.

7 CONCLUDING REMARKS

There has been growing interest in the impact of shifts in geopolitical risk, particularly in the oil market. In this paper, we introduced a stochastic growth model of the global economy that is designed to examine how this risk affects the price of oil, oil price uncertainty, and the macroeconomy. Geopolitical risk is modeled as downside risk to oil production and both oil price and macroeconomic uncertainty are determined endogenously. As was the case during the Twelve-Day War between Iran and Israel in June 2025, both the price of oil and oil price uncertainty sharply increase in response to higher geopolitical risk to oil production, even if that risk is never realized. We find that a 20 percentage point increase in the probability of a 5% shortfall in global oil production causes a 0.12% reduction in output. When considering a 20% shortfall, which roughly corresponds to the cessation of oil supplies from the Persian Gulf, the drop in output quadruples. These results provide a benchmark for assessing the quantitative impact of this risk.

Our analysis also highlighted the importance of jointly modeling macroeconomic and geopolitical risk. We showed that oil price uncertainty not only responds to geopolitically driven oil production disaster probability shocks but also to level shocks in the macroeconomy and to macroeconomic disaster probability shocks. In our baseline model, more than half of the observed oil price uncertainty tends to be driven by the macroeconomy, which helps explain why oil price uncer-

[26]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 generates meaningful recessionary effects. Thus, one would not expect large recessionary effects of shocks to oil price uncertainty when estimating VAR models with SV.

tainty has historically been associated with reductions in real activity. 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 view that oil price uncertainty plays a major role in driving the business cycle. These results suggest that economists and policymakers need to be cognizant of the interplay between oil price uncertainty, macroeconomic uncertainty, and the state of the economy.

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Online Appendix: Geopolitical Oil Price Risk and Economic Fluctuations*

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ABSTRACT

This appendix describes the methodology for constructing a time series of oil price uncertainty, our data sources, and the solution method for our general equilibrium model. It plots the time series of the real price of oil underlying our analysis as well as the U.S. oil expenditure share. It presents the responses to a macroeconomic disaster and to positive and negative macroeconomic disaster probability shocks. It provides the results of several robustness exercises, including an alternative CES production function, an alternative utility function that allows households to consume oil, and a higher average oil expenditure share. It concludes by comparing the CES production technology to the putty-clay technology.

*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.

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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,

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

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,

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

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,

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

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

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

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

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

Data moments are computed with quarterly data. The average oil expenditure share is based on annual data.

C 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 they cover at least 99% of the ergodic distribution, reducing the need for extrapolation. Specifically, the bounds on capital, k_t, range from -15% to $+10\%$, the bounds on storage, s_t, range from -50% to $+80\%$, 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. 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, $[\varepsilon_{g,t+1}(m), \varepsilon_{go,t+1}(m), \varepsilon_{p,t+1}^g(m), \varepsilon_{p,t+1}^e(m)]$. The transition matrices for the discrete states determine the integration weights for their future realizations, $[v_{t+1}^g(m), v_{t+1}^e(m)]$. 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_p^g and ε_p^e, 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 Sims' `csolve` code 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 $\text{maxdist}_j < 10^{-5}$, 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.

Ergodic Probabilities Since the probability of entering an oil production or macroeconomic disaster is time varying, there is no closed-form solution for the ergodic probabilities of these disasters. We therefore compute π_1^g and π_1^e by simulating v_t^g and v_t^e for 1 million periods and then computing the fraction of periods where $v_t^g = 1$ and the fraction of periods where $v_t^e = 1$.

D DETRENDED EQUILIBRIUM OF THE BASELINE MODEL

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

$$\tilde{w}_t = (1-\xi)\tilde{y}_t/n_t$$

$$p_t^o = \xi\alpha \frac{(\tilde{o}_t/o_0)^{1-1/\sigma}}{(1-\alpha)(\tilde{k}_t/k_0)^{1-1/\sigma}+\alpha(\tilde{o}_t/o_0)^{1-1/\sigma}} \frac{\tilde{y}_t}{\tilde{o}_t}$$

$$E_t[x_{t+1} r_{t+1}^i] = 1$$

$$r_t^i = e^{-\zeta v_t} \frac{1}{p_{t-1}^k}(r_t^k + (1-\delta+a_1+\tfrac{a_2}{\nu-1}(\tilde{\imath}_t/\tilde{k}_t)^{1-1/\nu})p_t^k)$$

$$p_t^k = \tfrac{1}{a_2}(\tilde{\imath}_t/\tilde{k}_t)^{1/\nu}$$

$$r_t^k = \xi(1-\alpha)\frac{(\tilde{k}_t/k_0)^{1-1/\sigma}}{(1-\alpha)(\tilde{k}_t/k_0)^{1-1/\sigma}+\alpha(\tilde{o}_t/o_0)^{1-1/\sigma}} \frac{\tilde{y}_t}{\tilde{k}_t}$$

$$E_t[x_{t+1} r_{t+1}^s] = 1$$

$$r_t^s = \frac{1}{p_{t-1}^o}(1-\omega+\pi\tilde{s}_t^{-3})p_t^o$$

$$\chi\tilde{w}_t\ell_t = (1-\chi)\tilde{c}_t$$

$$x_t = (\beta/g_t^\gamma)(\tilde{u}_t/\tilde{u}_{t-1})^{1-1/\psi}(\tilde{c}_{t-1}/\tilde{c}_t)(\tilde{J}_t/\tilde{z}_{t-1})^{1/\psi-\gamma}$$

$$\tilde{u}_t = \tilde{c}_t^\chi \ell_t^{1-\chi}$$

$$\tilde{z}_t = (E_t[(g_{t+1}J_{t+1})^{1-\gamma}])^{1/(1-\gamma)}$$

$$\tilde{J}_t = \left((1-\beta)\tilde{u}_t^{1-1/\psi} + \beta\tilde{z}_t^{1-1/\psi}\right)^{\frac{1}{1-1/\psi}}$$

$$\tilde{y}_t = y_0 n_t^{1-\xi}\left((1-\alpha)(\tilde{k}_t/k_0)^{1-1/\sigma} + \alpha(\tilde{o}_t/o_0)^{1-1/\sigma}\right)^{\xi/(1-1/\sigma)}$$

$$g_{t+1}\tilde{k}_{t+1} = e^{-\zeta_g v_{t+1}^g}(1-\delta+a_1+\tfrac{a_2}{1-1/\nu}(\tilde{\imath}_t/\tilde{k}_t)^{1-1/\nu})\tilde{k}_t$$

$$g_{t+1}\tilde{s}_{t+1} = (1-\omega)\tilde{s}_t + \tilde{o}_t^s - \tilde{o}_t - \tfrac{\pi}{2}\tilde{s}_t^{-2}$$

$$\tilde{o}_t^s = e_t/\epsilon_t$$

$$\tilde{c}_t + \tilde{\imath}_t = \tilde{y}_t$$

$$n_t + \ell_t = 1$$

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

$$\ln\epsilon_t = \ln g_t - \ln g_{o,t} + \ln\epsilon_{t-1}$$

$$\ln g_t = \ln\bar{g} + \sigma_g\varepsilon_{g,t} - \zeta_g(v_t^g - \bar{\pi}_1^g)$$

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

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

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

$$\ln p_t^g = (1-\rho_p^g)\ln\bar{p}^g + \rho_p^g \ln p_{t-1}^g + \sigma_p^g\varepsilon_{p,t}^g$$

$$\ln p_t^e = (1-\rho_p^e)\ln\bar{p}^e + \rho_p^e \ln p_{t-1}^e + \sigma_p^e\varepsilon_{p,t}^e$$

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

$$1 = E_t[x_{t+1} r_{t+1}^e]$$

$$r_t^e = g_t(\tilde{p}_t^e + \tilde{d}_t^e)/\tilde{p}_{t-1}^e$$

$$\tilde{d}_t^e = \tilde{y}_t - \tilde{\imath}_t - \tilde{w}_t n_t - \vartheta(\tfrac{1}{g_t}E_{t-1}[g_t\tilde{k}_t] - \tfrac{1}{r_t}E_t[g_{t+1}\tilde{k}_{t+1}])$$

E OIL MARKET DATA

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

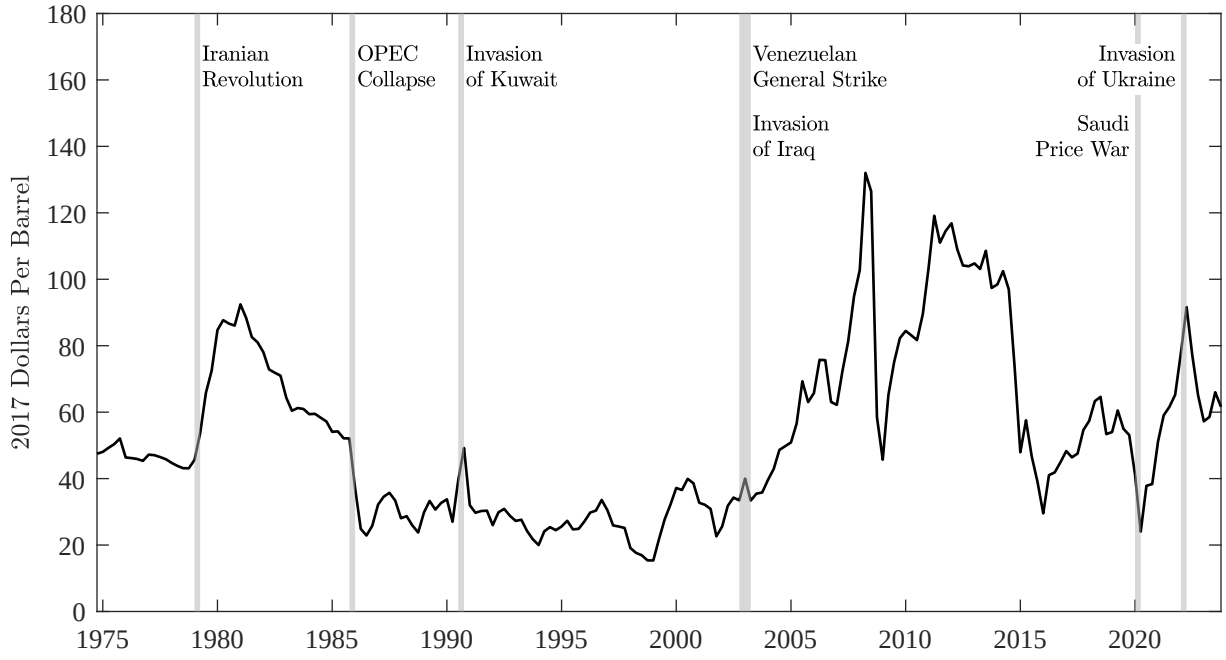
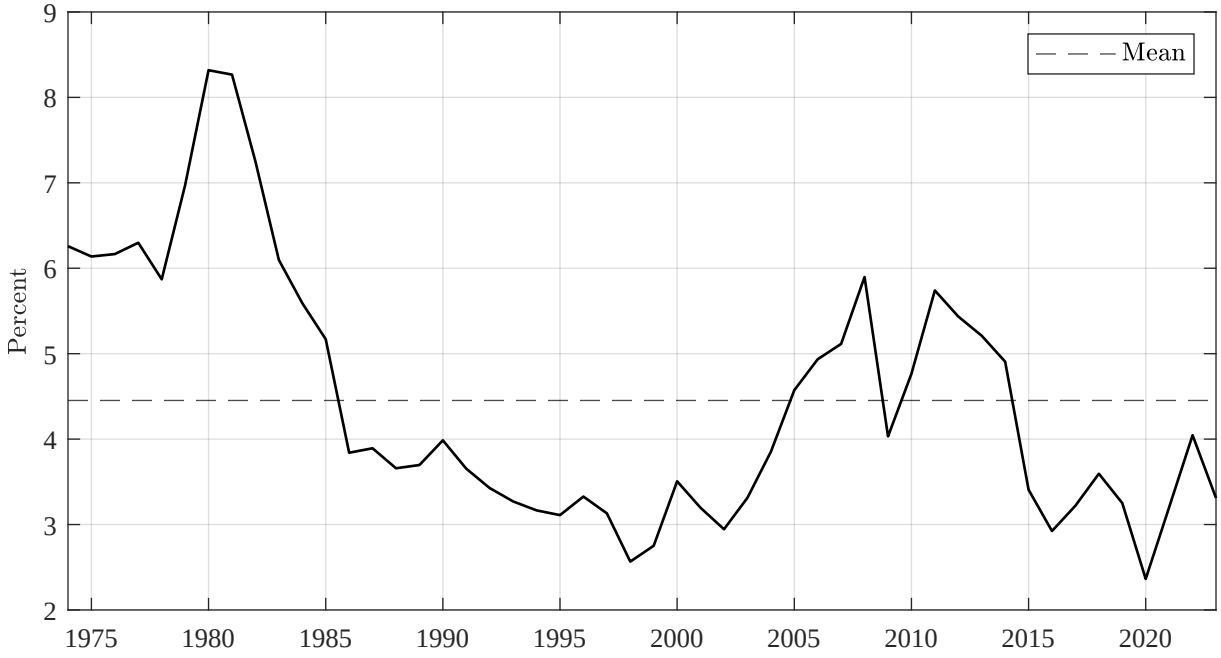


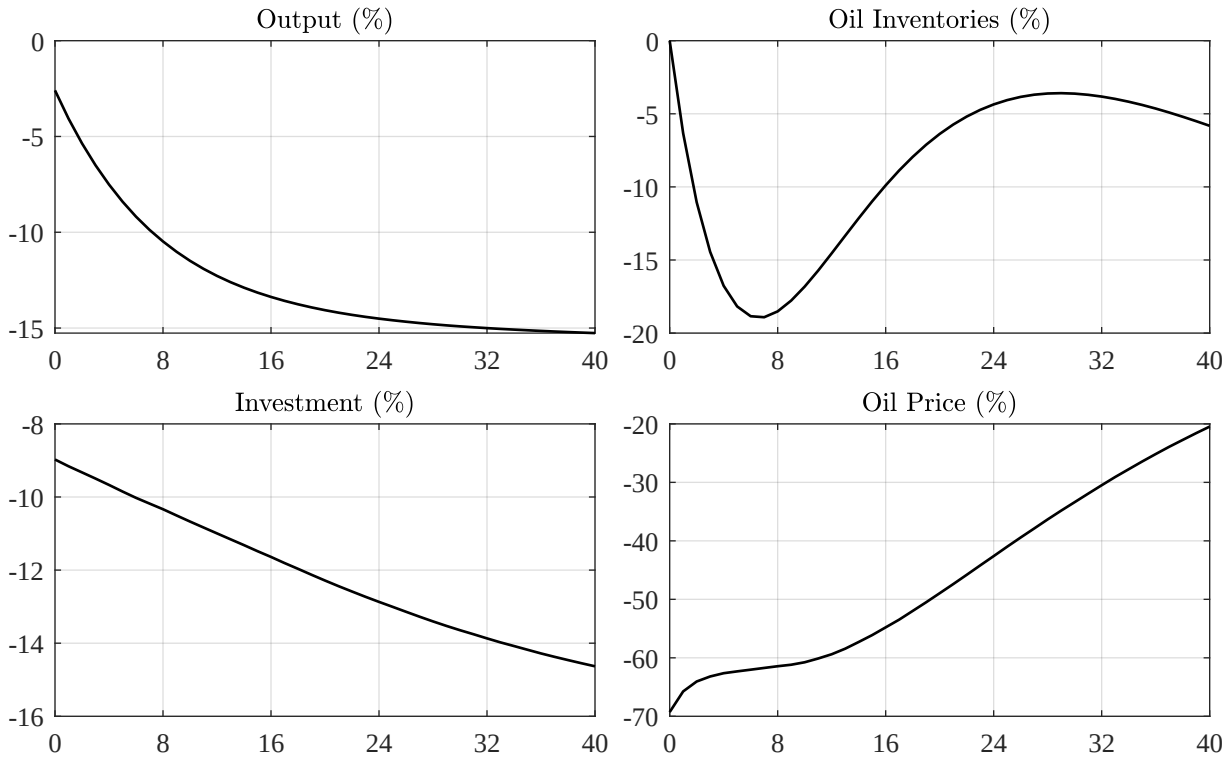
Figure 2: U.S. petroleum oil expenditure share, 1974-2023



F ADDITIONAL DISASTER RISK RESULTS

F.1 DISASTER REALIZATION Figure 3 shows how the economy responds to a macroeconomic disaster realization. The output and investment responses are broadly in line with the results reported in Gourio (2012). The oil price drops by nearly 70% on impact and oil inventories decline.

Figure 3: Responses to a macroeconomic disaster realization



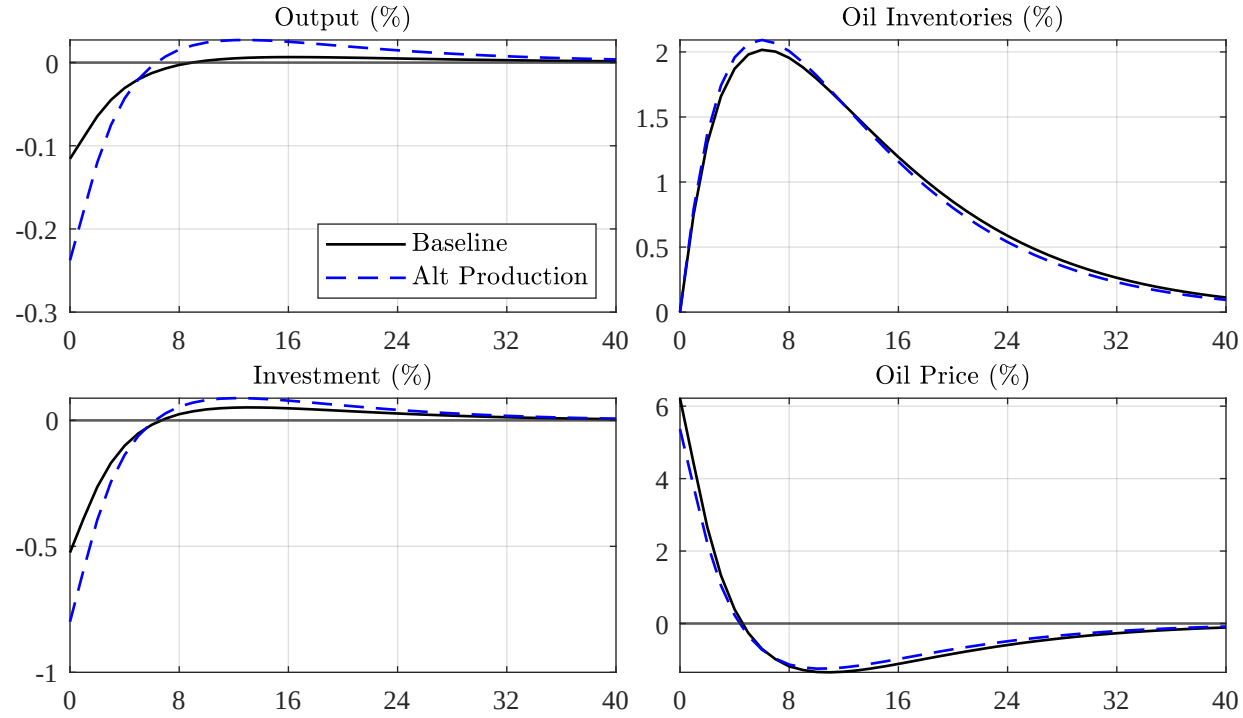
F.2 PRODUCTION FUNCTION The specification of the production function in our baseline model follows the seminal work of Kim and Loungani (1992) and Backus and Crucini (2000). Some more recent studies, such as Başkaya et al. (2013), Hassler et al. (2021), Olovsson (2019), and Ready (2018), use the following specification

$$y_t = y_0 \left((1-\alpha)(v_t/v_0)^{1-1/\sigma} + \alpha(o_t/o_0)^{1-1/\sigma}\right)^{1/(1-1/\sigma)},$$

where $v_t = (a_t n_t)^{1-\xi} k_t^{\xi}$ is value added and σ is the elasticity of substitution between oil and the capital-labor bundle, rather than just capital. Under this specification, the factor prices are given by

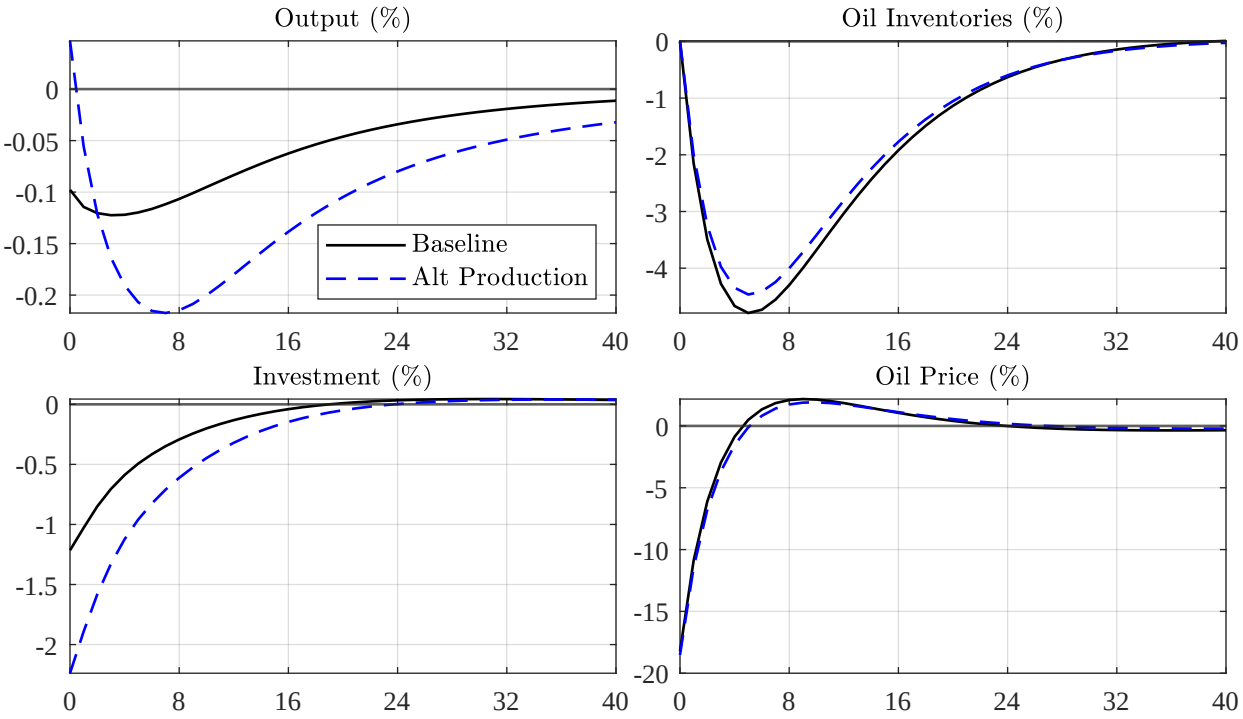
$$w_t = (1-\alpha)(1-\xi)(y_0/n_t)(y_t/y_0)^{1/\sigma}(v_t/v_0)^{1-1/\sigma},$$
$$p_t^o = \alpha(y_0/o_0)(y_t/y_0)^{1/\sigma}(o_t/o_0)^{-1/\sigma},$$
$$r_t^k = (1-\alpha)\xi(y_0/k_t)(y_t/y_0)^{1/\sigma}(v_t/v_0)^{1-1/\sigma}.$$

Figure 4: Responses to a 20pp oil production disaster probability shock



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

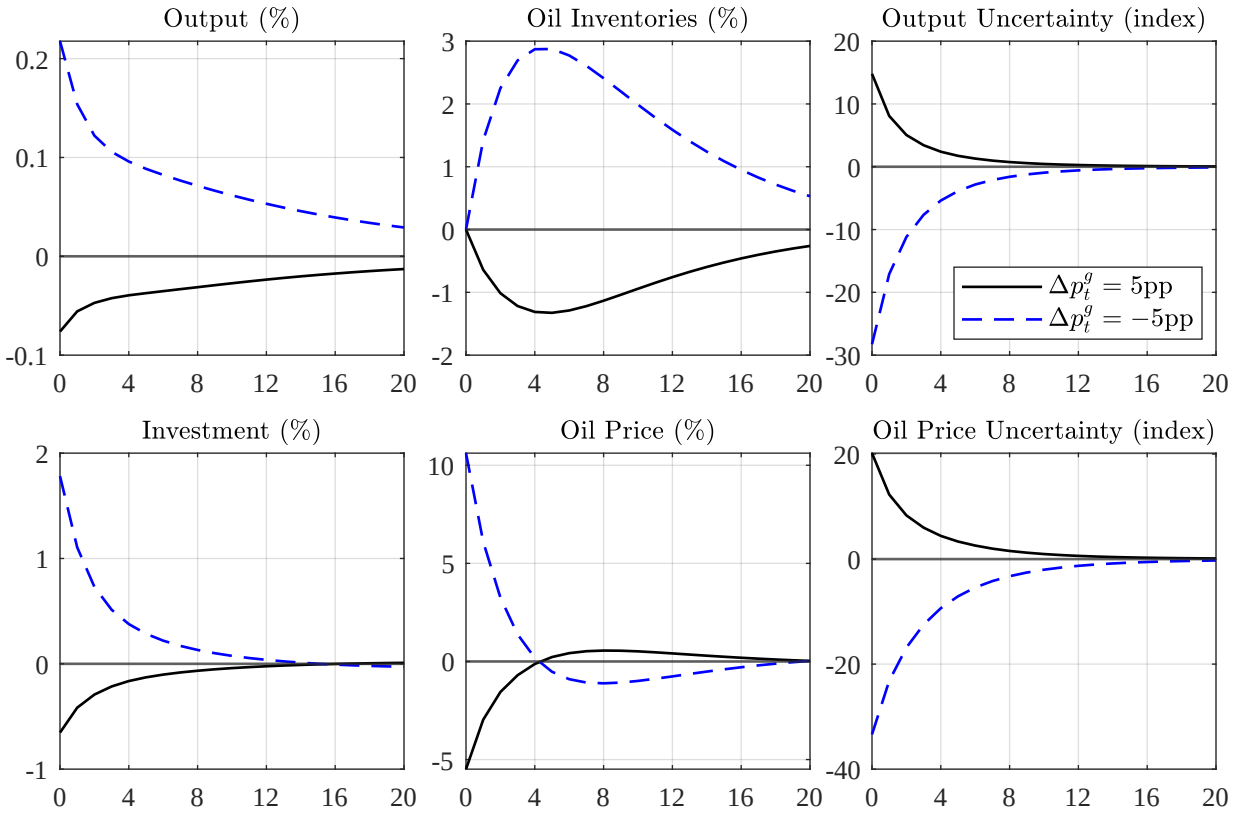
Figure 5: Responses to 5pp macroeconomic disaster probability shock



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

We recalibrate the model to match the data moments. All of the parameters are unchanged, except that we set $\alpha = 0.063$ in order to match the cost share of oil.[1] Figures 4 and 5 illustrate that our substantive conclusions are robust to this alternative functional form of the production function.

Figure 6: Responses to positive and negative macroeconomic disaster probability shocks

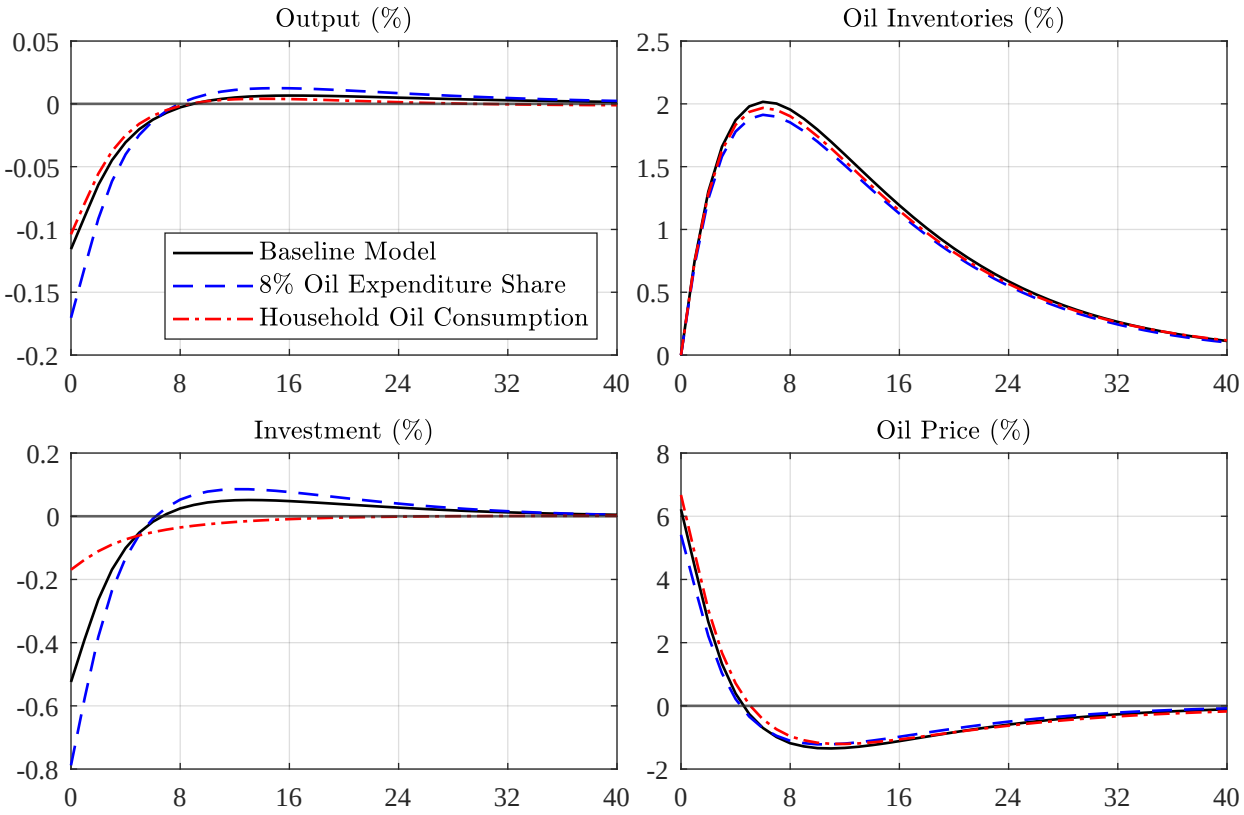


Notes: Responses in deviations from the baseline. Simulations assume no disasters are realized.

F.3 SIGN OF THE DISASTER PROBABILITY SHOCK In the paper, we show how the sign of an oil disaster probability shock affects the responses. Figure 6 shows the responses to a ± 5pp macroeconomic disaster probability shock. The simulations are initialized at a 15% disaster probability to permit a positive and negative shock. Consistent with the responses to an oil disaster probability shock, we find that increases and decreases in the price of oil do not have the same effects on uncertainty. A decrease in the probability of a macroeconomic disaster increases the price of oil and reduces oil price uncertainty on impact, while an increase in this probability lowers the oil price and raises oil price uncertainty. This result is inconsistent with a VAR model with GARCH errors.

[1] We set α to 0.063 so that the average oil expenditure share across simulations matches the share in the data. Similarly, the steady-state inventory share of oil consumption ($\bar{s}/\bar{o}$) is set to 1.18 to match the average share in the data. We set the steady-state labor cost share ($\bar{w}\bar{n}/\bar{y}$), which determines ξ, to 0.5957, in line with the baseline model. The elasticity of substitution, σ, is pinned down by the standard deviation of the price of oil and remains unchanged.

Figure 7: Responses to a 20pp oil production disaster probability shock



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

F.4 HIGHER OIL EXPENDITURE SHARE The average oil expenditure share in our baseline model is 4.5%, but there was a brief period in the early 1980s when the share reached 8% (see Figure 2). To examine the sensitivity of our results, we also consider a variation of the baseline model with an average oil expenditure share of 8%. As shown in Figure 7, even allowing for such an unrealistically high average expenditure share implies only a slightly larger response of real activity to an oil production disaster probability shock. There is little effect on the price of oil and oil inventories. Overall, these results show that our baseline results are robust to changes in the average oil expenditure share.

F.5 HOUSEHOLD OIL CONSUMPTION In our baseline model, all of the oil consumption takes place in the production sector. An alternative assumption would be to follow Bodenstein et al. (2008, 2011) in introducing oil consumption by households. In that case, the household's maximization problem becomes

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

subject to

$$u_t = c_{a,t}^{\chi}(a_t(1-n_t))^{1-\chi},$$
$$c_{a,t} = c_{a0}\left((1-\alpha_h)(c_t/c_0)^{1-1/\sigma_h} + \alpha_h(o_{h,t}/o_{h0})^{1-1/\sigma_h}\right)^{\sigma_h/(\sigma_h-1)},$$
$$c_t + p_t^o o_{h,t} + p_t^e s_{t+1}^e + b_{t+1}/r_t = w_t n_t + (p_t^e + d_t^e)s_t^e + b_t,$$

where c_t is goods consumption, $o_{h,t}$ is oil consumption, $c_{a,t}$ is aggregate consumption, and σ_h is the elasticity of substitution between goods and oil consumption. Just like in the production sector, we introduce scalars c_{a0}, c_0, and o_{h0} so that α_h is equal to the household oil expenditure share.

The first-order conditions are given by

$$1 = E_t[x_{t+1}r_{t+1}^e],$$
$$1 = E_t[x_{t+1}r_t],$$
$$(1-\alpha_h)\chi w_t(1-n_t)(c_0 c_{a,t}/c_{a0})^{1/\sigma_h-1} = (1-\chi)c_t^{1/\sigma_h},$$
$$p_t^o = \tfrac{\alpha_h}{1-\alpha_h}(c_t/o_{h,t})^{1/\sigma_h}(c_0/o_{h0})^{1-1/\sigma_h},$$

where

$$r_{t+1}^e = (p_{t+1}^e + d_{t+1}^e)/p_t^e,$$
$$x_t = \beta(u_t/u_{t-1})^{1-1/\psi}(c_{a,t}/c_{a,t-1})^{1/\sigma_h-1}(c_{t-1}/c_t)^{1/\sigma_h}(J_t/z_{t-1})^{1/\psi-\gamma},$$
$$z_t = (E_t[J_{t+1}^{1-\gamma}])^{1/(1-\gamma)}.$$

The oil storage firm now chooses how much to supply to the household and the final goods firm, but the first-order condition is unchanged. The problem for the final goods firm is unchanged.

We set $\sigma_h = \sigma = 0.105$ and the share of oil consumed by households $\bar{o}_h/(\bar{o}_h+\bar{o})$ to 0.5 to match the share in U.S. data, which is equal to personal consumption expenditures on gas and other energy goods (CNEA@USNA) divided by petroleum products expenditures (ZUSPATCV@USENERGY). The implied weight on oil in the production function is $\alpha = 0.0667$, while the implied weight on oil in the aggregate consumption function is $\alpha_h = 0.0407$. All other parameters are unchanged.

Figure 7 shows the responses to an oil production disaster probability shock. Intuitively, there is a smaller decline in investment because firms now only represent half of total oil consumption and are therefore less exposed to the risk of a large shortfall in oil production. However, there is a larger decline in goods consumption, given the complementarity with oil consumption in the household's aggregate consumption function. These two competing effects on output roughly cancel out, so the response the response of output is effectively unchanged from our baseline model. We also find little effect on the price of oil and oil inventories. These results show that the distinction between oil consumption by households and by firms has little effect on our baseline results.

G COMPARISON WITH THE PUTTY-CLAY MODEL

In the Atkeson and Kehoe (1999) model, the real price of oil, p_t^o, is exogenous. We postulate that p_t^o follows an autoregressive process with a stochastic volatility shock:

$$\ln p_t^o = (1-\rho_p)\ln \bar{p}^o + \rho_p \ln p_{t-1} + \sigma_{p,t-1}\varepsilon_{p,t},\ 0<\rho_p<1,\ \varepsilon_{p,t}\sim \mathbb{N}(0,1),$$
$$\ln \sigma_{p,t} = (1-\rho_{sv})\ln \bar{\sigma}_p + \rho_{sv}\ln \sigma_{p,t-1} + \sigma_{sv}\varepsilon_{sv,t},\ 0<\rho_{sv}<1,\ \varepsilon_{sv,t}\sim \mathbb{N}(0,1),$$

where $\varepsilon_{sv,t}$ affects the variance of the oil price and hence uncertainty about the price of oil.

In the production sector, there is a continuum of capital goods characterized by oil intensity v. Firms produce output using capital, oil, and labor inputs. Since different capital goods require a fixed oil intensity, existing capital goods use oil in the fixed proportion $1/v$. Thus, there is no substitutability between capital and oil in the short run. However, firms are able to invest in capital with a different energy intensity. Given the infinite number of capital goods, the model is intractable. However, if all types of existing capital are fully utilized, the state space can be represented by two aggregate state variables and each period there is positive investment in at most one type of capital with energy intensity v_t. Assuming this condition is satisfied and the production function is Cobb-Douglas in capital and oil, the firm's optimization problem can be written as

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

subject to

$$y_t = (a_t n_t)^{1-\xi} k_{s,t-1}^{\xi},$$
$$k_{s,t} = (1-\delta)k_{s,t-1} + i_t v_t^{\phi-1},$$
$$o_t = (1-\delta)o_{t-1} + i_t/v_t,$$

where n_t is labor that receives real wage rate w_t, i_t is physical investment, $k_{s,t}$ is aggregate capital services that depreciate at rate δ, o_t is aggregate oil use, y_t is aggregate output, ϕ is the cost share of oil, and ξ is the cost share of capital services. Labor productivity, a_t, evolves according to

$$\ln a_t = (1-\rho_a)\ln \bar{a} + \rho_a \ln a_{t-1} + \sigma_{a,t-1}\varepsilon_{a,t},\ 0<\rho_a<1,\ \varepsilon_{a,t}\sim \mathbb{N}(0,1).$$

The firm's optimality conditions imply

$$w_t = (1-\xi)y_t/n_t,$$
$$\lambda_{k,t} = E_t[x_{t+1}(r_{t+1}^k + (1-\delta)\lambda_{k,t+1})],$$
$$\lambda_{o,t} = E_t[x_{t+1}(-p_{t+1}^o + (1-\delta)\lambda_{o,t+1})],$$

where $\lambda_{k,t} = v_t^{1-\phi}/\phi$, $\lambda_{o,t} = (\phi-1)v_t/\phi$, and $r_t^k = \xi y_t/k_{s,t-1}$.

The household's problem is unchanged from the paper. However, following Atkeson and Kehoe (1999), there is no labor productivity growth and no oil storage, so the resource constraint becomes

$$c_t + i_t = y_t - p_t^o o_{t-1}.$$

We compare the Atkeson-Kehoe (AK) putty-clay model to a model that replaces the putty-clay technology by a CES production function that aggregates capital and oil as in our baseline model. In particular, the firm's optimization problem in this CES model is given by

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

subject to

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

where σ is the elasticity of substitution between capital and oil. The optimality conditions imply

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

where

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

Calibration Table 1 summarizes the parameter values used for both the AK and CES models. Table 2 compares the data and simulated moments. In the AK model, we set $\phi = 0.89$ to match the oil expenditure share in the data. In the CES model, $\sigma \in \{0.1, 0.2, 0.3\}$. For each σ, we set the investment adjustment cost parameter, ν, to achieve the same standard deviation of investment. The moments are almost identical across the four model specifications, providing a credible framework to compare responses to oil price uncertainty shocks.

Results Figure 8 shows responses to a 2 standard deviation oil price uncertainty shock. The less substitutable capital and oil are, the better the responses from the CES model approximate those from the AK model. In particular, for $\sigma = 0.1$, which corresponds to the value in our baseline model, the responses are close. This indicates that our model captures the mechanisms in Bernanke (1983) and Atkeson and Kehoe (1999), while remaining tractable in general equilibrium even when the oil price is endogenous.

Table 1: Common model parameters

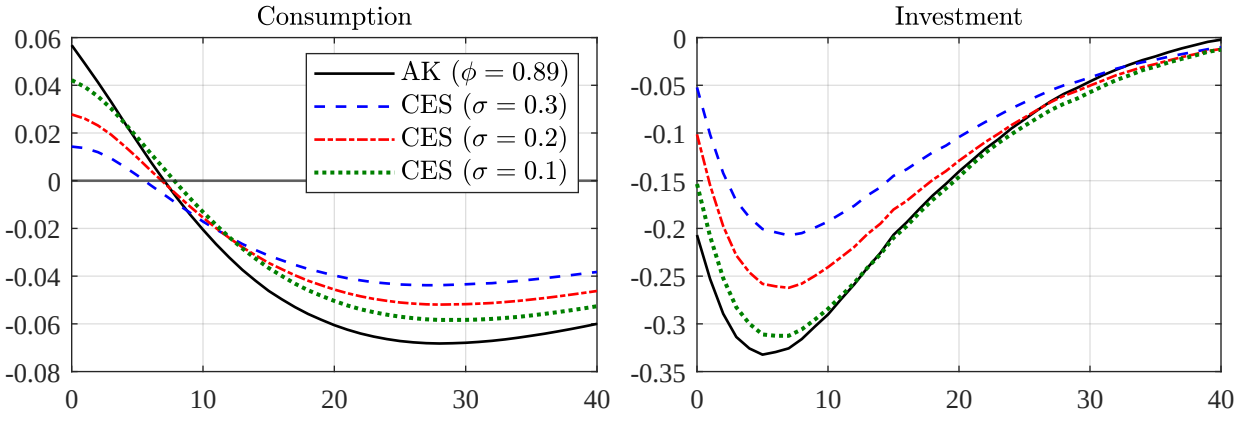
Parameter	Value	Target
Discount Factor (β)	0.997	$E(r)$
Risk Aversion (γ)	10	Gao et al. (2022), Croce (2014)
Intertemporal Elasticity of Substitution (ψ)	2	Gao et al. (2022), Croce (2014)
Frisch Labor Supply Elasticity (η^{λ})	2	Peterman (2016), Basu-Bundick (2017)
Capital Depreciation Rate (δ)	0.025	Depreciation on fixed assets, durables
Capital Services Share of Production (ξ)	0.4	Avg. labor share of income
Technology Persistence (ρ_a)	0.9	$AC(\tilde{y})$
Technology Shock SD (σ_a)	0.012	$SD(\tilde{y})$
Oil Price Persistence (ρ_{p^o})	0.9	$AC(\tilde{p}^o)$
Oil Price Shock SD (σ_{p^o})	0.13	$SD(\tilde{p}^o)$
Oil price volatility shock persistence (ρ_{sv})	0.95	$AC(\mathcal{U}_{p^o})$
Oil price volatility shock SD (σ_{sv})	0.115	$SD(\mathcal{U}_{p^o})$

Table 2: Data and simulated moments

		AK	CES		
Moment	Data	$\phi = 0.89$	$\sigma = 0.30$	$\sigma = 0.20$	$\sigma = 0.10$
$E(p^o o/y)$	0.043	0.043	0.043	0.043	0.043
$SD(\tilde{y})$	2.9	2.6	2.8	2.7	2.6
$SD(\tilde{i})$	8.7	9.0	8.9	8.9	8.9
$SD(\tilde{p}^o)$	38.1	31.4	31.4	31.4	31.4
$SD(\mathcal{U}_{p^o})$	29.5	29.6	29.6	29.6	29.6
$AC(\tilde{y})$	0.90	0.90	0.90	0.90	0.90
$AC(\tilde{p}^o)$	0.88	0.87	0.87	0.87	0.87
$AC(\mathcal{U}_{p^o})$	0.92	0.92	0.92	0.92	0.92

Notes: A tilde denotes a variable that was detrended in the data using a Hamilton (2018) filter with 4 lags and a delay of 8 quarters. $SD(\mathcal{U}_{p^o})$ is normalized by $SD(\Delta p^o)$. Standard deviations are percents. The data sample begins in 1980Q1 instead of 1975Q1 due to lost observations from detrending the data.

Figure 8: Responses to an oil price uncertainty shock



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