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Mirela Miescu, Haroon Mumtaz and Konstantinos Theodoridis

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Cardiff Business School Cardiff University Colum Drive Cardiff CF10 3EU United Kingdom t: +44 (0)29 2087 4000 f: +44 (0)29 2087 4419 business.cardiff.ac.uk

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Non-linear dynamics of oil supply news shocks^{*}

Mirela Miescu[†] H

Haroon Mumtaz[‡] Konstantinos Theodoridis[§]

September 4, 2024

Abstract

This paper employs Threshold (T)VAR models to investigate the asymmetric impact of oil supply news shocks, analysing variations in both the size and direction of the shocks. Our findings reveal that large and adverse oil shocks exert a stronger effect on real activity, labour market indicators, and risk variables compared to small and favourable shocks. Interestingly, we observe no asymmetry in the response of prices and monetary policy to oil shocks of different magnitudes and signs. Using a theoretical nonlinear model and predictive prior analysis, we demonstrate that search and matching labour frictions cause the risk of becoming unemployed to increase after an oil shock. This rise in unemployment risk triggers strong precautionary savings motives, which increase with the size of the shock, leading to asymmetric responses in real economic and labour market variables, whereas price indicators and the policy rate do not exhibit such nonlinearities consistently with the empirical findings.

1 Introduction

Oil price fluctuations are often large and unpredictable, marked by sudden rises and falls. Given the global nature of oil trading, these disruptions impact numerous sectors of the economy across different nations, making them crucial for scholars, policymakers, and industry stakeholders worldwide. In recent decades, major economic shocks like the 2008-2009 recession and the COVID-19 pandemic, coupled with frequent significant fluctuations in oil prices, have attracted considerable attention towards the impacts of large macroeconomic shocks. During a speech at the Money Marketeers of New York University in July 2023, Christofer J. Waller contended that "Big shocks travel fast," suggesting that they instigate changes in economic behaviour not typically associated with smaller shocks. Consequently, an ongoing debate exists regarding whether the magnitude (large versus small) and direction (increases versus decreases in oil price) of oil fluctuations propagate differently throughout the economy. This emphasizes the critical need to address this research gap.

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[†]Lancaster University. email: m.miescu@lancaster.ac.uk

[‡]Queen Mary University of London. email: h.mumtaz@qmul.ac.uk

[§]European Stability Mechanism and Cardiff Business School. email: k.theodoridis@esm.europa.eu

In this paper, we show that the size and direction of oil supply news shocks are important factors that affect real activity, labour markets, and risk premiums in the U.S. By using Threshold (T)VAR models designed to address the asymmetries resulting from shocks of different sizes (size asymmetry) and signs (sign asymmetry), we provide novel insights into the non-linear dynamics of oil supply news shocks in the U.S. Our empirical results are reinforced by a theoretical framework that combines search and matching frictions with Epstein-Zin preferences and mechanisms that give rise to "concerns" of the oil the shock having a long-lasting effects on productivity (i.e. the probability of a rare disaster becomes a function of the size of the shock).

We find that big oil shocks, which increase oil prices by 50%, exert a stronger effect on real economic activity compared to smaller shocks (which lead to a 10% increase in oil prices). Additionally, adverse shocks that increase oil prices have a more contractionary effect than shocks causing oil price drops. Interestingly, our findings do not uncover evidence of size and sign asymmetry in the response of financial conditions, prices and monetary policy to oil supply shocks. This result initially appears surprising, given the existing literature suggesting a recessionary effect of oil shocks stemming from the endogenous response of monetary policy to the inflation induced by the shock (Bernanke et al., 1997, Leduc and Sill, 2004, Bodenstein et al., 2011 and Miyamoto et al., 2024). In other words, conventional wisdom would suggest that the asymmetries in economic activity result from a larger increase in the policy rate due to higher inflation pressure induced by a larger oil shock.

Conversely, we find significant sign and size asymmetry in the impact of oil shocks on labour market indicators and risk measures. The unemployment rate displays a more substantial increase after large shocks compared to smaller ones. Similarly, adverse oil shocks leading to price increases have a more detrimental effect on unemployment rates than those causing price decreases. Job vacancies decrease more in response to large adverse shocks, while the probability of finding a job shows stronger non-linearities in response to large shocks but is less affected by small shocks, regardless of their sign. A positive correlation between unemployment and job separation following oil shocks is observed, with stronger effects noted for large adverse shocks compared to small favourable shocks.

Finally, risk indicators increase more following large and adverse oil shocks, aligning with studies emphasizing the importance of time-varying risk premia for generating significant fluctuations in aggregate quantities and labour market dynamics (Basu et al., 2021, Kehoe et al., 2023 Meeuwis et al., 2023). Several sensitivity checks demonstrate the robustness of the results across various dimensions, including the use of an alternative instrumental variable, model specification, and extending the sample period to include the Covid-19 period.

This paper brings three main contributions to the literature. First, we introduce a novel algorithm designed to estimate a Bayesian TVAR model, employing instrumental variables for identification purposes. This model offers a comprehensive framework for elucidating various forms of asymmetries. These include sign asymmetry, which addresses the differential impact of shocks with distinct signs, such as those influencing oil prices positively versus negatively; size asymmetry, which accounts for variations in the effects of shocks of differing magnitudes; and state-dependency, reflecting shifts in shock effects under different economic conditions, such as different oil price regimes. Moreover, our model incorporates state-of-the-art techniques for identifying oil shocks using instrumental variables. Specifically, we detect oil supply shocks by employing the instrumental variable developed by Känzig (2021), which exploits high-frequency fluctuations in oil price futures around OPEC announcements to pinpoint exogenous changes in oil supply. Lastly, the preference for the TVAR model over alternative models is justified for two additional reasons. Firstly, it avoids the use of censored data for analyzing sign and/or size asymmetry, a practice shown to yield invalid estimates by Kilian and Vigfusson (2011a). Second, the TVAR model circumvents the critique put forth by Gonçalves et al. (2022), who demonstrate that in cases where the state of the economy is endogenous, the local projections' estimator of the response function tends to be asymptotically biased, except for the impact response.

The paper's second contribution involves presenting original evidence regarding the effects of oil shocks of varying magnitudes and signs. To our knowledge, this study is the first to examine the asymmetry in the transmission of oil shocks of different sizes. This addresses a significant gap in the literature, particularly given the growing interest among researchers and policymakers in understanding the role of shock size in the propagation mechanism of economic disturbances, as highlighted in Waller (2023) and Cavallo et al. (2023). Regarding sign asymmetry, there exists a longstanding tradition of analyzing the differing impact of oil price increases versus decreases, initiated by Hamilton (1983) and Mork (1989). However, this topic is still highly debated, as evidenced by studies like Hamilton (2011b) and Kilian and Vigfusson (2011a), and the empirical support for this mechanism remains unclear, calling for additional evidence.

The third contribution of this paper is the theoretical model and the application of predictive prior analysis to identify the structural features that explain the observed patterns of nonlinearities in the data. We develop a New Keynesian (NK), Dynamic Stochastic General Equilibrium (DSGE) model incorporating search and matching frictions (endogenous job separation), recursive (Epstein-Zin) preferences, limited information on the persistence of oil disturbances, and a rare disaster mechanism where the probability of a rare disaster is a function of the oil shock's size. The lack of nonlinearities in the price and external finance cost indicators complicates the ex-ante selection of a suitable model consistent with these stylized facts. Consequently, we developed a comprehensive structural model and used predictive prior analysis to isolate the mechanisms that could explain the empirical findings.

Our analysis indicates that search and matching (SaM) frictions and real wage rigidity are critical for our structural model to replicate the nonlinearities observed in the data. This finding, consistent with the works of Petrosky-Nadeau and Zhang (2017), Petrosky-Nadeau et al. (2018), Mumtaz and Theodoridis (2020a), Pizzinelli et al. (2020) and Bernstein et al. (2024), underscores the importance of real labour market frictions in generating substantial nonlinear data dynamics. The model demonstrates that precautionary savings are the driving force behind these observed nonlinearities. As Bernstein et al. (2024) and Bernstein et al. (2024) explain, SaM frictions create employment risk, which escalates with the number of job seekers, particularly after an adverse oil supply shock. This risk is further compounded by endogenous separation (Gnocato, 2024) and firing costs, as firms are less inclined to post new jobs due to the costs associated with the incomplete adjustment of the real wage to the fall in productivity, leading to fewer vacancies and increased job competition. In response to these risks, employed individuals increase their desire to save, and we demonstrate that the magnitude of the oil shock directly correlates with the intensity of this desire. The absence of instruments for transferring consumption across time results in lower

real interest rates needed to mitigate precautionary motives. In our analysis, we leverage the difference between the responses of the probability of becoming unemployed, consumption, and real interest rates to large and small oil shocks to gauge the degree of precautionary savings.

Two additional factors further strengthen the nonlinearities induced by SaM friction: the complementarity between oil imports and the value-added used to produce the final output and monetary policy actions. As explained by Gagliardone and Gertler (2023) and Lorenzoni and Werning (2023), low elasticity substitution enhances the sensitivity of inflation responses to oil shocks and, consequently, to the policy rate. Furthermore, inertia in the Taylor Rule and the ability of the monetary authority to deviate unexpectedly from its reaction function make an adverse oil shock extremely costly following an unanticipated policy tightening, which is further endogenised by agents when they decide about the degree of hedging needed to ensure themselves from these risks.

Section 2 relates our study to the existing literature and highlights our contributions. Section 3 reviews the empirical model employed in this study and provides information regarding the estimation of the model and the identification of the oil news shock. Section 4 presents the empirical results, while Section 5 reviews the DSGE model and discusses the simulation results. Finally, Section 6 concludes.

2 Relation to the literature.

From an empirical perspective, we link to the literature that examines the asymmetric impacts of shocks of varying sign and magnitude. Studies such as Barnichon et al. (2022), Forni et al. (2024), and Mumtaz and Piffer (2022) focus on financial shocks, while Barnichon and Matthes (2018), Angrist et al. (2018), and Debortoli et al. (2020) investigate monetary policy shocks. Additionally, Barnichon et al. (2022) study fiscal shocks, De Santis and Tornese (2023) analyze energy shocks in the Euro area, and Fasani et al. (2024) explore inflation target shocks. Like our study, these papers provide evidence supporting the presence of size and sign asymmetry in the transmission of macroeconomic shocks.

Of particular relevance to our research are contributions investigating non-linearities, especially sign asymmetries, in the transmission of oil shocks. Hamilton (2003) proposes a flexible approach to characterise the nonlinear relation between oil price changes and GDP growth, while Balke et al. (2002) and Hamilton (2011b) use US data to support the sign asymmetry of oil shocks. Conversely, Kilian and Vigfusson (2011b), Herrera and Karaki (2015), Kilian and Vigfusson (2017) argue against the presence of such non-linearities. Additionally, Herrera et al. (2011) and Herrera et al. (2015) provide further support for a linear relationship between aggregate activity and oil price shocks in the US and OECD countries. We contribute to this literature by offering novel empirical support to the existence of both size and sign asymmetry in the transmission of oil shocks. To that end, we employ state-of-the-art empirical models and identification strategies that address criticisms raised about previous results (see Kilian and Vigfusson, 2011a and Gonçalves et al., 2022).

Closer to our analysis, Forni et al. (2023) brings evidence in favour of sign asymmetry in the effects of oil supply news shocks in the U.S. They use a non-linear Proxy VAR identified with the instrumental variable proposed by Känzig (2021), similar to our identification approach. However, our study diverges by employing a different empirical model that accommodates the size asymmetry of shocks and state

dependency in the results. Additionally, we extend the analysis by exploring the effects of oil shocks on a large number of variables, which helps us refine the non-linear transmission mechanism of oil shocks and incorporate asymmetries observed in labour market dynamics and risk premia. Importantly, we provide a theoretical framework to support our empirical findings.

From a theoretical perspective, our study is related to the literature that uses DSGE models to understand the transmission of oil supply shocks to the economy and the contribution of the monetary policy shaping these dynamics (Blanchard and Gali (2007), Leduc and Sill, 2004, Bjørnland et al., 2018 and Gagliardone and Gertler (2023) among others). Our work differentiates from this literature along two (not necessarily mutually exclusive) dimensions; we focus on the nonlinear transmission of the oil new shocks and identify how the contribution of precautionary saving motives, which are absent in the above studies, shape agents' responses.

We contribute to the literature which illustrates that DSGE models augmented with SaM frictions are capable of producing highly nonlinear dynamics (Petrosky-Nadeau and Zhang (2017), Petrosky-Nadeau et al. (2018), Mumtaz and Theodoridis (2020a), Pizzinelli et al. (2020) and Bernstein et al. (2024) among others) and, consequently, push the criticism rose after the Great Financial Crisis that structural models are incapable of producing events such as the Great Recession.

Our work relates to the literature that augments a textbook SaM DSGE model with mechanisms that give rise to time-varying risk premium to avoid being subject to Shimer (2005) criticism (Hall (2017), Kilic and Wachter (2018), Kehoe et al. (2023), and Meeuwis et al. (2023) among others). The model developed in this paper builds on this literature and, consequently, successfully replicates the (conditional) correlation among unemployment, vacancies and job-finding rates. Similarly, we also contribute to the research field that explains how nonlinear structural models with homoskedastic shocks can generate time-varying higher moments (see Mumtaz and Theodoridis (2020a) and Cacciatore and Ravenna (2021) among others).

Finally, our study also relates to the Heterogenous Agents (HA) models literature, where unemployment fears within an imperfect insurance environment trigger substantial precautionary saving motives, which are (mostly) absent from the Representative Agent (RA) models and could make adverse economic outcome severely worse than predicted by the RA models (see Ravn and Sterk (2017), Den Haan et al. (2018), Challe (2020), Ravn and Sterk (2021) and Gnocato (2024) among others).

3 Empirical Model

Our empirical model is a Bayesian Threshold Proxy VAR that extends the proxy BVAR proposed in Caldara and Herbst (2019). We consider the following VAR (P) model:

$$Y_{t} = \sum_{j=1}^{M} (B_{j}X_{t}) \mathcal{I} (S_{t} = j) + u_{t}$$
(1)

where Y_t is a $N \times 1$ vector of endogenous variables, $X_t = [Y'_{t-1}, ..., Y'_{t-P}, 1]'$ is $(NP+1) \times 1$ vector of lagged regressors in each equation and $B_j, j = 1, ...M$ denotes the $N \times (NP+1)$ matrix of coefficients $B_j = [B_{1,j}, ..., B_{P,j}, c_j]$. The baseline empirical specification includes six variables: the real price of oil, world oil production, world oil inventories, world industrial production, US industrial production, and the US consumer price index (CPI). The error covariance of the VAR model is given by:

$$var(u_t) = \Sigma_t = \sum_{j=1}^M \mathcal{I}(S_t = j) \odot \Sigma_j$$
(2)

3.1 Regime Switching

The indicator variable $\mathcal{I}(S_t = j)$ equals 1 when regime j is active. As described below, the model that fits the data best features three regimes which are defined as:

$$S_t = 1 \iff \tilde{o}_{t-d} \le o^* \tag{3}$$

$$S_t = 2 \Longleftrightarrow o^{**} \ge \tilde{o}_{t-d} > o^* \tag{4}$$

$$S_t = 3 \Longleftrightarrow \tilde{o}_{t-d} > o^{**} \tag{5}$$

The threshold variable \tilde{o}_t is the annual growth in real oil price o_t . This choice is partly motivated by earlier studies that emphasise the importance of increases in the oil price relative to previous highs (see for e.g. Hamilton, 1996). The structure in equations 3 to 5 implies that the dynamic relationship between the oil market and the economy is allowed to change if the difference in o_t relative to its past exceeds unknown threshold values. Regime 1 represents a state where oil price inflation is low, while the intermediate regime (regime 2) is defined so that oil inflation lies between the two thresholds o^* and o^{**} . Regime 3 is a state characterised by larger oil inflation values. Note that this model allows for regime-dependent dynamics and features non-linearities associated with size and signs of shocks. For example, large shocks that push the system from Regime 1 to Regime 2 or 3 can have different effects from shocks where the dynamics of Regime 1 apply. The importance of the magnitude of changes in the oil price is also implied by the DSGE model described in Section 5 below. Note also that the lag or delay in the threshold variable d_i is treated as an unknown parameter and is allowed to take on values $d_i = 1, 2, ..., 6$.

3.2 Identification and Generalized Impulse Responses

The time-varying covariance matrix of the reduced form residuals u_t can be written as:

$$\Sigma_t = (A_t q) \left(A_t q \right)' \tag{6}$$

where A_t is a lower triangular matrix with time-varying elements and q is a column of the family of orthogonal matrices of size N, satisfying $q'q = I_N$. By considering all possible values of q, the matrix A_tq spans the space of all possible contemporaneous matrices. The structural shocks of the VAR model ε_t are defined as

$$\varepsilon_t = A_{0,t}^{-1} u_t,\tag{7}$$

where $A_{0,t} = A_t q$. Following Känzig (2021), we identify an oil supply news shock. Without loss of generality, we assume that this is the first shock ε_{1t} in the $N \times 1$ vector of shocks $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{.t}]$, where $\varepsilon_{.t}$ contains the remaining N - 1 elements in ε_t . To do this, we employ an instrument m_t described by the

following equation:

$$m_t = \beta \varepsilon_{1t} + \sigma v_t, \quad v_t \sim \mathcal{N}(0, 1) \tag{8}$$

where $\mathbb{E}(v_t \varepsilon_t) = 0$. The instrument is assumed to be relevant ($\beta \neq 0$) and orthogonal to other structural shocks ($\mathbb{E}(m_t \varepsilon_t) = 0$). In our benchmark model, we employ the instrument constructed by Känzig (2021), which is based on variations in oil futures prices around OPEC announcements. The relevance of the instrument can be empirically evaluated by calculating the reliability statistic of Mertens and Ravn (2013) which is defined as the squared correlation between m_t and ε_{1t} :

$$\rho^2 = \frac{\beta^2}{\beta^2 + \sigma^2}.\tag{9}$$

It is clear from Equation 8 that the relevance of the instrument is assumed to be fixed over time. This is a convenient feature of the model because it implies that shifts in relevance do not drive changes in the impulse response functions across regimes but reflect changes in the dynamic relationship between the endogenous variables included in the model.

As for the impulse responses, when considering non-linear models, the appropriate measures to use are the generalized impulse response functions (GIRF), as described by equation 10 (see Koop et al., 1996). In a non-linear model, the GIRFs cannot usually be expressed in a closed form. Instead, their effects depend on the size and sign of the shock, as well as the historical context, requiring the use of simulation methods.

$$GIRF_{ij}^{S}(k,\Psi_{t},e_{j},Y_{t-1}^{S}) = E(Y_{i,t+k} \mid \Psi_{t},Y_{t-1}^{S},e_{j}^{S} = A_{0}^{-1}u^{S}) - E(Y_{i,t+k} \mid \Psi_{t},Y_{t-1}^{S})$$
(10)

where Ψ_t denotes all the parameters and hyper-parameters of the model, k is the forecasting horizon under consideration, S = 1, 2, 3 denotes the regime. Equation (10) characterizes the GIRF as the difference between two conditional expectations, one in which we condition on the structural shock e_j , and one in which we assume the shock to be equal to zero.

3.3 Estimation and model specification

The model is estimated using Bayesian methods. The appendix provides details on the Gibbs sampling algorithm. The algorithm exploits the fact that conditional on the value of the thresholds o^* and o^{**} , the model collapses to a sequence of Bayesian Proxy SVARs. The conditional posterior distributions of Bayesian Proxy SVARs have already been derived by Caldara and Herbst (2019), and their algorithm can be applied to the regime-specific models. The thresholds are sampled from their conditional posteriors using a Metropolis Hasting step.¹

We select the type and number of regimes using predictive density (see Geweke and Amisano, 2010). Let $M = M_0$ denote the benchmark model, a fixed coefficient BVAR. We consider three alternative models (denoted by M_1): a threshold BVAR with two oil price regimes, a threshold BVAR with three oil price regimes, and a threshold BVAR with three boom-bust regimes.²

¹The algorithm is also related to the one used by Mumtaz and Petrova (2018) for time-varying proxy VARS

²The boom-bust regimes are computed using the US Industrial production as the threshold variable.

For each model $M = M_0, M_1$ we compute:

$$\log p(Z_T | Z_S, M) = \sum_{t=S+1}^{T-h} \log p(Z_{t+h} | Z_t)$$
(11)

where $\log p(Z_{t+h}|Z_t)$ denotes the predictive likelihood of a variable of interest, h = 3 is the horizon of the forecast and t = S + 1, ..., T - h is the evaluation period for S < T. The models are first estimated using the training sample 1974m1-2003m12. The posterior predictive density of the growth of US industrial production and CPI is constructed for a horizon of 3 months and the predictive likelihood is evaluated.³ The estimation sample is then moved forward by one month, and the posterior distribution of the model parameters and the forecast is re-estimated. This recursion continues until the end of the effective sample in 2017.

Figure A3.1 illustrates the cumulative difference in the predictive likelihoods between the three regimeswitching models in M_1 and the linear VAR model M_0 over the evaluation sample. Several noteworthy observations emerge from this figure. Firstly, it is evident that regime-switching models incorporating oil price regimes outperform the fixed coefficient alternative across all three variables. Secondly, the model with three oil price regimes (represented by the solid black line) exhibits superior performance in terms of industrial production and CPI compared to the model with two oil price regimes (represented by the dashed red line). Consequently, the three oil price regimes model is preferred as the benchmark over the two regimes model. Furthermore, when comparing the three oil price regimes model to other regime types, such as boom-bust regimes (represented by the dashed blue line), the oil price regimes is selected as the both US IP and CPI. Thus, the regime-switching model with three oil price regimes is selected as the baseline. However, the appendix demonstrates that the results from the two regimes model are similar to the benchmark case.

3.4 Data

The empirical specification utilized in this study is based on the framework established by Känzig (2021) and consists of six variables: the real price of oil, global oil production, global oil inventories, global industrial production, US industrial production, and the US consumer price index (CPI).

In order to obtain a more comprehensive understanding of the non-linear relationship between oil supply news shocks and the overall macroeconomy, we investigate the impact of these shocks on various additional variables. These include labour market indicators, housing prices, risk measures, productivity, prices, and short and long-term interest rates. Additionally, we construct a composite risk premia index by principal component analysis using several risk measure indicators available for our sample. These indicators include the 10-year term premium, U.S. Consumer Confidence Index, Macroeconomic Skewness, Excess Bond Premium (EBP), the GZ Spread, Recession Risk Index, and the Macroeconomic Uncertainty Index by Jurado et al. (2015) (JLN). A detailed explanation of these variables, their transformations, and their respective sources can be found in Table A3.1. We introduce one additional variable at a time to the baseline VAR model to generate impulse responses for the expanded model.

³We use a nonparametric kernel density to evaluate $p(Z_{t+h}|Z_t)$.

The variables are at a monthly frequency and cover the sample from January 1974 to December 2017. The sample excludes the Covid-19 period, which might cause parameter instability, but we show the robustness of our results to extend the sample to May 2023. We use a shorter sample for identification from April 1983 to December 2017 due to the instrument availability. The motivation for using a longer sample for estimation is to get more precise estimates of the reduced-form coefficients. The VAR is estimated in log levels, and the lag length is set at 12.

4 Results

Our findings are presented in four subsections. The first subsection introduces the oil price regimes that have been identified using the TVAR model. In the second subsection, we provide evidence supporting the presence of non-linearities in the transmission of oil supply shocks. This is demonstrated by two key observations: (i) the effects of oil supply shocks vary depending on the regime, with stronger effects observed during periods of high oil prices, and (ii) larger magnitude shocks and positive shocks (i.e., shocks that lead to an increase in oil prices) result in more pronounced effects.

In the third subsection, we further enhance our understanding of the non-linear characteristics of oil shocks by examining a broader range of variables. These encompass labour market indicators, risk measures, productivity, short and long-term yields, stock prices, and house prices. Lastly, we assess the robustness of our results across various dimensions in the final subsection.

4.1 Oil price regimes

As outlined in Section 3.1, the TVAR model identifies three distinct oil price regimes, which are visually represented in Figure A4.1. These regimes are determined based on the threshold variable, specifically the year-on-year growth in real oil price at time t - d. The purple bands indicate periods when oil price inflation remains below the threshold level o^* , referred to as the low oil price regime. Regime 2 represents an intermediate state characterized by oil price inflation between the thresholds o^* and o^{**} . Finally, the red bands indicate the high oil price regime, where the change in oil price relative to its past surpasses the high threshold level o^{**} .

The median estimates for the two threshold levels (o^* and o^{**}) are -2.9% and 20.3%, respectively. The delay parameter (d) has a median estimate of one month, suggesting that the economy transitions into the high oil price regime immediately after breaching the threshold. These oil price regimes identified by the empirical model align with significant historical oil events documented in the literature (Hamilton, 2011a, Kilian and Murphy, 2014, and Baumeister and Kilian, 2016).

Specifically, for the high oil price regime, we highlight (i) the OPEC crisis in 1979-1980, which resulted in a substantial oil price surge; (ii) the sharp increase in oil prices during the Persian Gulf War in the early 1990s; (iii) two episodes of a significant oil price surge, one in 2002-2003 due to the Iraq war and civil unrest in Venezuela, followed by another from 2003-2008 associated with global economic expansion; and (iv) the Libyan crisis in 2011, which led to an increase in oil prices.

The low oil price regime is characterized by: (v) a sustained decline in oil prices in the early 1980s

attributed to Volcker's contractionary monetary policy and the subsequent recession that reduced oil demand and prices; (vi) a historically low oil price period caused by the Asian financial crisis; and (vii) a decline in oil prices during the Global Financial Crisis due to a contraction in demand for industrial commodities.

The intermediate regime, indicating moderation in oil prices, is observed between the two OPEC crises in the 1970s, between the Global Financial Crisis and the 2015 decline in oil prices, and as a transitional period between the low and high price regimes.

4.2 Baseline model results

In this section, we report the non-linearities observed in the transmission of oil supply news shocks by reporting the Generalized impulse responses.

Regime dependence. We commence our investigation by examining regime-dependent impulse responses. Although these responses are not the primary focus of our analysis, it is important to highlight and explain them. This is because the size and sign asymmetry, which constitute the central focus of the paper, are influenced by the shock's ability to transition the economy between different regimes. Consequently, if there were no regime dependency, neither size nor sign asymmetry would manifest.

Figure A4.2 illustrates the impulse responses of variables in the baseline model to a 10% increase in the oil price index attributed to an oil supply news shock. It presents the median responses for low (black line), moderate (blue line), and high (red line) oil price regimes alongside 68% confidence bands. The observed responses align qualitatively with findings from Känzig (2021), indicating a decrease in global oil production, increased oil inventories, and reduced global industrial production. Notably, the moderate and high oil price regimes experience more significant contractions in oil production and global and U.S. output compared to the low regime. The shock induces higher inflationary pressures in the U.S. within the moderate oil price regime compared to the low and high one, suggesting that the pass-through from oil shocks to prices is stronger if the shocks occur in times of relatively stable oil prices.

Figure A4.3 illustrates statistically significant differences in responses across the three states for oil production, oil inventories, and global and US output, supporting the hypothesis of a non-linear transmission mechanism of oil supply shocks. Surprisingly, price reactions are statistically significant only when comparing the moderate oil price regime to the low one.

Size and sign asymmetry. Next, we explore the impact of the size and sign of the shock as sources of non-linearity. We aim to determine whether large oil shocks, which lead to an increase in the oil prices by 50%, lead to different economic consequences compared to smaller ones, which result in a 10% price hike.⁴ Additionally, we investigate whether there is an asymmetry in the transmission of adverse (positive) oil shocks, raising oil prices by 10%, compared to their negative counterparts, which decrease oil prices by the same amount.

 $^{^{4}}$ We opt to calibrate the size of the large shock to 50% since, as illustrated in Figure A4.1, fluctuations in oil price growth exceeding 50% are relatively common, accounting for approximately 13% of all occurrences.

Figure 1 compares the responses to large shocks (blue line) versus small shocks (red line) in the first column and positive shocks (green line) versus negative shocks (red line) in the second column for the baseline model. For ease of comparison, all shocks are normalized to increase the real price of oil by 10%. The results suggest that larger oil shocks have more pronounced recessionary effects compared to smaller shocks. Similarly, adverse shocks that increase oil prices lead to recessionary effects of a stronger magnitude compared to shocks decreasing oil prices.

Interestingly, the response of prices to oil supply shocks does not seem to be significantly influenced by the sign and magnitude of the shock. This observation is further supported when examining the posterior difference of the impulse responses between Large minus Small shocks (third column) and Positive minus Negative shocks (fourth column), revealing significant non-linearities in the reaction of output to oil supply shocks but not in the response of prices. This observation differs somewhat from the conclusions of Forni et al. (2023), De Santis and Tornese (2023), and Cavallo et al. (2023), who indicate that prices may be influenced by the size and/or sign of supply-side shocks. However, it's important to acknowledge that these studies utilize different empirical models, analyze different types of shocks and countries, or employ different samples and data.

4.3 Oil shocks non-linearities and the U.S. economy

This section aims to identify the strategic variables responsible for the non-linear transmission of oil supply news shocks to the U.S. real activity. We examine the existence of size and sign asymmetries in the transmission of oil supply news shocks to a large set of variables, including nominal indicators, labour market metrics, risk factors, stock prices, house prices, and total factor productivity (TFP). We find the significant size and sign asymmetries in the labour market and risk variables, while no such patterns are evident in the other sectors analyzed.

Nominal indicators. Asymmetric responses of prices to supply-side shocks of varying magnitudes and signs can trigger asymmetric reactions in output. This can occur through a more aggressive response of monetary policy to large and adverse oil price shocks, which drive price increases, compared to small shocks or shocks that decrease prices. To ensure this channel's relevance is not omitted in our analysis, we examine several additional nominal variables, including the Producer Price Index (PPI), Personal Consumption Expenditure (PCE) price index, inflation expectations, short- and long-run interest rates, and Nominal Exchange Rates (NEER). Results depicted in Figure A4.5 confirm that the asymmetries observed in the real economy do not stem from a greater increase in the policy rate, as one might anticipate if prices surged significantly following a major oil shock.

Labor market dynamics and risk indicators. We will now examine the presence of asymmetries within our primary variables of interest, namely risk premium and labour market indicators. Our goal is to ascertain whether the observed non-linear patterns in real activity can be attributed to a mechanism combining the asymmetric reactions of risk and labour market indicators to oil shocks of varying signs and magnitudes.

Figure 2 examines the existence of size and sign asymmetry in labour market dynamics. It is evident that

unemployment demonstrates significant non-linear behaviour following oil shocks, with a more substantial increase observed in response to large shocks (first column, red line) compared to smaller ones (first column, blue line). Similarly, albeit to a slightly lesser extent, we observe asymmetry in response to shocks of different directions; adverse shocks that increase oil prices (second column, red line) have a more pronounced detrimental effect on the unemployment rate compared to those that decrease oil prices (second column, blue line).

Similarly, real wages appear to contract more after a large than a small oil shock, while sign-related nonlinearities materialise a year after the shock takes place, but they last significantly longer than those related to the size.

Furthermore, we find significant non-linearities in the responses of job vacancies and the probability of job finding to the oil shocks as well. Specifically, vacancies decrease more in response to large and adverse (positive) shocks. Conversely, the probability of finding a job displays stronger non-linearities in response to large shocks but is less affected by small shocks, regardless of their sign.

Finally, we document a positive correlation between unemployment and job separation following oil shocks, with stronger effects recorded for large and adverse shocks than small and favourable shocks.

We now explore whether the observed risk indicators display asymmetric responses to oil shocks. Before proceeding, it is crucial to clarify the interpretation of these indicators. In the next section, we demonstrate that external finance cost measures (for households, firms, and the government), which serve as proxies for financial frictions, do not exhibit significant (size or sign) non-linearities. Therefore, we consider these indicators as measures of uncertainty or asymmetry of risk regarding future outcomes. They influence consumption, investment and employment hiring decisions without causing a non-linear impact on the financial sector's functionality or arising from impaired capital markets.

Following the approach outlined by Meeuwis et al. (2023), we construct a composite risk premia index by combining existing risk measures (refer to Section A3.1 for details).

In Figure 3, we present the non-linearities detected in the composite risk measure, as well as in two additional risk indicators: Macroeconomic Skewness and the JLN Macro Uncertainty. The findings support the existence of both sign and size asymmetries in the response of risk premia to oil shocks. Consequently, the risk increases more significantly following large and adverse shocks compared to small shocks or favourable shocks that decrease oil prices.

In summary, our analysis reveals asymmetric reactions to oil shocks in both risk premia and labour market indicators. These findings imply that these channels may significantly contribute to the observed non-linearities in real economic activity.

4.4 Additional results and robustness checks

We provide additional evidence to dismiss the significance of other channels as primary contributors to the asymmetries observed in our analysis. Figure A4.6 demonstrates that Total Factor Productivity (TFP) and house prices have minimal influence on the asymmetric transmission of oil shocks to real economic activity. Furthermore, we investigate the response of Excess Bond Premium and stock prices to explore

the potential amplification mechanisms of oil shocks asymmetries through financial frictions. Additionally, we analyze the stock prices of the automotive sector to determine if there is a reallocation effect away from industries that heavily consume energy (e.g., motor vehicles) following an oil price increase, as suggested by Hamilton (1988) and Davis and Haltiwanger (2001). No sign and size asymmetry is detected in these variables either.

Furthermore, we also highlight the presence of asymmetries in additional labour market indicators. Specifically, Figure A4.4 illustrates that employment in full-time positions decreases more following large adverse oil shocks. Interestingly, a contrasting trend is observed in part-time employment, which sees an increase following adverse oil shocks, with larger magnitudes observed for both large and adverse shocks compared to small or favourable ones. This suggests a potential reallocation effect from full-time to part-time positions.

Real personal income displays (size and signs) nonlinearities to oil news shocks, a finding consistent with results about wages and labour market variables discussed earlier.

Finally, we assess the robustness of our results by (i) adopting an alternative identification for the shock using the oil supply shock identified by Baumeister and Hamilton (2019); (ii) extending the sample up to May 2023; (iii) using high reliability prior for the instrument; and (iv) using CPI inflation regimes instead of oil price regimes. Figure A4.7 demonstrates that the size and sign asymmetry detected in response to oil shocks of U.S. real activity, but not in prices, survives these additional checks.



Figure 1: Size and sign asymmetry in the baseline model variables to oil supply news shocks. Large vs. small (first column) and positive vs. negative (second column) oil supply news shocks are reported. Large shocks increase oil prices by 50%, while small shocks increase oil prices by 10%. For positive and negative shocks, small shocks are considered (10% shock size). The third and fourth columns display the distribution of the difference between impulse responses for Large minus Small and Positive minus Negative shocks, respectively. Solid lines represent medians, while shaded areas represent the corresponding 68 credibility sets. All responses are normalized to increase the real price of oil by 10% on impact. The IRFs are expressed in percent.



Figure 2: Size and sign asymmetry for selected labour market variables to oil supply news shocks. The additional variables are added to the baseline model one at a time. Large vs. small (first column) and positive vs. negative (second column) oil supply news shocks are reported. Large shocks increase oil prices by 50%, while small shocks increase oil prices by 10%. For positive and negative shocks, small shocks are considered (10% shock size). The third and fourth columns display the distribution of the difference between impulse responses for Large minus Small and Positive minus Negative shocks, respectively. Solid lines represent medians, while shaded areas represent the corresponding 68 credibility sets. All responses are normalized to increase the real price of oil by 10% on impact. The IRFs are expressed in percentage points except for wages which are in percent.



Figure 3: Size and sign asymmetry for selected risk variables to oil supply news shocks. The additional variables are added to the baseline model one at a time. Large vs. small (first column) and positive vs. negative (second column) oil supply news shocks are reported. Large shocks increase oil prices by 50%, while small shocks increase oil prices by 10%. For positive and negative shocks, small shocks are considered (10% shock size). The third and fourth columns display the distribution of the difference between impulse responses for Large minus Small and Positive minus Negative shocks, respectively. Solid lines represent medians, while shaded areas represent the corresponding 68 credibility sets. All responses are normalized to increase the real price of oil by 10% on impact. The IRFs are expressed in the following units: index units for PCA risk, Skewness index, and the JLN macro uncertainty index, while EBP is expressed in percentage points and Recession risk in percent.

5 DSGE Model Analysis

In this section, we review the model developed to help us understand the transmission mechanism of the stylised facts discussed in the previous section. Briefly, the model presented here can be viewed as an extension of the work by Blanchard and Gali (2007) allowing for: i) recursive preferences, ii) search & matching frictions, iii) "concerns" of permanent terms of trade deterioration that depend on the magnitude of the adverse news oil supply shock.

5.1 A Model with Epstein-Zin Preferences and Search & Matching Frictions

Households: The economy is populated by a continuum of households $(h \in [0, 1])$ that attain utility from consumption $\tilde{C}_t(h)$ and leisure $1 - L_t(h)$, where $L_t(h)$ denotes the fraction of the household that is employed. Household's preferences are separable

$$u\left(\tilde{C}_{t}(h),\tilde{Z}_{t},L_{t}(h)\right) = \frac{\left(\tilde{C}_{t}(h) - b\tilde{C}_{t-1}\right)^{1-\sigma_{C}}}{1-\sigma_{C}} - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}\frac{L_{t}(h)^{1+\sigma_{L}}}{1+\sigma_{L}}$$
(12)

where σ_L is the inverse of the Frisch elasticity, σ_C stands for the inverse of intertemporal elasticity of substitution and \tilde{Z}_t denotes the non-stationary productivity process (the tilde indicates that the variable is non-stationary)

$$Z_{t} = \frac{\tilde{Z}_{t}}{\tilde{Z}_{t-1}} = Z \left(Z_{t-1} \right)^{\rho_{z}} e^{\sigma_{z} \omega_{z,t}}$$
(13)

where Z is the steady-state value of the productivity growth, ρ_z indicates the degree of persistence and σ_z is the standard deviation of the productivity growth process. Furthermore, households have recursive preferences (Epstein and Zin, 1989, Weil, 1989, 1990)

$$V_t(h) = u\left(\tilde{C}_t(h), \tilde{Z}_t, L_t(h)\right) + \beta\left(E_t V_{t+1}(h)^{1-\gamma}\right)^{\frac{1}{1-\gamma}}$$
(14)

The attractive feature of Epstein-Zin preferences is that the coefficient of relative risk aversion decouples from the intertemporal elasticity parameter. The parameter γ illustrates the degree of agents' desire for an early resolution of uncertainty over future consumption. Household maximises its utility function subject to its budget constraint which is:

$$\tilde{P}_{t}^{C}\tilde{C}_{t}(h) + \frac{\tilde{D}_{t}(h)}{R_{t}} + T_{t}(h) = \tilde{P}_{t}^{C}\tilde{W}_{t}L_{t}(h) + (1 - L_{t}(h))\tilde{P}_{t}^{C}\tilde{B}_{t} + \tilde{D}_{t-1}(h) + \tilde{\Xi}_{t}(h)$$
(15)

where \tilde{P}_t is the price index, $\tilde{D}_t(h)$ is the one-period risk-free government debt, R_t is the return on investing on the government debt, \tilde{W}_t stands for the real wage, $T_t(h)$ is the lump sum taxes, \tilde{B}_t is the unemployment benefit and $\tilde{\Xi}_t(h)$ denotes firms' profits. This optimisation problem delivers (after some substitutions) the labour supply

$$\chi_0 \tilde{Z}_t^{1-\sigma_C} \left(L_t \left(h \right) \right)^{\sigma_L} \left(\tilde{C}_t \left(h \right) - b \tilde{C}_{t-1} \right)^{\sigma_C} + \tilde{B}_t = \tilde{W}_t$$
(16)

and the consumption Euler equation

$$\frac{1}{R_t} = \beta E_t \left(\frac{\tilde{C}_t(h) - b\tilde{C}_{t-1}}{\tilde{C}_{t+1}(h) - b\tilde{C}_t} \right)^{\sigma_C} \frac{\tilde{P}_t^C}{\tilde{P}_{t+1}^C} \left(E_t V_{t+1}^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} V_{t+1}^{-\gamma}$$
(17)

If the stochastic discount factor is defined as:

$$M_{t+1} = \left[\frac{V_{t+1}}{\left(E_t V_{t+1}^{1-\gamma}\right)^{\frac{1}{1-\gamma}}}\right]^{-\gamma} \left(\frac{\tilde{C}_t\left(h\right) - b\tilde{C}_{t-1}}{\tilde{C}_{t+1}\left(h\right) - b\tilde{C}_t}\right)^{\sigma_C},\tag{18}$$

then the former equation becomes:

$$\frac{1}{R_t} = \beta E_t \frac{M_{t+1}}{\Pi_{t+1}^C}$$
(19)

Labour Market: The existence of a real SaM friction in the labour market (Mortensen and Pissarides, 1994) prevents all job-seekers $(U_t = 1 - (1 - \overline{\delta}_{N,t}) L_{t-1})$ from being matched with vacancies (Υ_t) posted by firms and they end up unemployed $(u_t = 1 - L_t)$. The matching technology is described by the following Cobb-Douglas function:

$$\mathcal{M}_t = \bar{\mu} U_t^{\mu} \Upsilon_t^{1-\mu} \tag{20}$$

while the probability of filling the vacancy is given by

$$Q_t^{\Upsilon} = \frac{\mathcal{M}_t}{\Upsilon_t} \tag{21}$$

and the probability of finding a job by

$$Q_t^U = \frac{\mathcal{M}_t}{U_t} \tag{22}$$

employment evolves according to

$$L_t = \left\{ 1 - \bar{\delta}_{N,t} \left(\bar{\alpha}_t \right) \right\} \left(L_{t-1} + Q_{t-1}^{\Upsilon} \Upsilon_{t-1} \right)$$
(23)

where the separation rate

$$\bar{\delta}_{N,t}\left(\bar{\alpha}_{t}\right) = \delta_{N}^{x} + \left(1 - \delta_{N}^{x}\right)\delta_{N,t}\left(\bar{\alpha}_{t}\right) \tag{24}$$

has an endogenous $\delta_{N,t}$ and endogenous component δ_N^x According to the endogenous component of the job separation rate

$$\delta_{N,t} = P\left(\alpha_t > \bar{\alpha}_t\right) = G\left(\bar{\alpha}_t\right) \tag{25}$$

the match is destructed if the relation of the idiosyncratic productivity shock α_t exceeds a $\bar{\alpha}_t$. $G(\alpha)$ denotes the log-normal cumulative distribution function with parameters μ_{α} , $\sigma_{\alpha,t}$ and density g. The $log(\sigma_{\alpha,t})$ follows an AR process

$$log\left(\frac{\sigma_{\alpha,t}}{\sigma_{\alpha}}\right) = \rho_{\sigma}log\left(\frac{\sigma_{\alpha,t-1}}{\sigma_{\alpha}}\right) + \sigma_{\sigma}\omega_{\sigma,t}$$
(26)

Firms, in order to be able to hire a worker, need to post a vacancy, and this incurs a cost

$$\Psi_{h,t} = \kappa_h \tilde{Z}_t \Upsilon_t \tag{27}$$

Following most of the literature, we assume that the vacancy posting cost is linear (Mortensen and Pissarides, 1994). Firing also incurs a cost to the corporates

$$\Psi_{f,t} = \kappa_f \tilde{Z}_t W \tag{28}$$

Aggregate Value Added Producer: The final good is produced via the following production function

$$\tilde{Y}_{t} = \left[\int_{0}^{1} \tilde{Y}_{t} \left(f \right)^{\frac{\varepsilon - 1}{\varepsilon}} df \right]^{\frac{\varepsilon}{\varepsilon - 1}}$$
(29)

where ε denotes the elasticity of substitution between differentiated intermediate goods ($f \in [0 \ 1]$). The demand for intermediate goods

$$\tilde{Y}_t(f) = \left(\frac{P_t(f)}{P_t}\right)^{-\varepsilon} Y_t \tag{30}$$

results from profit maximisation and the assumption that the final good producer operates under perfect competition.

Value Added Producers: Similar to Krause and Lubik (2007) and Krause et al. (2008) we assume that there is a continuum of firms ($f \in [0, 1]$) that post vacancies, combine employment, fixed capital and employ the following technology:

$$\tilde{Y}_{t}(f) = \tilde{Z}_{t}L_{t}(f)\int_{\bar{\alpha}_{f,t}}^{\infty} a \frac{g(\alpha)}{1-G(\bar{\alpha}_{f,t})} d\alpha$$

$$= \tilde{Z}_{t}L_{t}(f)H(\bar{\alpha}_{f,t})$$
(31)

to produce the intermediate good. These producers solve a two-stage problem. In the first stage, taking the wage and the cost of filling a vacancy as given, they decide how many vacancies to post, the productivity cut-off value and people to employ. These choices result from the maximisation of their profit function:

$$E_{t}\sum_{j=0}^{\infty}M_{t+j}\beta^{j}\left\{\begin{array}{c}MC_{t+j}\left(f\right)\tilde{Y}_{t+j}\left(f,\alpha_{t}\right)-\frac{P_{t}}{P_{t}^{C}}L_{t+j}\left(f\right)\int_{\bar{\alpha}_{f,t}}^{\infty}\tilde{W}_{t+j}\left(\alpha\right)\frac{g(\alpha)}{1-G(\bar{\alpha}_{t})}d\alpha-R^{K}K\\-\kappa_{h}\tilde{Z}_{t+j}\Upsilon_{t+j}\left(f\right)-\left(1-\delta_{N}^{x}\right)\delta_{N,t+j}\left(L_{t+j-1}+Q_{t+j-1}^{\Upsilon}\Upsilon_{t+j-1}\right)\kappa_{f}\tilde{Z}_{t+j}W\\+\tilde{\Theta}_{t+j}\left(f\right)\left\{\left(1-\delta_{N}^{x}\right)\left(1-\delta_{N,t+j-1}\right)\left[L_{t+j-1}\left(f\right)+Q_{t+j-1}^{\Upsilon}\left(f\right)\Upsilon_{t+j-1}\left(f\right)\right]-L_{t+j}\left(f\right)\right\}\right\}$$

$$(32)$$

with respect to employment delivers the relative price of good $\tilde{Y}_t(f)$ summarised by the following equations:

$$\tilde{\Theta}_{t} = MC_{t}Z_{t}H(\bar{\alpha}_{t}) - \frac{P_{t}}{P_{t}^{C}}\bar{W}_{t} + \beta E_{t}\left(1 - \bar{\delta}_{N,t+1}\right)M_{t+1}\left\{\tilde{\Theta}_{t+1} - \frac{(1 - \delta_{N}^{x})\delta_{N,t+1}}{(1 - \bar{\delta}_{N,t+1})}\kappa_{f}\tilde{Z}_{t+1}W\right\}$$
(33)

where $\bar{W}_t = \int_{\bar{\alpha}_t}^{\infty} \tilde{W}_t(\alpha) \frac{g(\alpha)}{1 - G(\bar{\alpha}_t)} d\alpha$

$$MC_{t} = Z_{t}L_{t}\frac{\partial H\left(\bar{\alpha}_{t}\right)}{\partial\bar{\alpha}_{t}} \begin{bmatrix} \frac{P_{t}}{P_{t}^{C}}L_{t}\frac{\partial\int_{\bar{\alpha}_{t}}^{\infty}\tilde{W}_{t}\left(\alpha\right)\frac{g\left(\alpha\right)}{1-G\left(\bar{\alpha}_{t}\right)}d\alpha}{\partial\bar{\alpha}_{t}} \\ +\left(1-\delta_{N}\right)\left(L_{t-1}+Q_{t-1}^{\Upsilon}\Upsilon_{t-1}\right)\kappa_{f}\tilde{Z}_{t}W\frac{\partial\delta_{N,t}}{\partial\bar{\alpha}_{t}} \\ +\tilde{\Theta}_{t}\left(1-\delta_{N}\right)\left[L_{t-1}+Q_{t-1}^{\Upsilon}\Upsilon_{t-1}\right]\frac{\partial\delta_{N,t}}{\partial\bar{\alpha}_{t}} \end{bmatrix}$$
(34)

and

$$\frac{\kappa_h \tilde{Z}_t}{Q_t^{\Upsilon}} = \beta E_t \left(1 - \bar{\delta}_{N,t+1} \right) M_{t+1} \left\{ \tilde{\Theta}_{t+1} - \frac{\left(1 - \delta_N^x \right) \delta_{N,t+1}}{\left(1 - \bar{\delta}_{N,t+1} \right)} \kappa_f \tilde{Z}_{t+1} W \right\}$$
(35)

The combination of the vacancy and employment first-order conditions delivers the job creation condition

$$\frac{\kappa_{h}\tilde{Z}_{t}}{Q_{t}^{\Upsilon}} = \beta E_{t} \left(1 - \bar{\delta}_{N,t+1}\right) M_{t+1} \left\{ \begin{array}{c} MC_{t+1}Z_{t+1}H\left(\bar{\alpha}_{t+1}\right) - \bar{W}_{t+1} \\ + \frac{\kappa_{h}\tilde{Z}_{t+1}}{Q_{t+1}^{\Upsilon}} - \frac{\left(1 - \delta_{N}^{X}\right)\delta_{N,t+1}}{\left(1 - \bar{\delta}_{N,t+1}\right)} \kappa_{f}\tilde{Z}_{t+1}W \end{array} \right\}$$
(36)

In the second stage, producers set the price of the intermediate good that maximises their profits. The optimisation problem, in this case, reflects that prices are set in a staggered manner. This means that every period a fraction $(1 - \xi)$ of firms receive a random signal and set prices optimally $(\breve{P}_t(f))$, while those firms who miss the signal set prices based on a rule of thumb backward-looking indexation scheme $(\breve{P}_t(f) = \prod_{t=1}^{\iota} \breve{P}_{t-1}(f))$. The pricing problem is summarised by the following profit maximisation

$$\max_{\check{P}_{t}(f)} E_{t} \sum_{j=0}^{\infty} M_{t,t+j} \left(\beta\xi\right)^{j} \left[\left\{ \frac{\check{P}_{t}\left(f\right) \Pi_{t+j-1}^{\iota}}{\tilde{P}_{t+j}} - MC_{t+j}\left(f\right) \right\} \tilde{Y}_{t+j}\left(f\right) \right]$$
(37)

subject to

$$\tilde{Y}_{t+j}\left(f\right) = \left(\prod_{s=0}^{j} \Pi_{t+j-1}^{\iota} \frac{P_{t}\left(f\right)}{P_{t+j}}\right)^{-\varepsilon} Y_{t+j}$$

and this results in a system of equations that describe firms' optimal pricing decisions

$$\tilde{K}_{P,t} = MC_t \tilde{Y}_t + \beta \xi E_t M_{t+1} \left(\frac{\Pi_{t+1}}{(\Pi^C)^{1-\iota} \Pi_t^{\iota}} \right)^{\varepsilon} \tilde{K}_{P,t+1}$$
(38)

$$\tilde{F}_{P,t} = \tilde{Y}_t + \beta \xi E_t M_{t+1} \left(\frac{\Pi_{t+1}}{\left(\Pi^C \right)^{1-\iota} \Pi^{\iota}_t} \right)^{\varepsilon - 1} \tilde{F}_{P,t+1}$$
(39)

$$\bar{\Pi}_{P,t} = \frac{\varepsilon}{\varepsilon - 1} \frac{K_{P,t}}{F_{P,t}}$$
(40)

$$1 = \xi \left(\frac{\Pi_t}{\left(\Pi^C\right)^{1-\iota} \Pi_{t-1}^{\iota}}\right)^{\varepsilon-1} + (1-\xi) \left(\bar{\Pi}_{P,t}\right)^{1-\varepsilon}$$

$$\tag{41}$$

Final Output: The final good (\tilde{X}_t) producers use the aggregate intermediate value-added good (\tilde{Y}_t) and oil imports (\tilde{O}_t) and the following technology

$$\tilde{X}_{t} = \left[(1 - \phi_{o})^{\frac{1}{\mu_{o}}} \tilde{Y}_{t}^{\frac{\mu_{o}-1}{\mu_{o}}} + \phi_{o}^{\frac{1}{\mu_{o}}} \tilde{O}_{t}^{\frac{\mu_{o}-1}{\mu_{o}}} \right]^{\frac{\mu_{o}}{\mu_{o}-1}}$$
(42)

The price of the final good is given by

$$P_t^C = (1 - \phi_o) \left(P_t \right)^{1 - \mu_o} + \phi_o \left(P_t^o \right)^{1 - \mu_o}$$
(43)

where P_t and P_t^o are the price indices of the domestically produced and oil-imported goods, respectively. The profit maximisation problem delivers the demand for value-added

$$\tilde{Y}_t = (1 - \phi_o) \left(\frac{P_t}{P_t^C}\right)^{-\mu_o} \tilde{X}_t \tag{44}$$

and oil imports

$$\tilde{O}_t = \phi_o \left(\frac{P_t^o}{P_t^C}\right)^{-\mu_o} \tilde{X}_t \tag{45}$$

Wage Determination: The wage is determined by solving a Nash bargaining problem between workers and firms that take place in order to decide how to split the surplus produced by a match see (see Mortensen and Pissarides (1994) and Krause et al. (2008) among others). To set the problem we need to define the value of the firm, which can be derived from (??) after we use the value of an open vacancy and the free entry condition:

$$\tilde{J}_{t}^{F}(\alpha_{t}) = MC_{t}Z_{t}\alpha_{t} - \tilde{W}_{t}(\alpha_{t}) - \frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\bar{\delta}_{N,t})}\kappa_{f}\tilde{Z}_{t}W
+\beta E_{t}\left(1-\bar{\delta}_{N,t+1}\right)M_{t+1} \begin{cases} \int_{\bar{\alpha}_{t+1}}^{\infty}\tilde{J}_{t+1}^{F}(\alpha)\frac{g(\alpha)}{1-G(\bar{\alpha}_{t+1})}d\alpha \\ -\frac{(1-\delta_{N}^{x})\delta_{N,t+1}}{(1-\bar{\delta}_{N,t+1})}\kappa_{f}\tilde{Z}_{t+1}W \end{cases}$$
(46)

where $\tilde{Y}_t^d = \frac{\tilde{Y}_t}{\Delta_t}$ and Δ_t is defined below. On the other hand, the value of an employed and unemployed worker is given by:

$$\tilde{J}_{t}^{W}(\alpha_{t}) = \tilde{W}_{t}(\alpha_{t}) - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} + \beta E_{t}M_{t+1}\left\{\left(1 - \bar{\delta}_{N,t+1}\right)\int_{\bar{\alpha}_{t+1}}^{\infty}\tilde{J}_{t+1}^{W}(\alpha)\frac{g(a)}{1 - G(\bar{\alpha}_{t+1})}d\alpha + \bar{\delta}_{N,t+1}\tilde{J}_{t+1}^{U}\right\}$$
(47)

$$\tilde{J}_{t}^{U} = \tilde{B}_{t} + \beta E_{t} M_{t+1} \left\{ Q_{t}^{U} \left(1 - \bar{\delta}_{N,t+1} \right) \int_{\bar{\alpha}_{t+1}}^{\infty} \tilde{J}_{t+1}^{W} \left(\alpha \right) \frac{g\left(a \right)}{1 - G\left(\bar{\alpha}_{t+1} \right)} d\alpha + \left[1 - Q_{t}^{U} \left(1 - \bar{\delta}_{N,t+1} \right) \right] \tilde{J}_{t+1}^{U} \right\}$$
(48)

and the bargaining problem is described by:

$$\max_{\tilde{W}_t} \left(\tilde{J}_t^W - \tilde{J}_t^U \right)^{\eta} \left(\tilde{J}_t^F \right)^{1-\eta} \tag{49}$$

The total surplus is defined as:

$$\tilde{S}_t = \tilde{J}_t^F + \tilde{J}_t^W - \tilde{J}_t^U \tag{50}$$

and the solution to the problem is given by:

$$\tilde{J}_t^F = (1 - \eta) \,\tilde{S}_t \tag{51}$$

$$\tilde{J}_t^W - \tilde{J}_t^U = \eta \tilde{S}_t \tag{52}$$

Which can be used to derive the Nash wage:⁵

$$\tilde{W}_{t}^{Nash}(\alpha_{t}) = \eta \left\{ MC_{t}Z_{t}\alpha_{t} + \kappa_{h}\tilde{Z}_{t}\frac{\Upsilon_{t}}{U_{t}} - \frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\delta_{N,t})}\kappa_{f}\tilde{Z}_{t}W \right\} + (1-\eta) \left\{ \tilde{B}_{t} + \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} \right\}$$
(53)

The aggregate Nash bargain wage is given by

$$\tilde{\tilde{W}}_{t}^{Nash} = \eta \left\{ MC_{t}Z_{t}H\left(\alpha_{t}\right) + \kappa_{h}\tilde{Z}_{t}\frac{\Upsilon_{t}}{U_{t}} - \frac{\left(1-\delta_{N}^{x}\right)\delta_{N,t}}{\left(1-\delta_{N,t}\right)\left(1-\delta_{N,t}\right)}\kappa_{f}\tilde{Z}_{t}W\right\} + \left(1-\eta\right)\left\{\tilde{B}_{t}+\chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t}-b\tilde{C}_{t-1}\right)^{\sigma_{C}}\right\}$$
(54)

Similarly to Hall (2005) and Krause and Lubik (2007), we allow for real wage rigidity via the following norm:

$$\tilde{W}_t^{Norm}(\alpha_t) = \iota_w \tilde{W}_t^{Nash}(\alpha_t) + (1 - \iota_w) \tilde{W}^{Nash}(\alpha)$$
(55)

Similarly, the aggregate wage becomes

$$\tilde{\bar{W}}_t^{Norm} = \iota_w \tilde{\bar{W}}_t + (1 - \iota_w) \tilde{\bar{W}}$$
(56)

⁵The derivation can be found in Section A2.1

Finally, we derive the productivity cut-off value using job destruction condition (i.e. $J_t^F(\alpha_t) = 0$) and the individual wage Nash bargain equation

$$(1 - \iota_w \eta) M C_t Z_t \bar{\alpha}_t = \iota_w \eta \kappa_h \tilde{Z}_t \frac{\Upsilon_t}{U_t} + \iota_w (1 - \eta) \left\{ \tilde{B}_t + \chi_0 \tilde{Z}_t^{1 - \sigma_C} L_t^{\sigma_L} \left(\tilde{C}_t - b \tilde{C}_{t-1} \right)^{\sigma_C} \right\} \\ + (1 - \iota_w) \tilde{W}^{Nash}(\alpha) + (1 - \iota_w \eta) \frac{(1 - \delta_N^x) \delta_{N,t}}{(1 - \bar{\delta}_{N,t})} \kappa_f \tilde{Z}_t W - \frac{\kappa_h \tilde{Z}_t}{Q_t^{\Upsilon}}$$
(57)

Government: The government in this economy runs a balanced budget:

$$\tilde{P}_{t}\tilde{G}_{t} + \tilde{D}_{t-1} + (1 - L_{t})\tilde{P}_{t}\tilde{B}_{t} = \tilde{T}_{t} + \frac{\tilde{D}_{t}}{R_{t}}$$
(58)

where G_t is government consumption, and g_t is the the government share in the economy:

$$\tilde{G}_t = g_t \tilde{Y}_t \tag{59}$$

that evolves in a stochastic manner:

$$\hat{g}_t = g + \rho_g \left(\hat{g}_{t-1} - g \right) + \sigma_g \omega_{g,t} \tag{60}$$

Monetary policy is set based on the Taylor-type rule:

$$\log(R_t) = r_t = \rho_R r_{t-1} + (1 - \rho_R) \left\{ \zeta_{\Pi} \log\left(\frac{\Pi_t}{\Pi}\right) + \zeta_Y \log\left(\frac{\tilde{Y}_t}{\tilde{Z}_t Y}\right) \right\} + \omega_{R,t}$$
(61)

$$\omega_{R,t} = \rho_{\epsilon_R} \omega_{R,t-1} + \sigma_R \epsilon_{R,t} \tag{62}$$

where Π is the inflation target, ρ_R is the interest rate smoothing parameter, ζ_{Π} and ζ_{Y^d} are the policy reaction coefficients to inflation and demand growth, respectively.

Aggregation: The aggregated labour quantity demanded by firms is:

$$L_t = \int_0^1 L_t\left(f\right) df \tag{63}$$

and it is equal to the quantity supplied by the household due to the flexibility of wages. Using the latter equation and the intermediate good producer's production function, we obtain:

$$\tilde{Y}_t = \frac{\tilde{Z}_t L_t H\left(\bar{a}_t\right)}{\int_0^1 \left(\frac{\tilde{P}_t(h)}{\tilde{P}_t}\right)^{-\varepsilon} dh} = \frac{\tilde{Z}_t H\left(\bar{a}_t\right) L_t}{\Delta_t}$$
(64)

where Δ_t denotes the price dispersion, and it evolves as follows:

$$\Delta_t = (1 - \xi) \,\bar{\Pi}_t^{\varepsilon} + \xi \left(\frac{\Pi_t}{\Pi_{t-1}^{\iota}}\right)^{\varepsilon} \Delta_{t-1} \tag{65}$$

Finally, using the expression about the aggregate profits and household's budget constraint, we derive the market clearing condition:

$$\frac{\tilde{Z}_{t}H\left(\bar{a}_{t}\right)L_{t}}{\Delta_{t}} = \tilde{C}_{t} + \tilde{G}_{t} + \tilde{\Psi}_{t} + \left(1 - \delta_{N}^{x}\right)\delta_{N,t}\left(L_{t-1} + Q_{t-1}^{\Upsilon}\Upsilon_{t-1}\right)\kappa_{f}\tilde{Z}_{t+j}W$$

$$\tag{66}$$

Signal Extraction Problem: The real price of oil is subject to a measurement error,

$$log\left(\bar{P}_{t}^{o,obs}\right) = log\left(\bar{P}_{t}^{o}\right) + \sigma_{o}^{obs}\omega_{t}^{o,obs}$$
$$log\left(\bar{P}_{t}^{o}\right) = \rho_{o}log\left(\bar{P}_{t-1}^{o}\right) + \sigma_{o}\omega_{t}^{o}$$

meaning that agents solve a (Kalman Filter) signal extraction problem to infer the value of ω_t^o

5.1.1 Concerns about Long Lasting Term of Trade Deterioration after a Large Oil Supply Shock

The prospect of a large oil supply shock raises worries about an enduring impact on the competitiveness of oil-importing nations. For instance, numerous countries, particularly those in the Euro Area, experienced persistently elevated energy costs for several years following the Russian-Ukrainian war in 2022, surpassing (by a lot) the levels observed before the Russian invasion. These concerns could still impact agents' consumption/saving and firms' hiring/firing decisions even if these concerns are never realised. To capture these "fears", we consider two mechanisms in this study.

Rare Disaster Probability Becomes a Function of the Magnitude of the Shock: In the first case, the model considered in the previous sections is augmented with a "rare disaster" event as in Barro (2009), Gourio (2012), Isore and Szczerbowicz (2017), Kilic and Wachter (2018) and Fernández-Villaverde and Levintal (2018) (among others).

$$\begin{split} \Delta \log Z_t &= (1 - \rho_Z) \left(\Delta \log Z - d_t \log \varpi_t \right) + \rho_Z \Delta \log Z_{t-1} + \sigma_Z \omega_{Z,t} \\ \log \varpi_t &= (1 - \rho_{\varpi}) \varpi + \rho_{\varpi} \log \varpi_{t-1} \\ d_t &= \begin{cases} 1 & \text{with probability} & \varrho_t \\ 0 & \text{with probability} & 1 - \varrho_t \end{cases} \end{split}$$

where d_t is an indicator variable that takes a value of 1 with probability ρ_t and 0 with probability $1 - \rho_t$. The term $\log \varpi$ captures the size of the rare disaster shock.

Similar to Gourio (2012), Isore and Szczerbowicz (2017), Kilic and Wachter (2018), the focus of this study is to understand the implications of an increase in the probability of a rare disaster and not the adverse shock per se. However, in our case, the probability is a the function of the observed oil price

$$\varrho_t = \frac{1}{1 + v_c e^{-v_v log\left(\bar{P}_t^{o,obs}\right)}} \tag{67}$$

and not an exogenous auto-regressive process. Similar to Isore and Szczerbowicz (2017), the steady state



value of the rare probability is $\rho = 0.009$ (i.e. $v_c = 110.1$), and the size of the rare disaster has been set equal to $100\log \varpi = 0.22$. The (prior mean of the) slope parameter (v_v) has been selected to ensure that the rare disaster increases above 50% after a large shock (i.e. $v_v = 12.5$, Table 4).

Modifying the Signal Extraction Problem: In the second case, the agents cannot infer immediately whether the increase in the observed oil price is due to a stationary shock or it reflects permanent terms of trade deterioration:

$$log\left(\bar{P}_{t}^{o,obs}\right) = log\left(\bar{P}_{t}^{o}\right) + \Delta log\left(\bar{P}_{t}^{p}\right) + \sigma_{o}^{obs}\omega_{t}^{o,obs}$$
$$log\left(\bar{P}_{t}^{o}\right) = \rho_{o}log\left(\bar{P}_{t-1}^{o}\right) + \sigma_{o}\omega_{t}^{o}$$
$$\Delta log\left(\bar{P}_{t}^{p}\right) = \rho_{p}\Delta log\left(\bar{P}_{t-1}^{p}\right) + \sigma_{p}\omega_{t}^{p}$$
$$\Delta \log Z_{t} = -\Delta \bar{P}_{t}^{p}$$

As mentioned above, the agents do not observe $\omega_t^{o,obs}, \omega_t^o$ and ω_t^p and they solve a Kalman Filter signal extraction problem, meaning that the values of $\Delta \bar{P}_t^p$ are non-zero until learning is completed.⁶

5.1.2 Model Risk Measures

Similarly to Kehoe et al. (2023), the Hansen-Jagannathan Bound is used to proxy to

$$\mathcal{HJB}_{t} = \frac{\sigma_{t}\left(M_{t+1}\right)}{E_{t}\left(M_{t+1}\right)} \tag{68}$$

to proxy the (aggregate) price of risk in the economy. Motivated by Gnocato (2024), the probability of being unemployed the next period

$$\mathcal{R}_t = E_t \left(\bar{\delta}_{N,t+1} \left(\bar{\alpha}_{t+1} \right) \left(1 - Q_{t+1}^U \right) \right) \tag{69}$$

is used to proxy unemployment risk.

 $^{^{6}}$ To save space, the results of these simulations are reported in the Online Appendix A2.4, Figure A2.1.

5.2 Predictive Prior Analysis

Predictive prior analysis is used in this study to identify those aspects of the model's transmission mechanism that could potentially explain the VAR impulse responses and the associated non-linearities.⁷ To illustrate this point, some additional notation is required, starting by denoting the prior density function of the DSGE parameter vector by $p(\theta|\mathcal{M})$. As the impulse responses of the endogenous variables are a function of the structural parameter vector $(IRFS = f(\theta|\mathcal{M}))$ their prior density is defined as $p(\mathcal{IRFS}(\theta|\mathcal{M}))$, and it can be derived readily via simulation techniques.⁸ In our exercise, an additional set of sign restrictions are imposed on the prior distribution of impulse-response functions in the first period:

- The responses of selected variables to a 1 and 5 standard deviation shocks satisfy specific sign restrictions (S_{signs}^L , Table 1)
- The scaled difference between selected variables between a 5 and 1 standard deviation shock satisfies sign restrictions (S_{signs}^D , Table 2)

Variable	GDP	Consumption	Wage	Unemployment	Vacancies
Signs	-	-	-	+	-
Variable	Job Finding	Separation	CPI	Policy	\mathcal{HJB}
	Probability	Rate	inflation	Rate	
Signs	-	+	+	+	+

Table 1: Sign Restrictions on the Responses

Table 2: Sign Restrictions on the difference between Large and Small Shocks Responses

Variable	GDP	Consumption	Wage	Unemployment	Vacancies
Signs	-	-	-	+	-
Variable	Job Finding	Separation	CPI	Policy	\mathcal{HJB}
	Probability	Rate	inflation	Rate	
Signs	-	+	?	?	+

These simulations deliver the prior distribution of the structural parameter vector, $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$, and impulse responses, $p\left(\mathcal{IRFS}\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{L}\right)\right)$ that satisfy the conditions reported in Tables 1 and 2.

The purpose of employing prior predictive analysis techniques is twofold. The first objective is to identify whether the model can reproduce—both qualitatively and quantitatively—the stylised facts studied earlier. The second, and perhaps a more important goal, is to assess whether the model can replicate the empirical evidence only for a specific calibration or a wide range of parameters. The latter feature would maximise the model's robustness and help us better understand the transmission mechanism that is consistent with the data.

⁷See Canova (2005), Traum and Yang (2011), Leeper et al. (2017), Nelson et al. (2018) and Mumtaz and Theodoridis (2020b) for recent applications of this technique.

⁸All the calculations have been implemented using Dynare 5.6. The codes and model files can be downloaded from the authors' personal pages.

Finally, differences across the $p(\theta|\mathcal{M})$ and $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ probability density functions help us identify those structural parameters that are crucial for the model replicating the data moments (see the discussion in Mumtaz and Theodoridis (2020b)).

Mnemonic	Description	Value
Ζ	Steady State Productivity Growth	1.004
Q^{Υ}	Steady State Job Filling Probability	0.700
П	Inflation Target	1.006
U	Steady State Unemployment Rat	0.060
β	Time Discount Factor	0.997
ϵ	Intermediate Goods Elasticity of Substitution	11.00
δ^x_N	Exogenous Job Separation Rate	0.068
$\overline{\delta}_N$	Steady State Endogenous Job Separation Rate	0.100
μ_{lpha}	Mean of idiosyncratic productivity shock	1.000

 Table 3: Calibrated Parameters

Table 3 illustrates the parameters that are kept fixed, while Table 4 reports the functional form of the probability density function and the prior moments $(i.e.p(\theta|\mathcal{M}))$ of the structural parameter vector. It should be evident from these tables that the calibration of the moments of the structural parameter vector aims to capture the wide range of values used in the literature.

Finally, the model is solved using a third-order perturbation approximation (no pruning), and the IRFs have been derived as (percentage or percentage point) deviations from the stochastic steady-state, which are produced by simulating the model for many periods after setting the values all structural shocks to zero.

5.3 Simulation Results

5.3.1 Assessing Model's Ability to Replicate the Empirical Evidence

Figure 5 plots the distribution of $p(\theta|\mathcal{M})$ against $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$, the comparison of the two set of distributions reveals information about the contribution of certain structural parameters meeting the sign restrictions reported in Tables 1 and 2. Figure 6 displays the prior median of the impulse responses after one (blue solid line) and five (red dashed line) deviation oil shock; the latter responses are divided by five. In the absence of economically significant non-linearities, the two responses must lie on top of each other. Figure 7 illustrates the prior density of the difference between the small and large shock responses, and it gives a sense of how prominent the nonlinearities are across different draws form $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$. All three figures reveal many interesting features of the model, which are discussed in the rest of the section. It is important that the reader keeps in mind that when the text mentions large (five standard deviations) shock responses, it refers to responses that have been divided by five, so they become comparable to the small (one standard deviation) shock responses.

From figure 7, it is evident that the nonlinear responses of real economy and labour market variables to large oil shocks are not always associated with more inflation and, consequently, higher policy rates. It is important to remind the reader that although the searching algorithm focuses on identifying structural parameters consistent with the sign restrictions reported in Tables 1 and 2, the responses of inflation and

policy rates are left unconstrained (together with the real interest rate and unemployment risk variables). Similar to the empirical findings (Charts 1, 2 and 3), model simulations suggest that the larger adjustments observed for real economy and labour market variables do not arise from a larger increase in the policy rate, which would have been expected if prices surged by more after a big oil shock. This exercise acts implicitly as a "test" assessing the model's ability to explain the stylised facts.

The fact that the model predictions hold for a large number of different realisations of the structural parameter vector (i.e. draws form $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$), and not just for a unique parameterisation, further enhance the usefulness of the model understand the stylised facts. Importantly, this message is further reinforced by the significant overlap between $p\left(\theta|\mathcal{M}\right)$ and $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ (Figure 5), as the structural model does not need to rely on "exotic" parameter values to replicate the empirical regularities. In other words, the DSGE model discussed in the previous section contains all the necessary mechanisms to reproduce the first and higher-order dynamics discussed in Section 4.

Figure 7 also captures the distribution of the magnitude of the nonlinearities produced by the DSGE model given draws form $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$. Under some (naive) assumptions and "back to envelope" calculations regarding the type and frequency differences of the variables entering the empirical and structural models, the size of the nonlinearities observed in the data (Figures 1 and 2) are well captured by the model simulation. This informal metric could also be used to infer the model's ability to reproduce complicated data patterns. These results align exceptionally well with the findings of Petrosky-Nadeau and Zhang (2017), Petrosky-Nadeau et al. (2018), Mumtaz and Theodoridis (2020a), Pizzinelli et al. (2020) and Bernstein et al. (2024), indicating that models featuring SaM frictions are capable of replicating severe data non-linearities.

The model successfully replicates the (conditional) negative correlation among unemployment, job-finding probability, and vacancies. It is known from the work of Hall (2017), Kilic and Wachter (2018), Kehoe et al. (2023) that textbook SaM models augmented with mechanisms that can induce significant time-variation in risk premia can reproduce the dynamics of unemployment, job-finding rate and vacancies observed in the data, and consequently, not being subject to Shimer (2005) criticism. Similar to Kehoe et al. (2023), the Hansen Jagannathan (HJ) bound – i.e. the ratio of the conditional standard deviation of the stochastic discount factor to its conditional mean $\left(\frac{\sigma_t(M_{t+1})}{E_t(M_{t+1})}\right)$ is used in this study to proxy the price of the risk in the economy. Figure 6 plots the pointwise mean of the responses of the HJ bound after a small (blue solid line) and large (red dashed line) oil news supply shock, indicating that the price of risk rises for a protracted period (i.e. well beyond the horizon restricted by the prior predictive analysis of one quarter).

Finally, the model successfully reproduces the conditional positive correlation between unemployment and the job separation rate. A recent study by Meeuwis et al. (2023) utilises US administrative data on worker earnings to illustrate that an uptick in risk premia correlates with an increased job separation rate, which is also what it is observed in the data after a news oil supply shock (Section 4). The model allows for endogenous separation and, for reasons explained in the following section, replicates the increase in both the price of risk and job-destruction rate after an adverse shock.

5.3.2 Economic Intuition

As explained by Auclert et al. (2023), a recession in an otherwise standard representative agent New Keynesian DSGE model (such as Blanchard and Gali, 2007) after an oil supply shock is induced by monetary policy response to the inflation. The empirical evidence discussed in Section 4 make clear that the more severe impact on the real economy and labour market variables after a larger shock cannot be associated with higher inflation and, consequently, the higher policy rate response.

From the discussion so far, it should be clear that the responses of the real interest rate and expectation of becoming unemployed are also left unconstrained (1 and 2). This feature is emphasised here as the behaviour of these variables turns out to be the most important ones in understanding the transmission mechanism.

As illustrated by Bernstein et al. (2024) and Bernstein et al. (2024), SaM frictions create employment risk, which increases with the number of job seekers. For example, a negative oil shock reduces economic activity below its potential, increasing unemployment and higher competition for scarce jobs. As it is explained by Gnocato (2024), this channel is further enhanced by the endogenous separation mechanism, which further diminishes the likelihood of securing employment, intensifying employment uncertainty and contributing to heightened economic volatility.

Charts 6 and 7 illustrate that the larger the shock is, the higher the risk of becoming unemployed in the near future and, consequently, the higher the desire to save against these adverse events. Due to the absence of assets in this model to facilitate consumption smoothing across time, the real interest rate must decrease to mitigate these precautionary motives, and although the real interest rate decreases (Figure 6), this reduction cannot stop economic activity from contracting. The consumption and real interest rate subplots of Figure 7 can be seen as the distribution of the size of agents' precautionary motive as a function of the structural parameter vector.

In other words, the search and matching frictions give rise to unemployment risks, causing precautionary motives to arise and economic activity to fall. The magnitude of these effects is positively correlated with the size of the disturbances. In the next section, it will become apparent that the additional nonlinear features model (i.e., recursive preferences and concerns of permanent terms of trade deterioration) have only a limited contribution to the level (i.e., first-order moment) responses, and the major source of nonlinearities is the SaM frictions.

Mnemonic	Description	PDF	Mean	STD
κ_h	Firing Cost (% of GDP)	Normal	2.00	2.00
κ_f	Hiring Cost(% of GDP)	Normal	2.00	2.00
ι_w	Real Wage Indexation	Beta	0.50	0.20
σ_o	Noise to Signal Ratio	Normal	3.00	0.50
μ	Matching Function Elasticity	Normal	1.25	0.25
ι	Wage Bargain	Normal	0.50	0.10
ŝ	Calvo Price Probability	Beta	0.50	0.20
ι_p	Price Indexation	Beta	0.50	0.20
p	Consumption Smoothing	Beta	0.75	0.10
$\frac{B}{WL}$	Income Replacement Ratio	Normal	0.50	0.10
- ~	Epstein-Zing Risk	Normal	150	25.0
σ_C	Inverse of Intertemporal Elasticity of Substitution	Normal	1.50	0.38
σ_{L}	Inverse of Frisch Elasticity	Normal	2.00	1.00
$ ho_R$	Interest Rate Smoothing	Beta	0.75	0.10
ζπ	Inflation Policy Reaction	Normal	1.50	0.25
ζ_Y	Unemployment Policy Reaction	Normal	0.25	0.10
0η	Import Oil Elasticity Substitution	Gamma	0.75	0.50
v_v	Slope of the Logistic Function	Gamma	12.5	0.75
ρ_Z	LAP Persistence	Beta	0.50	0.20
$ ho_g$	Government Consumption Persistence	Beta	0.50	0.20
$ ho_{\sigma}$	Variance of Idiosyncratic Productivity Shock Persistence	Beta	0.50	0.20
$ ho_{arpi}$	Rare Disaster Shock Persistence	Beta	0.50	0.20
σ_Z	LAP Shock Standard Deviation	Inv-Gamma	0.50	0.20
σ_g	Government Consumption Shock Standard Deviation	Inv-Gamma	0.50	0.20
σ_R	Monetary Policy Shock Standard Deviation	Inv-Gamma	0.50	0.20
σ_{σ}	Variance of Idiosyncratic Productivity Shock Standard Deviation	Inv-Gamma	0.50	0.20

Table 4: Prior Distribution of Structural Parameters







Figure 6: IRF Predictive Prior Distribution

Notes: The blue solid line illustrates the predictive prior (pointwise) mean response to 1 standard deviation oil news supply shock. The red dashed line displays the predictive prior (pointwise) mean response (divided by 5) to a 5 standard deviation shock. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$. The x-axis denotes quarters.



Figure 7: IRF Differences Predictive Prior Distribution

Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$. The x-axis denotes quarters.

5.3.3 Sensitivity Analysis

This section aims to identify the (structural) modelling features that give rise to the nonlinearities studied in the previous sections. It was mentioned on the previous section mentioned that the distribution of the difference between the large and small shock IRFs provides a summary statistic of the severity of the nonlinearities for a given distribution of the structural parameter vector (Figure 7). The same metric is employed here to assess the nonlinear propagation of the oil shocks, as certain features of the model vary.

SaM Frictions: Figure 8 illustrates the importance of the SaM firctions. The distribution of the IRF difference between large and model shocks has been produced using again the same draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ as in the benchmark model, but now the parameters κ_h and κ_f are not multiplied by 0.5 for each draw. The blue-solid-circle line is the pointwise mean derived using the benchmark model (i.e. Figure 7). Figure 8 demonstrates that less pronounced real labour market frictions decrease the



Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ but this time the values of κ_h and κ_f have been decreased by 50% relative to benchmark distribution. The blue-solid-circle line is the pointwise mean derived using the benchmark model. The x-axis denotes quarters.

severity of the nonlinearities, aligning with the economic interpretation provided in the previous section. Specifically, lower firing costs make corporations less cautious about engaging in long-term contractual agreements with households. As a result, the job-finding probability decreases less, mitigating households' desire for precautionary savings (as reflected in the probability of becoming unemployed, the real interest rate and consumption responses), which leads to a smaller decrease in real wages. This reduction in the importance of the precautionary savings channel leads to significant nonlinearities for inflation and the policy rate (Auclert et al., 2023).

It is shown in the Online Appendix (Section A2.4, Figure A2.2) that lower wage indexation leads to a very similar results for the same economic reasons.

Import Oil Elasticity of Substitution: As discussed in Gagliardone and Gertler (2023), strong complementarities between oil imports and value-added output amplify the impact of oil shocks on inflation, resulting in more substantial increases in policy interest rates (see also Lorenzoni and Werning (2023), for further discussion). Figure 9 presents the pointwise mean of the distribution of the IRF differences for a



Notes: The red-solid line captures the pointwise mean of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses derived by multiplying μ_o with 3 for each draw from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^L, \mathcal{S}_{signs}^D\right)$. The red dashed line is the pointwise mean derived by multiplying μ_o with 0.5. The blue-solid-circle line is the pointwise mean derived using the benchmark model. The x-axis denotes quarters.

set of μ_o parameter draws that are 50% lower than the benchmark simulation values (red-dashed line), those that are 300% higher (red-solid line), and the median from the benchmark simulation (blue-solidcircle line).⁹ The simulations demonstrate that as the response of inflation to an oil shock diminishes with higher values of μ_o , the precautionary motives weaken due to a subdued policy response, reducing the economic significance of the nonlinearities.

The Role of Monetary Policy: The previous discussion has not addressed the role of monetary policy in the simulation results presented in this section. To better understand the contribution of the monetary authority, we introduce a large oil shock to the economy once again. This time, we compare how agents respond under two different scenarios: one where there was an unexpected policy tightening (i.e., a positive monetary policy shock) the quarter before the adverse supply shock, and another where there was an unexpected policy loosening (i.e., a negative monetary policy shock). It should emphasised

⁹The full distribution for both exercises can be in the Online Appendix A2.4, Figures A2.3 and A2.4.



Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses when the period before there was a monetary policy tightening, minus again the 5 standard deviation shock responses but the period before there was a loosening. The light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}^L_{signs}, \mathcal{S}^D_{signs}\right)$. The x-axis denotes quarters.

that the structural parameters are the same in both simulations and the only difference is due to the state occurring at the time of the oil shock.

Figure 10 illustrates the distribution of the differences between these two responses. The only variable displaying no asymmetry around a zero median value is inflation, reflecting the central bank's determination to achieve the inflation target. However, price stability comes at a significantly higher cost following an unexpected monetary policy tightening, primarily due to inertia in the Taylor Rule. This is evident in Figure 11, where the same analysis is conducted with the interest rate smoothing parameter set to zero for all scenarios.

The monetary policy authority's desire to limit interest rate volatility and maximize policy communication effectiveness can incur substantial costs if the central bank makes a "mistake." This is how agents perceive the monetary policy shock when inflation is on target, and the output gap is zero prior to an unexpected interest rate decision. Agents, well aware of this aspect of monetary policy, adjust their consumption and hiring decisions to hedge against this potential outcome.

Additional Simulations: It is illustrated in the Online Appendix A2.4 that altering the way that permanent productivity deterioration concerns are modelled has a minimal impact on the results (Figure A2.1), suggesting that this channel plays a minor role in explaining the empirical findings. Similarly, Epsteing-Zing preferences contribution to the benchmark simulation results is limited (Figures A2.5 and A2.6). As explained in Rudebusch and Swanson (2012) and Swanson (2021), recursive preferences can be helpful in matching the second moments of asset prices and risk premia. However, their impact on the



Figure 11: Assessing the Role of Interest Rate Smoothing

Notes: The dark shadow area captures the 5th – 95th percentiles of the differences between the 5 standard deviation responses when the period before there was a monetary policy tightening, minus again the 5 standard deviation shock responses but the period before there was a loosening. The light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^L, \mathcal{S}_{signs}^D\right)$ but this time the values of ρ_R has been set equal to zero. The blue-solid-circle line is the pointwise mean from Figure 10. The x-axis denotes quarters.

level of aggregate macro variables is limited. Furthermore, a significant degree of consumption smoothing is assumed in all simulations, in line with the estimated DSGE literature, which mitigates the benefits arising from using Epstein-Zin preferences.

6 Conclusion

In this paper, we present robust evidence that economic activity, labour market variables and risk indicators respond nonlinearly to oil news shocks, while, price variables, financial cost indicators, and the policy rate do not exhibit similar asymmetries. To infer these conclusions: i) we rely on a Threshold VAR model, ii) develop a novel VAR narrative shock identification scheme and iii) employ an extensive data set. Finally, the empirical results are robust to alternative narrative measures and different samples.

To infer the economic mechanism that explains the stylised facts, we develop an extremely flexible model NK DSGE model with search & matching frictions, Epstein-Zin preferences and mechanisms that give rise to concerns of a long-lasting productivity deterioration after adverse oil news supply shocks. We employ predictive prior analysis to identify the channels required to reproduce the empirical findings. Our analysis indicates that labour market frictions are needed to reproduce the nonlinear dynamic patterns observed in the data. These fictions give rise to unemployment risks that trigger strong precautionary savings motives and increase with the size of the shock, causing the nonlinearities discussed before. The low degree of oil import substitution elasticity enhances the sensitivity of inflation to the oil shock, together with the

inertia in the Taylor Reaction that prevents the monetary authority from fully correcting potential policy mistakes, further strengthening the precautionary motives induced by the risks of becoming unemployed.

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Appendix

A1 MCMC algorithm

The model is defined as:

$$Y_{t} = \sum_{j=1}^{M} (B_{j}X_{t}) \mathcal{I} (S_{t} = j) + u_{t}$$
(A1.1)

$$var(u_t) = \Sigma_t = \sum_{j=1}^M \mathcal{I}(S_t = j) \odot \Sigma_j$$
(A1.2)

$$\varepsilon_t = A_{0,t}^{-1} u_t \tag{A1.3}$$

$$m_t = \beta \varepsilon_{1t} + \sigma v_t, \quad v_t \sim \mathcal{N}(0, 1)$$
 (A1.4)

The regimes are determined as:

$$S_t = 1 \Longleftrightarrow \tilde{o}_{t-d} \le o^* \tag{A1.5}$$

$$S_t = 2 \Longleftrightarrow o^{**} \ge \tilde{o}_{t-d} > o^* \tag{A1.6}$$

$$S_t = 3 \iff \tilde{o}_{t-d} > o^{**} \tag{A1.7}$$

The covariance between the reduced form residuals and the instrument in regime j can be defined by:

$$\begin{pmatrix} u_{jt} \\ m_{jt} \end{pmatrix} | L_j \sim \mathcal{N}\left(0, L_j L'_j\right), \quad L_j = \begin{pmatrix} A_j q & 0 \\ \overline{b} & \sigma \end{pmatrix}$$
(A1.8)

where \bar{b} is a $1 \times N$ vector $\bar{b} = \begin{bmatrix} \beta & 0_{1 \times (N-1)} \end{bmatrix}$, since

$$\left(\begin{array}{c} u_{jt} \\ m_{jt} \end{array}\right) = L_j \left[\begin{array}{c} \varepsilon_{jt} \\ v_{jt} \end{array}\right]$$

To consider the role of the instrument, we follow Caldara and Herbst (2019) and factor the likelihood of the model as:

$$p(Y_{jt}, m_{jt}|\Xi) = p(Y_{jt}|\Xi) p(m_{jt}|Y_{jt}, \Xi),$$
 (A1.9)

where Ξ denotes all parameters and state variables of the model and A_j is the lower Cholesky factor of Σ_j . Given the conditional normality assumption in equation A1.8, the conditional density $p(m_{jt}|Y_{jt}, \Xi)$ is also normal with mean $\mu_j = \beta q'_1 A_j^{-1} u_t$ and variance $s = \sigma^2$, where q_1 is the first column of q.

As discussed in Caldara and Herbst (2019), μ_j can be interpreted as a linear combination of the orthogonalised residuals $A_j^{-1}u_{jt}$.

A1.1 Priors

1. We use a conjugate prior for the VAR coefficients $b_j = vec\left(B'_j\right)$, Σ implemented via dummy observations (see Banbura et al., 2010). The same prior is used for the coefficients in each regime.

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_{1}\sigma_{1}...\gamma_{N}\sigma_{N})}{\tau} \\ 0_{N\times(P-1)\times N} \\ \\ diag(\sigma_{1}...\sigma_{N}) \\ \\ 0_{1\times N} \end{pmatrix}, and X_{D,1} = \begin{pmatrix} \frac{J_{P}\otimes diag(\sigma_{1}...\sigma_{N})}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP+1} \\ \\ 0_{1\times NP} & I_{1}\times c \end{pmatrix}$$
(A1.10)

where γ_1 to γ_N denotes the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients, c is the tightness of the prior on the constant terms and N is the number of endogenous variables, i.e. the columns of Y_t . In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable. We use a non-informative prior and set $\tau = 1$. The scaling factors σ_i are set using the standard deviation of the error terms from these preliminary AR(1) regressions. Finally, we set c = 1/1000 in our implementation indicating a flat prior on the constant. We also introduce a prior to the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{diag\left(\gamma_1\mu_1\dots\gamma_N\mu_N\right)}{\lambda}, \ X_{D,2} = \left(\begin{array}{c} \frac{(1_{1\times P})\otimes diag(\gamma_1\mu_1\dots\gamma_N\mu_N)}{\lambda} \ 0_{N\times 1} \end{array}\right)$$
(A1.11)

where μ_i denotes the sample means of the endogenous variables. The prior tightness is $\lambda = 10$.

- 2. We assume a normal prior for β : $\mathcal{N}(\underline{\beta}, \underline{V})$. The prior for σ^2 is inverse Gamma with mean σ_0 and standard deviation v_0 . To set the prior we use a frequentist proxy VAR to calculate the shock of interest. Denote \underline{b} as the OLS estimate of the coefficient of regression of m_t on this initial estimate of the shock. We then set $\underline{\beta} = \underline{b}, \underline{V} = 0.2, \sigma_0 = \frac{b}{2}, v_0 = 0.2$.
- 3. We assume a normal prior for the threshold $o^*: \mathcal{N}(\underline{o^*}, \underline{V_{o^*}})$ where $\underline{o^*}$ is set to the median of annual growth of oil prices and $\underline{V_{o^*}}$) equals 100. The prior for $o^{**}: \mathcal{N}(\underline{o^{**}}, \underline{V_{o^{**}}})$ where $\underline{o^{**}}$ is set to the 80th percentile of annual growth of oil prices and $V_{o^{**}}$) equals 100

A1.2 Gibbs algorithm

The Gibbs algorithm samples from the following conditional posterior distributions:

Step 1. $p(b_j|\Xi_{-b}, Y_{1:T}, m_{1:T})$. Ξ_{-b_t} denotes all parameters except b. Given a draw of S_t , the data can be divided into samples corresponding to each regime: Y_{jt}, X_{jt}, m_{jt} . In each regime, the model can be written as:

$$\begin{pmatrix} Y_{jt} \\ m_{jt} \end{pmatrix} = \begin{pmatrix} I_N \otimes X'_{jt} \\ 0 \end{pmatrix} b_j + \begin{pmatrix} u_{jt} \\ m_{jt} \end{pmatrix}$$
(A1.12)

The covariance matrix of the observation equation residuals is:

$$cov \begin{pmatrix} u_{jt} \\ m_{jt} \end{pmatrix} = \begin{pmatrix} A_j A'_j & A_j q'_1 \beta \\ \beta q_1 A'_j & \beta^2 + \sigma^2 \end{pmatrix}$$
(A1.13)

where A_j is the lower Cholesky factor of Σ_j . This system is conditionally linear and Gaussian. As m_{jt} is observed, one can re-write the model using the conditional normal distribution. In particular, partition the covariance $cov \begin{pmatrix} u_{jt} \\ m_{jt} \end{pmatrix} \Xi_{-b}$ as:

$$cov \begin{pmatrix} u_{jt} \\ m_{jt} \end{pmatrix} = \begin{pmatrix} \sigma_{u_{jt}u_{jt}} & \sigma_{u_{jt}m_{jt}} \\ \sigma'_{u_{jt}m_{jt}} & \sigma_{m_{jt}m_{jt}} \end{pmatrix}$$
(A1.14)

Then

$$u_{jt}|m_{jt} \sim \mathcal{N}\left(\mu_{j,u|m}, \Omega_{j,u|m}\right) \tag{A1.15}$$

where

$$\mu_{j,u|m} = \sigma_{u_{jt}m_{jt}} \left(\sigma_{m_{jt}m_{jt}}\right)^{-1} m'_{jt}$$

$$\Omega_{j,u|m} = \sigma_{u_{jt}u_{jt}} - \sigma_{u_{jt}m_{jt}} \left(\sigma_{m_{jt}m_{jt}}\right)^{-1} \sigma'_{u_{jt}m_{jt}}$$
(A1.16)

The model can be written as a standard VAR

$$Y_{jt}^* = (I_N \otimes X'_{jt}) b_j + u_{jt} | m_{jt};$$
$$u_{jt} | m_{jt} \sim \mathcal{N} \left(0, \Omega_{j,u|m} \right)$$

where:

$$Y_{jt}^* = Y_{jt} - \mu'_{j,u|m}$$

Thus the conditional posterior for b is normal: $\mathcal{N}(M, V)$ where:

$$M = vec\left(\left(x^{*'}x^{*}\right)^{-1}\left(x^{*'}y^{*}\right)\right)$$
$$V = \Omega_{j,u|m} \otimes \left(x^{*'}x^{*}\right)^{-1}$$

with:

$$y^* = \begin{pmatrix} Y_{j,t}^* \\ Y_{D,1} \\ Y_{D,2} \end{pmatrix}, x^* = \begin{pmatrix} X_{j,t} \\ X_{D,1} \\ X_{D,2} \end{pmatrix}$$

Step 2. $p(\Sigma_j | \Xi_{\Sigma_j}, Y_{1:T}, m_{1:T})$. We follow Caldara and Herbst (2019) and use a Metropolis step to sample Σ_j . This step is implemented for each regime j

(a) Draw a candidate $\Sigma_{j,new}$ from the proposal $Q(.) = IW\left(u_j^* u_j^*, T_j + T_D - K\right)$. The proposal density is the marginal posterior distribution of the error covariance matrix in the case of a

standard Bayesian VAR in regime j where u_j^* denotes the residuals $\tilde{y}_j^* - x_j^* M$ with $\tilde{y}_j^* = \begin{pmatrix} Y_{j,t} \\ Y_{D,1} \\ Y_{D,2} \end{pmatrix}$, T_j denotes the number of observations in regime j, T_D denotes the number of

dummy observations and K denotes the number of regressors in each equation.

(b) Accept the draw with probability $\alpha = \min \left[\frac{\frac{p\left(m_j, Y_j, \Sigma_{new}, \Xi_{-\Sigma_j}\right)}{Q(\Sigma_{new})}}{\frac{p\left(m_j, Y_j, \Sigma_{old}, \Xi_{-\Sigma}\right)}{Q(\Sigma_{old})}}, 1 \right]$. Here $p\left(m_j, Y_j\right)$ denotes the joint posterior distribution evaluated in regime j.

Step 3. $p(q_1|\Xi_{-q_1}, Y_{1:T}, m_{1:T})$. Following Caldara and Herbst (2019) we use a Metropolis step to sample q_1 :

- (a) Draw a candidate from as $q_{1,new} = \frac{z}{\|z\|}$ where z is a $N \times 1$ vector from the $\mathcal{N}(0,1)$ distribution.
- (b) Accept the draw with probability $\alpha = \min\left[\frac{P\left(m_{1:t}|Y_{1:t},q_{1,new},\Xi_{-q_1}\right)}{P\left(m_{1:t}|Y_{1:t},q_{1,old},\Xi_{-q_1}\right)},1\right]$ where $P\left(m_{1:T}|Y_{1:T},q_{1},\Xi_{-q_1}\right) = \prod_{t=1}^{T} P\left(m_t|Y_t,q_1\Xi\right)$ with $P\left(m_t|Y_t,q_1,\Xi_{-q_1}\right) \sim \mathcal{N}\left(\beta q_1'A_t^{-1}u_t,\sigma^2\right)$ where $A_t = \sum_{j=1}^{M} \mathcal{I}\left(S_t = j\right) \odot A_j$
- Step 4 $p\left(\beta,\sigma|\Xi_{-[\beta,\sigma]},Y_{1:T},m_{1:T}\right)$. The structural shock of interest ε_{1t} can be calculated as $\varepsilon_{1t} = A_t q_1 u$. Conditional on $\Xi_{-[\beta,\sigma]}$ equation A1.4 is a standard linear regression, so specifying a conditional Normal-Gamma prior delivers a Normal-Gamma posterior. Particularly, we first draw $p\left(\sigma^2|\Xi_{-[\beta,\sigma]},Y_{1:T},m_{1:T}\right)$. Assuming an inverse-Gamma prior, this conditional posterior is also inverse-Gamma. As the prior is parameterised in terms of mean σ_0 and standard deviation v_0 , it is convenient to draw the precision $\frac{1}{\sigma^2}$ using Gamma distribution. Note that $\frac{1}{\sigma^2} \sim \mathcal{G}(a,b)$ where $a = \frac{\nu_1}{2}, b = \frac{2}{s_1}$. The parameters of this Gamma density are given by $\nu_1 = \nu_0 + T$ and $s_1 = s_0 + \hat{v}'_t \hat{v}_t$ where $\hat{v}_t = m_t - \beta e_{1t}$. s_0 can be calculated as $2\sigma_0 \left(1 + \frac{\sigma_0^2}{v_0^2}\right)$ while $\nu_0 = 2\left(2 + \frac{\sigma_0^2}{v_0^2}\right)$. Moreover, assuming a prior for $\beta|\sigma^2, \Xi_{-[\beta,\sigma]} \sim \mathcal{N}(\underline{\beta}, \underline{V}^{-1})$, the posterior is also conditional Normal $p\left(\beta|\Xi_{-[\beta,\sigma]},\sigma,Y_{1:T},m_{1:T}\right) \sim \mathcal{N}(\bar{\beta}, \tilde{V}^{-1})$, where $\tilde{\beta} = \tilde{V}^{-1}\left[\sum_{t=1}^T m_t \varepsilon_{1t} + \underline{V}\underline{\beta}\right]$ and $\tilde{V} = \underline{V} + \frac{1}{\sigma^2}\sum_{t=1}^T \varepsilon_1^2$.
- Step 5 $p(o^+|\Xi_{-o^+}], Y_{1:T}, m_{1:T})$. Let $o^+ = \begin{pmatrix} o^* \\ o^{**} \end{pmatrix}$. We draw o^+ using a random walk metropolis algorithm (see Chen and Lee, 1995). We draw a candidate value: $o^J \sim \mathcal{N}(o^{J-1}, \Sigma_o)$ where o^J denotes the new draw while o^{J-1} is the previous draw. The acceptance probability is given by $F(Y_t | o^J, \Xi_{-o^+}]) / F(Y_t | J^{-1}, \Xi_{-o^+}])$, where F(.) denotes the posterior density: $F(Y_t | o^+, X_{i_{-o^+}}) \propto f(Y_t | o^+, X_{i_{-o^+}}) p(o^+)$ where f(.) is the likelihood function. Note that the likelihood function for the full sample is simply the product of the likelihood in the two regimes. The scale Σ_o is chosen to ensure that the acceptance rate is between 20% and 50%.
- Step 6 $p(d|\Xi_{-d})$. Chen and Lee (1995) show that the conditional posterior for d is a multinomial distribution with probability $f(Y_t | d_i, \Xi_{-d}) / \sum_{d=1}^{d_{i,\max}} f(Y_t | d, \Xi_{-d})$, where d_{\max} denotes the maximum delay allowed for.

A2 DSGE Model

A2.1 Derivation of Nash Bargain Wage Equation & Cut-Off Threshold

Notice that

$$\begin{split} \tilde{J}_{t}^{W}\left(\alpha_{t}\right) - \tilde{J}_{t}^{U} &= \tilde{W}_{t}\left(\alpha_{t}\right) - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} - \tilde{B}_{t} \\ &+ \beta E_{t}M_{t+1} \left\{ \begin{array}{c} \left(1 - Q_{t}^{U}\right)\left(1 - \bar{\delta}_{N,t+1}\right)\int_{\bar{\alpha}_{t+1}}^{\infty}\tilde{J}_{t+1}^{W}\left(\alpha\right)\frac{g(a)}{1 - \bar{G}(\bar{\alpha}_{t+1})}d\alpha \\ &- \left\{1 - Q_{t}^{U}\left(1 - \bar{\delta}_{N,t+1}\right) - \bar{\delta}_{N,t+1}\right\}\tilde{J}_{t+1}^{U} \end{array} \right\} \end{split}$$

$$\tilde{J}_{t}^{W}(\alpha_{t}) - \tilde{J}_{t}^{U} = \tilde{W}_{t}(\alpha_{t}) - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} - \tilde{B}_{t} \\
+\beta E_{t}M_{t+1} \left\{ \begin{array}{c} \left(1 - Q_{t+1}^{U}\right)\left(1 - \bar{\delta}_{N,t+1}\right)\int_{\bar{\alpha}_{t+1}}^{\infty}\tilde{J}_{t+1}^{W}(\alpha)\frac{g(\alpha)}{1 - G(\bar{\alpha}_{t+1})}d\alpha \\
-\left\{1 - \bar{\delta}_{N,t+1} - Q_{t+1}^{U}\left(1 - \bar{\delta}_{N,t+1}\right)\right\}\tilde{J}_{t+1}^{U} \end{array} \right\}$$

$$\begin{split} \tilde{J}_{t}^{W}\left(\alpha_{t}\right) - \tilde{J}_{t}^{U} &= \tilde{W}_{t}\left(\alpha_{t}\right) - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} - \tilde{B}_{t} \\ &+ \beta E_{t}M_{t+1} \left\{ \begin{array}{c} \left(1 - Q_{t}^{U}\right)\left(1 - \bar{\delta}_{N,t+1}\right)\int_{\bar{\alpha}_{t+1}}^{\infty}\tilde{J}_{t+1}^{W}\left(\alpha\right)\frac{g(a)}{1 - G(\bar{\alpha}_{t+1})}d\alpha \\ &- \left\{\left(1 - Q_{t}^{U}\right)\left(1 - \bar{\delta}_{N,t+1}\right)\right\}\tilde{J}_{t+1}^{U} \end{array} \right\} \end{split}$$

$$\tilde{J}_{t}^{W}(\alpha_{t}) - \tilde{J}_{t}^{U} = \tilde{W}_{t}(\alpha_{t}) - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} - \tilde{B}_{t} \\
+ \left(1 - Q_{t}^{U}\right)\beta E_{t}M_{t+1} \left\{\begin{array}{c} \left(1 - \bar{\delta}_{N,t+1}\right)\int_{\bar{\alpha}_{t+1}}^{\infty}\tilde{J}_{t+1}^{W}(\alpha)\frac{g(\alpha)}{1 - G(\bar{\alpha}_{t+1})}d\alpha \\
- \left(1 - \bar{\delta}_{N,t+1}\right)\tilde{J}_{t+1}^{U} \end{array}\right\} \quad (A2.1)$$

Using the first-order condition with respect to vacancies, the firm Bellman equation can be rewritten as

$$\tilde{J}_{t}^{F}\left(\alpha_{t}\right) = MC_{t}\frac{\left(1-\phi\right)\tilde{Y}_{t}^{d}}{L_{t}} - \tilde{W}_{t}\left(\alpha_{t}\right) - \frac{\left(1-\delta_{N}^{x}\right)\delta_{N,t}}{\left(1-\delta_{N}^{x}\right)\left(1-\delta_{N,t}\right)}\kappa_{f}\tilde{Z}_{t}W + \frac{\kappa_{h}\tilde{Z}_{t}}{Q_{t}^{\Upsilon}}$$
(A2.2)

The optimality-sharing condition implies that

$$\tilde{J}_t^W - \tilde{J}_t^U = \frac{\eta}{1 - \eta} \tilde{J}_t^F(\alpha_t)$$
(A2.3)

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which can be used to simplify the surplus of the worker expression

$$\tilde{J}_{t}^{W}\left(\alpha_{t}\right) - \tilde{J}_{t}^{U} = \tilde{W}_{t}\left(\alpha_{t}\right) - \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} - \tilde{B}_{t} + \left(1 - Q_{t}^{U}\right)\frac{\eta}{1-\eta}\frac{\kappa_{h}Z_{t}}{Q_{t}^{\Upsilon}}$$
(A2.4)

and to derive the Nash bargain equation

$$\tilde{W}_{t}(\alpha_{t}) = \eta \left\{ MC_{t} \frac{(1-\phi)\tilde{Y}_{t}^{d}}{L_{t}} + \kappa_{h}\tilde{Z}_{t}\frac{\Upsilon_{t}}{U_{t}} - \frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\delta_{N}^{x})(1-\delta_{N,t})}\kappa_{f}\tilde{Z}_{t}W \right\} + (1-\eta)\left\{\tilde{B}_{t} + \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}}\right\}$$
(A2.5)

Finally, we derive the productivity cut-off value using job destruction condition (i.e. $J_t^F(\alpha_t) = 0$) and the individual wage Nash bargain equation

$$0 = MC_{t}Z_{t}\alpha_{t} - \frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\bar{\delta}_{N,t})}\kappa_{f}\tilde{Z}_{t}W + \frac{\kappa_{h}\tilde{Z}_{t}}{Q_{t}^{\Upsilon}}$$

$$= MC_{t}Z_{t}\alpha_{t} - \iota_{w}\eta \left\{ MC_{t}Z_{t}\alpha_{t} + \kappa_{h}\tilde{Z}_{t}\frac{\Upsilon_{t}}{U_{t}} - \frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\delta_{N}^{x})(1-\delta_{N,t})}\kappa_{f}\tilde{Z}_{t}W \right\}$$

$$-\iota_{w}(1-\eta) \left\{ \tilde{B}_{t} + \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} \right\}$$

$$-(1-\iota_{w})\tilde{W}^{Nash}(\alpha) - \frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\bar{\delta}_{N,t})}\kappa_{f}\tilde{Z}_{t}W + \frac{\kappa_{h}\tilde{Z}_{t}}{Q_{t}^{\Upsilon}}$$

$$(1-\iota_{w}\eta)MC_{t}Z_{t}\alpha_{t} = \iota_{w}\eta\kappa_{h}\tilde{Z}_{t}\frac{\Upsilon_{t}}{U_{t}} + \iota_{w}(1-\eta) \left\{ \tilde{B}_{t} + \chi_{0}\tilde{Z}_{t}^{1-\sigma_{C}}L_{t}^{\sigma_{L}}\left(\tilde{C}_{t} - b\tilde{C}_{t-1}\right)^{\sigma_{C}} \right\}$$

$$+(1-\iota_{w})\tilde{W}^{Nash}(\alpha) + (1-\iota_{w}\eta)\frac{(1-\delta_{N}^{x})\delta_{N,t}}{(1-\bar{\delta}_{N,t})}\kappa_{f}\tilde{Z}_{t}W - \frac{\kappa_{h}\tilde{Z}_{t}}{Q_{t}^{\Upsilon}}$$
(A2.6)

A2.2 Stationary Equations

$$u\left(C_{t},L_{t}\right) = \frac{\left(C_{t}-h\frac{C_{t-1}}{\Gamma_{t}}\right)^{1-\sigma_{C}}}{1-\sigma_{C}} - \chi_{0}\frac{L_{t}^{1+\sigma_{L}}}{1+\sigma_{L}}$$

$$\breve{V}_{t} \equiv E_{t}\left(V_{t+1}\Gamma_{t+1}^{1-\sigma_{C}}\right)^{1-\gamma}$$

$$\dddot{V}_{t} \equiv \breve{V}_{t}^{\frac{1}{1-\gamma}}$$
(A2.7)

$$V_t = u\left(C_t, L_t\right) + \beta \overset{\dots}{V}_t \tag{A2.8}$$

$$\chi_0 N_t^{\sigma_L} \left[C_t - h \frac{C_{t-1}}{\Gamma_t} \right]^{\sigma_C} + B = W_t^E \tag{A2.9}$$

$$\frac{E_t \Pi_{t+1} \Gamma_{t+1}^{\sigma_C}}{R_t^A} = \beta E_t \frac{\lambda_{t+1}}{\lambda_t} \tag{A2.10}$$

$$\frac{1}{R_t^A} = E_t \left(\frac{C_t - h \frac{C_{t-1}}{\Gamma_t}}{C_{t+1} \Gamma_{t+1} - h C_t} \right)^{\sigma_C} \frac{1}{\Pi_{t+1}} \left(E_t V_{t+1}^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} V_{t+1}^{-\gamma}
M_{t+1} = E_t \left(\frac{C_t - h \frac{C_{t-1}}{\Gamma_t}}{C_{t+1} \Gamma_{t+1} - h C_t} \right)^{\sigma_C} \frac{1}{\Pi_{t+1}} \left(E_t V_{t+1}^{1-\gamma} \right)^{\frac{\gamma}{1-\gamma}} V_{t+1}^{-\gamma}
\frac{1}{R_t^A} = \beta E_t \frac{M_{t+1}}{\Pi_{t+1}}$$
(A2.11)

$$Y_t = L_t H\left(\bar{\alpha}_{f,t}\right)$$

$$\Theta_{t} = MC_{t}H(\bar{\alpha}_{t}) - \frac{P_{t}}{P_{t}^{C}}\bar{W}_{t}^{Norm} + \beta E_{t}\left(1 - \bar{\delta}_{N,t+1}\right)M_{t+1}\left\{\Theta_{t+1}\Gamma_{t+1} - \frac{(1 - \delta_{N}^{x})\delta_{N,t+1}}{(1 - \bar{\delta}_{N,t+1})}\kappa_{f}\Gamma_{t+1}W\right\}$$
(A2.12)
$$MC_{t} = L_{t}\frac{\partial H(\bar{\alpha}_{t})}{\partial\bar{\alpha}_{t}}\left[\begin{array}{c}\frac{P_{t}}{P_{t}^{C}}L_{t}\frac{\partial\int_{\bar{\alpha}_{t}}^{\infty}\tilde{W}_{t}(\alpha)\frac{g(\alpha)}{1 - G(\bar{\alpha}_{t})}d\alpha}{\partial\bar{\alpha}_{t}} \\ + (1 - \delta_{N})\left(L_{t-1} + Q_{t-1}^{\Upsilon}\Upsilon_{t-1}\right)\kappa_{f}W\frac{\partial\delta_{N,t}}{\partial\bar{\alpha}_{t}} \\ + \Theta_{t}\left(1 - \delta_{N}\right)\left[L_{t-1} + Q_{t-1}^{\Upsilon}\Upsilon_{t-1}\right]\frac{\partial\delta_{N,t}}{\partial\bar{\alpha}_{t}}\right]$$

$$\frac{\kappa_h}{Q_t^{\Upsilon}} = \beta E_t \left(1 - \bar{\delta}_{N,t+1} \right) M_{t+1} \left\{ \Theta_{t+1} \Gamma_{t+1} - \frac{\left(1 - \delta_N^x \right) \delta_{N,t+1}}{\left(1 - \bar{\delta}_{N,t+1} \right)} \kappa_f \Gamma_{t+1} W \right\}$$
(A2.13)

$$Y_t = (1 - \phi_o) \left(\frac{P_t}{P_t^C}\right)^{-\mu} X_t$$
$$O_t = \phi_o \left(\frac{P_t^o}{P_t^C}\right)^{-\mu} X_t$$
$$1 = (1 - \phi_o) \left(\bar{P}_t\right)^{1-\mu} + \phi_o \left(\bar{P}_t^O\right)^{1-\mu}$$

$$\Pi_t^C = (1 - \phi_o) \left(\Pi_t \bar{P}_{t-1} \right)^{1-\mu} + \phi_o \left(\Pi_t^O \bar{P}_{t-1}^O \right)^{1-\mu}$$

$$W_t^{Nash}(\alpha_t) = \eta \left\{ M C_t \bar{\alpha}_t + \kappa_h \frac{\Upsilon_t}{U_t} - \frac{(1 - \delta_N) \, \delta_{N,t}}{(1 - \delta_N) \, (1 - \delta_{N,t})} \kappa_f W \right\}$$

+ $(1 - \eta) \left\{ B_t + \chi_0 L_t^{\sigma_L} \left(C_t - b \frac{C_{t-1}}{\Gamma_t} \right)^{\sigma_C} \right\}$ (A2.14)

$$\bar{W}_{t}^{Nash} = \eta \left\{ MC_{t}H\left(\bar{\alpha}_{t}\right) + \kappa_{h}\frac{\Upsilon_{t}}{U_{t}} - \frac{\left(1-\delta_{N}^{x}\right)\delta_{N,t}}{\left(1-\delta_{N,t}\right)}\kappa_{f}W \right\} + \left(1-\eta\right) \left\{ B_{t} + \chi_{0}L_{t}^{\sigma_{L}}\left(C_{t} - b\frac{C_{t-1}}{\frac{C_{t-1}}{\Gamma_{t}}}\right)^{\sigma_{C}} \right\}$$
(A2.15)

$$W_t^{Norm}(\bar{\alpha}_t) = \iota_w W_t^{Nash}(\bar{\alpha}_t) + (1 - \iota_w) W^{Nash}(\bar{\alpha}_t)$$
(A2.16)

$$\bar{W}_t^{Norm} = \iota_W \bar{W}_t^{Nash} + (1 - \iota_w) \bar{W}^{Nash}$$
(A2.17)

$$(1 - \iota_w \eta) M C_t \bar{\alpha}_t = \iota_w \eta \kappa_h \frac{\Upsilon_t}{U_t} + \iota_w (1 - \eta) \left\{ B_t + \chi_0 L_t^{\sigma_L} \left(C_t - b \frac{C_{t-1}}{\frac{C_{t-1}}{\Gamma_t}} \right)^{\sigma_C} \right\} \\ + (1 - \iota_w) W_t^{Nash} (\alpha_t) + (1 - \iota_w \eta) \frac{(1 - \delta_N^x) \delta_{N,t}}{(1 - \bar{\delta}_{N,t})} \kappa_f W - \frac{\kappa_h}{Q_t^{\Upsilon}}$$
(A2.18)

$$K_{P,t} = MC_t Y_t^d + \beta \xi E_t M_{t+1} \left(\frac{\Pi_{t+1}}{(\Pi^C)^{1-\iota_{\pi}} \Pi_t^{\iota_{\pi}}} \right)^{\varepsilon} K_{P,t+1} \Gamma_{t+1}$$
(A2.19)

$$F_{P,t} = Y_t^d + \beta \xi E_t M_{t+1} \left(\frac{\Pi_{t+1}}{(\Pi^C)^{1-\iota_{\pi}} \Pi_t^{\iota_{\pi}}} \right)^{\varepsilon-1} F_{P,t+1} \Gamma_{t+1}$$
(A2.20)

$$\bar{\Pi}_{P,t} = \frac{\varepsilon}{\varepsilon - 1} \frac{K_{P,t}}{F_{P,t}}$$
(A2.21)

$$1 = \xi \left(\frac{\Pi_t}{(\Pi^C)^{1-\iota_{\pi}} \Pi_{t-1}^{\iota_{\pi}}} \right)^{\varepsilon-1} + (1-\xi) \bar{\Pi}_{P,t}^{1-\varepsilon}$$
(A2.22)

$$\Delta_t^{\frac{1}{1-\phi}} = (1-\xi)\,\bar{\Pi}_{P,t}^{-\frac{\varepsilon}{1-\phi}} + \xi \left(\frac{\Pi_t}{(\Pi^C)^{1-\iota_\pi}\,\Pi_{t-1}^{\iota_\pi}}\right)^{\frac{\varepsilon}{1-\phi}} \Delta_{t-1}^{\frac{1}{1-\phi}}$$
(A2.23)

$$Y_{t}^{d} = C_{t} + G_{t} + \kappa_{h} \Upsilon_{t} + (1 - \delta_{N}^{x}) \delta_{N,t} \left(L_{t-1} + Q_{t-1}^{\Upsilon} \Upsilon_{t-1} \right) \kappa_{f} W$$
(A2.24)

$$Y_t = \Delta_t Y_t^d \tag{A2.25}$$

$$X_t = \bar{P}_t Y_t + \bar{P}_t^O O_t \tag{A2.26}$$

A2.3 Steady States

We set L = 1 - 0.06, $\delta_N^x = 0.068$ and $\bar{\delta}_N = 0.1$, which can be used to define

$$\delta_N = \frac{\bar{\delta}_N - \delta_N^x}{1 - \delta_N^x} \tag{A2.27}$$

given $\mu_{\alpha} = 1$ and $\sigma_{\alpha} = 0.15$ we can derive

$$\bar{a} = G^{-1}\left(\delta_N\right) \tag{A2.28}$$

Given \bar{a} we obtain

$$H\left(\bar{a}\right) = \frac{1}{1 - G\left(\bar{a}\right)} exp\left(\mu_{\bar{a}} + \frac{1}{\sigma_{\bar{a}}}\right) \Phi\left(\frac{\mu_{\bar{a}} + \sigma_{\bar{a}} - \ln\left(\bar{a}\right)}{\sigma_{\bar{a}}}\right)$$
(A2.29)

The steady value of Y is given by

$$Y = LH\left(\bar{a}\right) \tag{A2.30}$$

From the stochastic discount factor, we obtain

$$M = \Gamma^{-\sigma_C}$$

From the Philips curve equation, we obtain

$$K_P = \frac{MCY^d}{1 - \beta \xi \Gamma^{1 - \sigma_C}}$$
$$F_P = \frac{Y^d}{1 - \beta \xi \Gamma^{1 - \sigma_C}}$$

We use the definition of the $\overline{\Pi}_P$

$$\bar{\Pi}_P = 1$$

and the PP curve to derive the steady-state value of the marginal cost

$$MC = \frac{\varepsilon - 1}{\varepsilon} \tag{A2.31}$$

Then from the price dispersion equation

$$\Delta = 1 \tag{A2.32}$$

From the marketing clearing condition, we also know that

$$Y^d = Y \tag{A2.33}$$

We use κ_h and κ_f to match the steady state the hiring and firing cost as a percentage of the GDP, meaning that the steady-state value of consumption can be derived from

$$C = Y - G - \kappa_h \Upsilon - (1 - \delta_N^x) \,\delta_N \left(L + Q^{\Upsilon} \Upsilon \right) \kappa_f W \tag{A2.34}$$

The value of Θ is derived by the job creation condition

$$\Theta = \frac{\kappa_h}{Q^{\Upsilon}\beta \left(1 - \bar{\delta}_N\right) M\Gamma} + \frac{\left(1 - \delta_N^x\right) \delta_N}{\left(1 - \bar{\delta}_N\right)} \kappa_f \Gamma W$$

$$\Theta = \frac{\kappa_h}{Q^{\Upsilon}\beta \left(1 - \bar{\delta}_N\right) M\Gamma} + \frac{\left(1 - \delta_N^x\right) \delta_N \left(L + Q^{\Upsilon}\Upsilon\right) \kappa_f W}{Y} \frac{Y\Gamma}{\left(1 - \bar{\delta}_N\right) \left(L + Q^{\Upsilon}\Upsilon\right)}$$
(A2.35)

The aggregate wage can be derived using the demand for labour schedule

$$\bar{W} = MCH(\bar{\alpha}) + \left\{\beta\left(1-\bar{\delta}_{N}\right)M\Gamma-1\right\}\Theta - \beta M\left(1-\delta_{N}^{x}\right)\delta_{N}\kappa_{f}\Gamma\bar{W}$$
$$\bar{W} = MCH(\bar{\alpha}) + \left\{\beta\left(1-\bar{\delta}_{N}\right)M\Gamma-1\right\}\Theta - \frac{\left(1-\delta_{N}^{x}\right)\delta_{N}\left(L+Q^{\Upsilon}\Upsilon\right)\kappa_{f}W}{Y}\frac{\beta M\Gamma Y}{L+Q^{\Upsilon}\Upsilon}$$
(A2.36)

From the aggregate Nash bargain wage we derive χ_0

$$\chi_0 = \frac{\bar{W} - \eta \left\{ MCH\left(\bar{\alpha}_t\right) + \kappa_h \frac{\Upsilon}{U} - \frac{\left(1 - \delta_N^x\right)\delta_N}{\left(1 - \delta_N^x\right)\left(1 - \delta_N\right)} \kappa_f W \right\} - \left(1 - \eta\right) B}{\left(1 - \eta\right) L^{\sigma_L} \left[C\left(1 - \frac{b}{\Gamma}\right)\right]^{\sigma_C}}$$
(A2.37)

While the individual Nash bargain wage

$$W^{Nash}(\alpha) = \eta \left\{ MC\bar{\alpha} + \kappa_h \frac{\Upsilon}{U} - \frac{(1-\delta_N^x)\delta_N}{(1-\delta_N^x)(1-\delta_N)}\kappa_f W \right\} + (1-\eta) \left\{ B + \chi_0 L^{\sigma_L} \left[C \left(1 - \frac{b}{\Gamma} \right) \right]^{\sigma_C} \right\}$$
(A2.38)

From the demand for value-added

$$X = \frac{Y}{1 - \phi_o} \tag{A2.39}$$

And the demand for oil

$$O = \frac{\phi_o}{1 - \phi_o} Y \tag{A2.40}$$

A2.4 Additional DSGE Simulations

This section contains the simulations discussed in the main text, but the charts have not been included there to save space.

Modifying the Signal Extraction Problem: As explained in Section 5, two approaches are used to capture "elevated concerns" about a permanent effect on productivity following a severe adverse oil news shock. In this section, we review the results by replacing the rare disaster mechanism with a Kalman Filter extraction problem. Similar to the benchmark case, predictive prior analysis is employed to derive a distribution of the structural parameters that meet the restrictions outlined in Tables 1 and 2. Figure A2.1 illustrates the size and type of nonlinearities produced by the structural model for a given distribution of the structural parameter vector. The comparison of Figures A2.1 and 7 reveals no substantial differences, indicating that the benchmark results are not sensitive to the modelling of permanent productivity deterioration concerns.

Lower Wage Indexation: The degree of wage indexation has been decreased by 20% in this simulation exercise. With the risk for entrepreneurs incurring the cost of maintaining an unproductive workforce significantly reduced, they become less cautious about engaging in contractual agreements with households. This reduction in caution decreases the risk of becoming unemployed, mitigating precautionary savings motives and leading to milder effects from large oil shocks on economic activity.

Import Oil Elasticity of Substitution: Figures A2.3 and A2.4 illustrate the sensitivity of the benchmark results to the degree of oil import substitution elasticity.



Figure A2.1: Concerns of a Permanent Productivity Loss: Kalman Filter

Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}_{KF}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$. The blue-solid-circle line is the pointwise mean derived using the benchmark model $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$. The x-axis denotes quarters.

Expected Utility Preferences: The importance of the recursive preferences is assessed in this simulation exercise. Figure A2.5 suggests that the contribution of using Epstein-Zin preferences is minimal. The benchmark preferences seem to affect only the tails of the distribution associated with the worst outcomes. To illustrate this point, we rely on the Kelly skewness. which is defined as

$$skew_{i,j} = \frac{Q_{90}\left(p\left(\mathcal{IRFS}_{i,j}\left(\theta|\mathcal{M}\right)\right)\right) + Q_{10}\left(p\left(\mathcal{IRFS}_{i,j}\left(\theta|\mathcal{M}\right)\right)\right) - 2Q_{50}\left(p\left(\mathcal{IRFS}_{i,j}\left(\theta|\mathcal{M}\right)\right)\right)}{Q_{90}\left(p\left(\mathcal{IRFS}_{i,j}\left(\theta|\mathcal{M}\right)\right)\right) - Q_{10}\left(p\left(\mathcal{IRFS}_{i,j}\left(\theta|\mathcal{M}\right)\right)\right)}$$
(A2.41)

where Q_{α} denotes the α^{th} quantile of the distribution p() of a variable *i* for a horizon *j*. Figure A2.6 illustrates that recursive preferences skew the distribution of the large shock IRFs to the worst outcomes.



Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ but this time the values of κ_{h} has been increased by 20% relative to benchmark distribution. The blue-solid-circle line is the pointwise mean derived using the benchmark model. The x-axis denotes quarters.





Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ but this time the values of μ_{o} have been increased by 300% relative to benchmark distribution. The blue-solid-circle line is the pointwise mean derived using the benchmark model. The x-axis denotes quarters.



Figure A2.4: Assessing Oil Import Substitution Elasticity: Low Elasticity

Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ but this time the values of μ_{o} have been decreased by 50% relative to benchmark distribution. The blue-solid-circle line is the pointwise mean derived using the benchmark model. The x-axis denotes quarters.



Notes: The dark shadow area captures the $5^{th} - 95^{th}$ percentiles of the differences between the 5 standard deviation responses (divided by 5) minus the 1 standard deviation shock responses, while the light shadow area captures the $16^{th} - 84^{th}$ percentiles. The red-solid line displays the pointwise mean. The distributions have been derived using the draws from $p\left(\theta|\mathcal{M}, \mathcal{S}_{signs}^{L}, \mathcal{S}_{signs}^{D}\right)$ but this time the values of γ has been set equal to 0 in all draws. The blue-solid-circle line is the pointwise mean derived using the benchmark model. The x-axis denotes quarters.



Figure A2.6: Kelly Skewness of the large shock IRFs

Notes: The red-solid line denotes the skewness of the large shock IRFs when the parameter γ is set equal to 0 for all draws, while the blue-solid-circle line is the skewness of the benchmark distribution. The x-axis denotes quarters.

A3 Predictive Likelihoods

Figure A3.1: Performance of benchmark model relative to a range of alternative specifications



The figure illustrates the cumulative difference in predictive likelihoods between the three regime-switching models in M_1 and the linear BVAR model in M_0 over the evaluation sample. Positive values indicate that the alternative models outperform the linear model. These alternative models include three oil price regimes (solid black line), two oil price regimes (dashed red line), and three boom-bust regimes (dashed blue line). A higher value for the predictive likelihood indicates better performance of the respective alternative model.

Figure A3.2: Performance of benchmark model relative to a range of alternative specifications



The figure illustrates the cumulative difference in the joint predictive likelihoods for US IP and CPI, between the three regime-switching models in M_1 and the linear BVAR model in M_0 over the evaluation sample. Positive values indicate that the alternative models outperform the linear model. These alternative models include three oil price regimes (solid black line), two oil price regimes (dashed red line), and three boom-bust regimes (dashed blue line). A higher value for the predictive likelihood indicates better performance of the respective alternative model.

A4 Additional results



Figure A4.1: The figure presents the estimated oil price regimes identified by the three regimes TVAR model. The black line represents the annual growth rate of real oil price. The purple, grey, and red bands correspond to sub-periods characterized by low, moderate, and high oil price regimes. These regimes are defined based on a state where the threshold variable, i.e., the oil price growth in period t - d, falls below or exceeds the critical thresholds $o^* = -2.9\%$ and $o^{**} = 20.3\%$ in the Threshold VAR model.



Figure A4.2: The figure displays the impulse response functions of the variables in the baseline model to an oil supply news shock, which is normalized to cause a 10 percent increase in the real price of oil on impact. The solid lines represent the median IRFs in the low oil price regime (black line), moderate oil price regime (blue line), and high oil price regime (red line). The shaded areas and dashed lines indicate the 68 percent credibility sets.



Figure A4.3: The figure presents the differences in the IRFs across oil price regimes in the baseline model. The oil supply news shock is normalized to cause a 10 percent increase in the real price of oil on impact. The solid lines represent the median differences between the moderate and low oil price regimes (black line), high and low oil price regimes (red line), and high and moderate oil price regimes (blue line). The shaded areas and dashed lines indicate the 68 percent credibility sets.



Figure A4.4: Size and sign asymmetry for additional labor market variables to oil supply news shocks. Large vs. small (first column) and positive vs. negative (second column) oil supply news shocks are reported. Large shocks increase oil prices by 50%, while small shocks increase oil prices by 10%. For positive and negative shocks, small shocks are considered (10% shock size). The third and fourth columns display the distribution of the difference between impulse responses for Large minus Small and Positive minus Negative shocks, respectively. Solid lines represent medians, while shaded areas represent the corresponding 68 credibility sets. All responses are normalized to increase the real price of oil by 10% on impact. The IRFs are expressed in percent.



Figure A4.5: Size and sign asymmetry for additional nominal variables, to oil supply news shocks. The additional variables are added to the baseline model one at a time. Large vs. small (first column) and positive vs. negative (second column) oil supply news shocks are reported. Large shocks increase oil prices by 50%, while small shocks increase oil prices by 10%. For positive and negative shocks, small shocks are considered (10% shock size). The third and fourth columns display the distribution of the difference between impulse responses for Large minus Small and Positive minus Negative shocks, respectively. Solid lines represent medians, while shaded areas represent the corresponding 68 credibility sets. All responses are normalized to increase the real price of oil by 10% on impact. The IRFs are expressed in the following units: the rates are in percentage points while the price indexes, exchange rates and the inflation expectations are in percent.



Figure A4.6: Size and sign asymmetry for additional variables to oil supply news shocks. Large vs. small (first column) and positive vs. negative (second column) oil supply news shocks are reported. Large shocks increase oil prices by 50%, while small shocks increase oil prices by 10%. For positive and negative shocks, small shocks are considered (10% shock size). The third and fourth columns display the distribution of the difference between impulse responses for Large minus Small and Positive minus Negative shocks, respectively. Solid lines represent medians, while shaded areas represent the corresponding 68 credibility sets. All responses are normalized to increase the real price of oil by 10% on impact. The IRFs are expressed in percent except for the GZ spread and the 10Y term premium which are in percentage points.



Figure A4.7: The figure illustrates the difference between impulse responses for large versus small, and positive versus negative, oil supply news shocks across various specifications. Solid black lines and shaded areas represent medians and the corresponding 68 credibility intervals in the baseline model. Dashed green lines depict medians in the model using BH instruments, while blue dashed lines show medians with a sample including the Covid-19 period up to May 2022. Dashed red lines represent medians in the model using a high reliability prior for the instrument. All responses are normalized to reflect a 10% increase in the real price of oil upon impact. The impulse response functions are expressed in percentages.

Variable name	Transformation	Source
Instrumental variable: oil supply news shocks	none	Känzig (2021)
Real oil price (WTI spot price, deflated by U.S. CPI)	$\log \times 100$	Känzig (2021)
World oil production	$\log \times 100$	Känzig (2021)
World oil inventories	$\log \times 100$	Känzig (2021)
World industrial production	$\log \times 100$	Känzig (2021)
U.S. industrial production	$\log \times 100$	Känzig (2021)
U.S. CPI	$\log \times 100$	Känzig (2021)
House price index (Deflated by PCE deflator)	$\log \times 100$	Haver (ID USFMHPIS@USECON) \ast
PCE deflator	none	FRED (ID:PCEPILFE)
PCE price index	$\log \times 100$	FRED (ID:PCEPI)
Producer price index (PPI)	$\log \times 100$	FRED (ID:PPIACO)
Inflation expectations	$\log \times 100$	FRED (ID:MICH)
Unemployment rate	none	Känzig (2021)
Unemployment rate: full-time workers	none	Haver (ID:LRFT@USECON)
Unemployment rate: part-time workers	none	Haver (ID:LRPT@USECON)
Average Duration of Unemployment	none	Haver (ID:LUAD@USECON)
Employment: full-time (divided by U.S. labor force)	none	Haver (ID:LEWFT@USECON)
Employment: part-time workers (divided by U.S. labor force)	none	Haver (ID:LEWPT@USECON)
Vacancies (Help wanted index over Labor force)	none	Barnichon (2010)
Job finding probability	none	Own calculations based on Shimer (2012)
Separation rate	none	Own calculations based on Shimer (2012)
U.S. labor force		BLS (ID:LNS11000000)
Real wage (Average hourly earnings, deflated by U.S. CPI)	$\log \times 100$	FRED-MD (ID:CES050000008)
TFP (Utilisation adjusted)	Interpolated to monthly freq.	Fernald (2012)
Real personal income	$\log \times 100$	FRED-MD (ID:RPI)
S&P500	$\log \times 100$	FRED-MD (ID:S&P 500)
Federal Fund Rate	none	FRED (ID:FEDFUNDS)
10 year zero coupon yield	none	Adrian et al. (2013)
10 year term premium	none	Adrian et al. (2013)
U.S. Consumer confidence index	$\log \times 100$	OECD
Macroeconomic Skewness	none	Iseringhausen et al. (2023)
Excess bond premium	none	Gilchrist et al. (2016)
GZ Spread	none	Gilchrist et al. (2016)
Recession risk index	none	Gilchrist et al. (2016)
JLN Macro Uncertainty	standardised	Jurado et al. (2015)
VXO	$\log \times 100$	Känzig (2021)
Automobiles stock price index	$\log \times 100$	Känzig (2021)
PCA Risk	none	own calculations

Table A3.1: Data series used in the model estimation

Notes. The table lists the variables included in the empirical application. The house price index series before 1975 is taken from Fieldhouse et al. (2018). The TFP measure is interpolated at monthly frequency using Industrial Production. The PCA Risk measure is computed as the principal component of the eight measures of risk in the Table going from the 10-year term premium to VXO.