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Oil Price Fluctuations and US Banks*

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Abstract

We document a sizable effect of oil price fluctuations on US banking variables by estimating an SVAR with sign restrictions as in Baumeister and Hamilton (2019). We find that oil market shocks that lead to a contraction in world economic activity unambiguously lower the amount of bank credit to the US economy, tend to decrease US banks' net worth, and tend to increase the US credit spread. The effects can be strong and long-lasting, or more modest and short-lived, depending on the source of the oil price fluctuations. The effects are stronger for smaller and lower leveraged banks.

Keywords: Oil market shocks, Bayesian SVAR models, sign restrictions, bank credit

JEL classification: E32, E44, Q35, Q43

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1 Introduction

In this paper, we study empirically the effect of oil price fluctuations on the balance sheets of US banks. This is relevant because, first, although the effects of oil price fluctuations on economic variables have been studied in the previous literature, very little attention has been given to banks' variables. Second, because from the perspective of a central bank aiming to preserve financial stability or a macroprudential authority with the same aim, knowing whether or not oil price fluctuations have an impact on the banking sector is of paramount importance. This mirrors why it is important for central banks to understand the impact of oil price fluctuations on inflation, typically the key target variable for those institutions. All this requires a thorough investigation because the existing evidence about the effects of oil price fluctuations on banks' variables is scant, at best indirect, if not only anecdotal.

Specifically, anecdotal evidence suggests a relationship between oil price fluctuations and banks' activity. Some Moody's credit outlook reports commenting on the large drop in oil prices in the period 2014-2015 stress that "lower oil prices will broadly support bank creditworthiness [and they] are positive for the operating environment of US banks."[1]

More formal empirical evidence also indirectly suggests a similar idea. For instance, the link between oil prices and the stock market is well established in the literature, e.g., Kilian and Park (2009), Aastveit (2014), and Sadorsky (2019). Based on that evidence, one can only guess that the relationship between banks' stock market and oil price fluctuations is the same, because a formal examination has not been explored. More recently, Abbritti et al. (2020) find that oil price movements have an impact on credit spreads, the latter being possibly related to banks' loan activities.

Hence, given the lack of direct empirical evidence on the relationship between oil price movements and banks' balance sheet, it is important to investigate further this issue and provide a rigorous analysis. To achieve our goal, we extend the state-of-the-art sign-restrictions-

[1] See Moody's (2015b), Moody's (2015c), and Moody's (2015a).

identified oil market Bayesian SVAR framework of Baumeister and Hamilton (2019) [BH henceforth] to incorporate a measure of US banks' net worth, a measure of the US credit spread, and a measure of the amount of credit extended by banks to the US economy. We estimate the model with monthly data over the sample period January 1974 through December 2019. We also want to adopt an agnostic approach in setting the sign restrictions on the newly added US block because we want our results in terms of the effects of oil market shocks on the banking variables to be driven mostly by data rather than by a priori or theory-based beliefs. Therefore, in our baseline specification we do not impose additional sign restrictions beyond those imposed by BH on the oil block of the model.

Our main contribution is to provide direct empirical evidence about the effects of oil price fluctuations on US banks' balance sheets and to evaluate whether or not the oil price pass-through depends on the different sources of shocks in the global oil market and on the banks' characteristics. As already stressed, Kilian and Park (2009) and Abbritti et al. (2020) point out that oil market shocks have an impact on the (overall) stock market and on the credit spread, respectively, but they look at those variables in isolation, and Abbritti et al. (2020) only look at the effects of an oil price shock. On the contrary, we put banks' variables together in a unified and coherent framework, also with the addition of credit.

This allows us to tell a complete story about the relationship between oil market shocks and US banks. We contribute with respect to the previous literature in four ways. First, we characterize the effect of those shocks on banks' net worth, something never done before. Second, we estimate the effects on the credit spread better than the previous literature, i.e., Abbritti et al. (2020). In fact, they only identify oil price shocks within a univariate regression-type framework, where the real price of oil is regressed on a bunch of US variables. The absence of oil supply and of global real economic activity measures makes their oil price shock of dubious interpretation. Third, we evaluate the effects of oil market shocks on the amount of bank credit extended in the economy, an issue that has been explored to a very limited extent, but never in the SVAR context, and for which there is no consensus yet. In fact, Bidder et al. (2021) and Wang (2021) are two examples of analysis conducted outside the SVAR realm.[2] The former finds that large US banks whose net worth is negatively impacted by oil price shocks tend to change their portfolio composition (de-risking) rather than reducing the amount of credit in the economy (de-leveraging). In particular, Bidder et al. (2021) find that the effect on total lending, total size of the balance sheet, and the degree of leverage appears ambiguous. On the contrary, Wang (2021) finds that small US regional banks tend to cut lending after facing a negative net worth shock induced by an oil price shock. It is also worth stressing that both papers, by focusing only on the period 2014-2015, might provide a set of results that is strictly related to that particular episode and that might not necessarily hold on average, or in other periods, if a long sample like ours with many oil episodes is considered.[3]

Fourth, we investigate if there is heterogeneity in the way banks included in our stock market index respond to oil market shocks. In fact, policies directed at guaranteeing financial stability might be more or less effective if different banks, or different groups of banks, are more or less impacted by oil market shocks. Knowing which type of bank is more affected is important to properly assess the effectiveness of those policies and to think about possibly more targeted policies, e.g., microprudential policies.[4]

Our main finding is that contractionary shocks in the oil market, i.e., those that lead

[2]These papers focus on the behavior of banks when affected by adverse shocks, the sequence of oil market shocks in 2014-2015 being a prominent example or even a quasi-natural experiment, rather than on the effects of oil market shocks on banks in general.

[3]This is reminiscent of the results in Kilian (2008): "Overall, exogenous oil supply shocks made remarkably little difference for the evolution of the U.S. economy since the 1970s, although they did matter for some historical episodes."

[4]This echoes the results in Fève et al. (2019) in a slightly different context. They show that the existence of shadow banks reduces the ability of macroprudential policies targeting traditional credit to reduce economic volatility because those banks are not subject to the same regulatory constraints as traditional intermediaries. They conclude that "a broader regulation scheme targeting both traditional and shadow credit would [be better] to stabilize the economy."

to a contraction in real economic activity, are associated with an unambiguous reduction in the amount of bank credit extended in the economy. There is also a tendency for net worth to drop and for the credit spread to increase. However, the effect on those two variables is the opposite if the contraction in economic activity is only temporary and it is followed by a period of economic expansion. This is because while credit is a lagging variable that reacts very slowly, net worth and spread typically react fast to changing economic conditions. Therefore, those two move consistently with the upcoming period of expansion, while credit drops due to the albeit temporary economic contraction.

The oil-sector model of BH includes shocks to oil supply, economic activity, oil consumption demand, and inventory demand. We show that the response of US banking variables differs greatly according to the source of oil market shocks hitting the economy in terms of their persistence. In particular, shocks to economic activity have sizable, long-lasting effects on all banks' variables, and especially on credit, while the other three shocks have more modest, short-lived effects.

Finally, the historical shock decomposition highlights that oil market shocks played a meaningful role in explaining banks' variables during commonly studied periods of economic significance. In particular, those shocks contributed between 40 and 60 percent of the variability in banking variables, with oil demand shocks playing, on average, a bigger role than supply shocks.

As for the heterogeneity analysis, we find a substantial degree of heterogeneity across banks, with smaller and lower leveraged banks responding more to oil market shocks.

The paper is structured as follows: in the next section we present a literature review. Section 3 reports our empirical methodology. Section 4 presents and discusses our results. Section 5 investigates the role of banks' heterogeneity. We report an array of robustness exercises in Section 6 and, finally, we offer our concluding remarks in Section 7.

2 Literature Review

In this section, we provide a review of the papers that analyze the relationship between the price of oil and the banking sector, with an attempt to emphasize the effects of oil market shocks on credit.

Bidder et al. (2021), although they do not primarily focus on oil market shocks, use the variation in US banks' loan exposure to industries adversely affected by the oil price declines of 2014 to explore how banks responded to a net worth shock in that period; they show that exposed banks tightened credit on on-balance-sheet corporate lending and mortgages, while mortgages to be securitized and shifted off balance sheet were expanded. However, they conclude that the effect on total lending, total size of the balance sheet, and the degree of leverage appears ambiguous. Wang (2021) conducts a similar analysis, but focusing on regional banks. He finds that exposed banks with significant operations in oil-concentrated counties were forced to also reduce lending to small businesses and mortgage lending in markets not affected by the oil shock. Boufateh and Saadaoui (2021) consider a broader perspective by including a measure of bank loans, together with inflation, in a VAR à la Kilian (2009). They analyze the time-varying response of bank loans to oil market shocks and find that those shocks have significant effects and, to some extent, those effects change over time. However, they add to the lack of consensus about the response of credit to oil market shocks because they find that bank loans mostly respond countercyclically, especially in response to a shock to aggregate economic activity. In that respect, Qin (2020) indirectly provides evidence about the procyclicality of credit's response to oil market shocks. In fact, by introducing a systemic financial stress index in a VAR à la Kilian (2009), he finds that contractionary oil market shocks tend to increase systemic financial stress (and vice-versa). It is eventually possible to infer that higher stress might be associated with lower credit and vice-versa.

3 Empirical Methodology

To estimate the effects of oil price fluctuations on the financial variables of interest to us, we jointly model the dynamics of global oil market variables with US financial variables using an SVAR model. We extend the SVAR model of the global crude oil market recently developed by BH. To their model, we add three financial variables. In contrast to the previous literature on oil modeling (e.g., Kilian, 2009; Kilian and Murphy, 2012, 2014), which relied on exact exclusion restrictions on certain contemporaneous relationships for identification, the BH approach allows for uncertainty about the identifying restrictions. More specifically, the BH model provides an explicit role for Bayesian priors in influencing the identification of the structural parameters and shocks. BH and Baumeister and Hamilton (2020a), among others, stress the importance of allowing for uncertainty about the identifying restrictions for drawing structural conclusions from SVAR models.

3.1 Structural VAR Model

Let $\mathbf{y}_t = (\mathbf{y}_t^{o'}, \mathbf{y}_t^{f'})'$ denote an $(n^o + n^f) \times 1$ vector in which $\mathbf{y}_t^o$ is an $n^o \times 1$ vector of variables associated with the global market for crude oil and $\mathbf{y}_t^f$ is an $n^f \times 1$ vector of financial variables. Following BH and Aastveit et al. (2023), $\mathbf{y}_t^o = (q_t, y_t, p_t, i_t)'$ in which q_t is the percentage change in global crude oil production, y_t is the percentage change in global real economic activity, p_t is the percentage change in the global real price of oil, and i_t is the observable change in global crude oil inventories as a percent of the previous month's world production. All variables are observed at a monthly frequency. As emphasized by BH and Aastveit et al. (2023), due to the lack of good data on global crude oil inventories, the best we could do is to use an estimate of OECD countries' crude oil inventories. Since OECD inventories constitute only a portion of the world total, BH proposed introducing a measurement error term in the equation specifying the measurement of the global inventories.

Specifically, the BH model for the global market for crude oil (also used in Aastveit et al.,

2023) is as follows:

$$q_t = c_1 + \alpha_{qp} p_t + \mathbf{b}_1' \mathbf{x}_t + u_{1t}^*, \tag{1}$$

$$y_t = c_2 + \alpha_{yp} p_t + \mathbf{b}_2' \mathbf{x}_{t-1} + u_{2t}^*, \tag{2}$$

$$q_t = c_3 + \beta_{qp} p_t + \beta_{qy} y_t + i_t^* + \mathbf{b}_3' \mathbf{x}_{t-1} + u_{3t}^*, \tag{3}$$

$$i_t^* = c_4 + \psi_1^* q_t + \psi_2^* y_t + \psi_3^* p_t + \mathbf{b}_4' \mathbf{x}_{t-1} + u_{4t}^*, \tag{4}$$

$$i_t = \chi i_t^* + e_t, \tag{5}$$

where $c_j,\ j = 1, 2, 3, 4$, are intercept terms and $\mathbf{x}_{t-1} = \left(\mathbf{y}_{t-1}', ..., \mathbf{y}_{t-12}'\right)'$ is a vector of lagged observations over the past year. Following, BH, Aastveit et al. (2023), Hamilton and Herrera (2004), and Wong (2015), a lag length of 12 months is used to capture the possibly delayed transmission of oil price shocks. Equation (1) represents the oil supply curve, where α_{qp} captures the short-run price elasticity of supply and u_{1t}^* is a shock to oil supply. Equation (2) specifies the dynamics of global real economic activity, with the parameter α_{yp} capturing the contemporaneous effects of oil prices, and u_{2t}^* is a shock to economic activity due to changes in the global business cycle. Equation (3) represents the oil demand curve, where the parameter β_{qp} reflects the short-run price elasticity of demand and β_{qy} reflects the contemporaneous effects of global real economic activity. The variable i_t^* refers to the true change in global inventories (as a fraction of the previous month's global oil production), and u_{3t}^* is a shock to oil consumption demand. Equation (4) specifies the dynamics of i_t^* and u_{4t}^* is a shock to an inventory demand. Equation (5) specifies the measurement equation for the observed global inventories with the measurement error term e_t added to reflect the fact that the observed inventories are an imperfect estimate of the true magnitude. This term e_t is assumed to be uncorrelated with identified structural shocks. The parameter χ, which is < 1, represents the fact that observed oil inventories (i.e., OECD countries) is a fraction of the world total (see BH).

To estimate the effects of the identified oil market shocks, u^*_{1t}, u^*_{2t}, u^*_{3t}, and u^*_{4t} on our financial variables, credit spread, S_t, banks' net worth, N_t, and the amount of credit, C_t, we define $\mathbf{y}^f_t = (S_t, N_t, C_t)'$, and specify the following three equations:

$$S_t = c_5 + \delta_1 q_t + \delta_2 y_t + \delta_3 p_t + \delta_4 N_t + \delta_5 C_t + \mathbf{b}'_5 \mathbf{x}_{t-1} + u^*_{5t} \tag{6}$$

$$N_t = c_6 + \omega_1 q_t + \omega_2 y_t + \omega_3 p_t + \omega_4 S_t + \omega_5 C_t + \mathbf{b}'_6 \mathbf{x}_{t-1} + u^*_{6t} \tag{7}$$

$$C_t = c_7 + \gamma_1 q_t + \gamma_2 y_t + \gamma_3 p_t + \gamma_4 S_t + \gamma_5 N_t + \mathbf{b}'_7 \mathbf{x}_{t-1} + u^*_{7t} \tag{8}$$

Equations (6), (7), and (8) model the credit spread, net worth, and the credit to firms, respectively. Moreover, u^*_{5t}, u^*_{6t}, and u^*_{7t} are the relative idiosyncratic shocks to the credit spread, the net worth, and the amount of credit, respectively.

It is worth mentioning that the above model specification assumes that the oil market variables are predetermined with regard to the US financial block. Hence, changes in US financial indicators will not impact the real price of crude oil or the decisions of global oil producers within the same month (Kilian and Vega, 2011). Following that argument, Aastveit et al. (2023) make the same assumption about the effect of inflation and inflation expectations on the oil variables. Finally, Kilian and Zhou (2022) apply the same argument to the US trade-weighted real exchange rate and the US ex-ante real market rate of interest.

It can be seen that substituting (5) into (3) and (4) and combining (6)-(8) yields a system of the form:

$$\tilde{\mathbf{A}} \mathbf{y}_t = \tilde{\mathbf{B}} \mathbf{x}_{t-1} + \tilde{\mathbf{u}}_t, \tag{9}$$

where $\mathbf{x}_{t-1} = \left(\mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-12}, 1\right)'$. Moreover:

$$\tilde{\mathbf{B}} = \begin{bmatrix} \mathbf{b}'_1 & c_1 \\ \mathbf{b}'_2 & c_2 \\ \mathbf{b}'_3 & c_3 \\ \mathbf{b}'_4 & c_4 \\ \mathbf{b}'_5 & c_5 \\ \mathbf{b}'_6 & c_6 \\ \mathbf{b}'_7 & c_7 \end{bmatrix}, \tilde{\mathbf{A}} = \begin{bmatrix} 1 & 0 & -\alpha_{qp} & 0 & 0 & 0 & 0 \\ 0 & 1 & -\alpha_{yp} & 0 & 0 & 0 & 0 \\ 1 & -\beta_{qy} & -\beta_{qp} & -\chi^{-1} & 0 & 0 & 0 \\ -\psi_1 & -\psi_2 & -\psi_3 & 1 & 0 & 0 & 0 \\ -\delta_1 & -\delta_2 & -\delta_3 & 0 & 1 & -\delta_4 & -\delta_5 \\ -\omega_1 & -\omega_2 & -\omega_3 & 0 & -\omega_4 & 1 & -\omega_5 \\ -\gamma_1 & -\gamma_2 & -\gamma_3 & 0 & -\gamma_4 & -\gamma_5 & 1 \end{bmatrix}, \tilde{\mathbf{u}}_t = \begin{bmatrix} u^*_{1t} \\ u^*_{2t} \\ u^*_{3t} - \chi^{-1} e_t \\ \chi u^*_{4t} + e_t \\ u^*_{5t} \\ u^*_{6t} \\ u^*_{7t} \end{bmatrix}$$

We observe that u^*_{3t} and u^*_{4t} are correlated. To generate a representation with uncorrelated shocks, the system in (9) is pre-multiplied by:

$$\Gamma = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & \rho & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix},$$

in which $\rho = \frac{\chi^{-1}\sigma_e^2}{d^*_{33} + \chi^{-2}\sigma_e^2}$, and d^*_{33} comes from the representation:

$$\mathbf{A}\mathbf{y}_t = \mathbf{B}\mathbf{x}_{t-1} + \mathbf{u}_t, \quad \mathbf{u}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{D}), \tag{10}$$

in which $\mathbf{A} = \Gamma\tilde{\mathbf{A}}, \mathbf{B} = \Gamma\tilde{\mathbf{B}}, \mathbf{u_t} = \Gamma\tilde{\mathbf{u}}_t$, and:

$$D = \begin{bmatrix} d^*_{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & d^*_{22} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & d^*_{33} + \chi^{-2}\sigma_e^2 & -\chi^{-2}\sigma_e^2 & 0 & 0 & 0 \\ 0 & 0 & -\chi^{-2}\sigma_e^2 & \chi^2 d^*_{44} + \sigma_e^2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & d^*_{55} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & d^*_{66} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & d^*_{77} \end{bmatrix}.$$

The above system, i.e., the SVAR in (10), is estimated with Bayesian methods, similar to BH and Aastveit et al. (2023). We next discuss the priors.

3.2 Priors

For the parameters of the oil block, we follow exactly the prior setting of BH. The setting is as follows: we assume a Minnesota prior on the lagged coefficients, with the overall prior tightness controlled by setting $\lambda_0 = 0.5$; the rate at which the prior variance decreases with increasing lag length, $\lambda_1 = 1$; and the tightness on the intercept, $\lambda_3 = 100$. The priors are also imposed on the determinant of $\tilde{\mathbf{A}}$ and the equilibrium feedback effects in the impact matrix, $\tilde{\mathbf{A}}^{-1}$. To identify the oil market shocks, $\psi_2 = 0$.

For the banking sector block, for the parameters of the lagged structure we apply the same prior setting as the oil block. That is, the same Minnesota prior used in the oil block is used on each of the lagged coefficients within the banking block, as well as on the lagged coefficients from the oil market block to the banking block. Since the US financial block is not the primary force driving oil price dynamics, we set a tighter variance on the lagged coefficients from the banking block to the oil market block through a new scale parameter $\lambda_4 = 0.01$.

In setting the priors affecting contemporaneous coefficients δs, ωs, and γs we could follow the approach proposed by BH and choose a set of priors for those coefficients based on different sources of information. However, there are no alternative sources we can exploit. Therefore, we rely on the approach proposed in Baumeister and Hamilton (2018) in which they set agnostic priors. This is achieved through a set of Student t prior densities with location parameter equal to 0, scale parameter equal to 0.5, and 3 degrees of freedom.[5] Those are also the same prior distributions chosen by BH for the parameters ψ_1 and ψ_3, which they define as relatively uninformative priors. We report all priors information in Appendix A.

3.3 Data

Our data sample consists of seven monthly variables spanning January 1958 to December 2019. Given the well-documented structural changes in the oil market starting in the mid-1970s, we perform our main analysis using data starting in January 1974 through the end of 2019. We use data from 1958 through December 1973 to inform our prior setting as in BH. The sample includes the four fundamental oil market variables, the US credit spread, banks' net worth, and credit.

The oil market variables are the same as in BH: the percentage change in global crude oil production is taken from the US Energy Information Administration (EIA); global real economic activity is measured using the OECD's (and six additional countries') industrial production index (available to download from Christiane Baumeister's website); the percentage change in the global real price of oil is measured by US refiners' acquisition cost (RAC) for imported crude oil from the EIA (deflated by the US consumer price index – all items – available from FRED); and the change in global oil inventories is measured as total US crude oil inventories scaled by the ratio of OECD petroleum stocks to US petroleum stocks available from the EIA.

[5] We also tried an approach using a scale parameter equal to 10, i.e., with a very uninformative prior, and results are the same. They are available upon request.

The financial variables are obtained from different sources. The US credit spread is measured as the difference between the BAA corporate bond yield and the 10-year government bond yield. Banks net worth is measured as the Dow Jones US bank stock market index. Finally, credit is measured using the commercial and industrial loans outstanding at all US banks. As with the oil market variables, we use the percentage change in those variables to perform the estimation. All data are described in detail in Appendix B.

4 Results

In this section, we report the results of our estimation. It is performed using Bayesian methods as in BH along with the priors discussed in Section 3.2. We take 5 millions draws and we burn-in the first half of those.[6] We assess the convergence properties using Geweke's convergence diagnostics, which we report in Appendix D. We first discuss the impulse response functions (IRFs), and then the historical shock decomposition.

4.1 Impulse response functions

We focus on a subset of variables, namely the three banking variables and the oil supply, world economic activity, and the real price of oil. As is common in the literature, all shocks are normalized to generate a 10 percent change in the real price of oil that would lead to a decline in credit. In the case of the oil supply, oil consumption demand, and inventory demand shocks, the responses are normalized such that the real price of oil increases by 10 percent on impact, whereas for the economic activity shock, the responses are normalized such that the real price of oil decreases by 10 percent. We display the 68 percent and 95 percent posterior credible sets along with the median.

We report the IRFs of the oil supply, economic activity, and the oil consumption demand

[6] We report the prior and posterior distributions in Appendix C.

shocks in Figure 1.[7] Before we describe the responses, it is worth highlighting that the responses of the oil block variables to those shocks are basically the same as in BH.

The first column shows the response of variables to an oil supply shock. An adverse shock to the oil supply contracts world economic activity. This generates a decrease in banks' net worth, a reduction in the amount of bank credit extended in the economy, and an increase in the credit spread. This shock only has modest, short-lived effects on banks' variables

In the second column, we observe that a shock to world economic activity that leads to a contraction in the economy implies a contraction in the stock market, a reduction in the amount of credit, and an increase in the credit spread. The effects of the economic activity shock are persistent. Net worth and the credit spread react on impact, as would be expected given their high sensitivity to the evolution of economic activity, while credit reacts only with some lags because it is typically a slow-moving variable, as largely documented in the literature (e.g., Drehmann et al., 2012, Aikman et al., 2015, Gelain et al., 2018, and Bluwstein et al., 2020). In comparison with the oil supply shock, we see that this shock has a much larger effect on banking variables. That is mainly because the given 10 percent change in the price of oil in this case is the result of a large drop in world industrial production (roughly 8 percent).

It is interesting to note that this shock has opposite effects on the financial variables through movements in the oil market variables. Because this shock is contractionary, it leads to a decrease in both world industrial production and the oil supply. However, this shock also pushes the price of oil down. The lower oil price, through potentially different channels, positively impacts the US economy.[8] Our analysis suggests that the former negative effects dominate the latter positive effect.

[7] We do not display the inventory demand shock. It is irrelevant to explaining the overall dynamics because it is mostly measurement error, as highlighted by BH.

[8] For instance, firms face lower costs for their energy inputs and they might increase their production. Or households face lower gasoline prices and might increase their consumption.

The oil consumption demand shock, in the third column, requires a more detailed explanation. This is a shock that leads to a large and persistent increase in the price of oil. The literature typically finds that this shock is contractionary. In keeping with that, BH impose a negative sign restriction on impact on the contemporaneous elasticity of world industrial production to oil price (α_{yp}). That restriction is satisfied for one month, but thereafter, economic activity reverts quickly to positive territory. Net worth and the credit spread, being forward-looking variables, respond immediately and as expected given the booming economy from the second month onward. The former goes up and the latter goes down. In contrast, credit responds with a lag to movements in economic activity. It decreases gradually for few months in response to the initial drop in economic activity. Since credit is slow in responding to a pickup in real economic activity, it takes a while for it to revert back to the steady state and eventually starts increasing, in keeping with the boom in economic activity. Like the oil supply shock, the oil consumption demand shock seems to have more modest and more short-lived effects on the banking variables than the economic activity shock.

It is worth stressing that the effects of oil supply and consumption demand shocks on financial variables strongly contrast with the effects of economic activity shocks. The oil supply and consumption demand shocks have reinforcing effects. In fact, they both move world industrial production and the price of oil in opposite directions. Therefore, the negative consequences for the US variables created by the drop in world industrial production are reinforced by the negative consequences, via the different channels, that are a result of the higher price of oil that such shocks induce.

Overall, we can conclude that contractionary oil market shocks unambiguously reduce the amount of credit extended in the economy. The effects of such shocks tend to also be negative for net worth and the credit spread, but only if the contraction in economic activity is sufficiently long-lasting. Otherwise, we observe the opposite sign for those two variables, as in the case of the consumption demand shock for which the contraction is temporary and is followed by an expansion. This has a positive effect on the stock market and on the credit spread.

Our results support the notion that the reaction of US banking variables to an oil market shock differs greatly depending on whether the change in the price of oil is driven by demand or supply shocks in the oil market. Interestingly, our results lend empirical support to the anecdotal evidence in the Moody's reports, according to which lower oil prices are "positive for the operating environment of US banks," but only if those lower prices are the outcome of an oil consumption demand shock. In fact, in such an instance, banks tend to extend more credit in the economy. Moreover, our results contrast with those in Abbritti et al. (2020). They find that a lower price of oil tends to be associated with decreased credit spreads. That is not the case in our analysis.

The main message emerging from our analysis for a macroprudential authority is that if the authority observes a 10 percent change in the price of oil, it should be much more concerned for the stability of the financial system if that change is the result of an economic activity shock rather than the other oil market shocks. This is because, as our results show, for a given change in the price of oil, the effects of an economic activity shock on the banking variables are orders of magnitude larger.

4.2 Historical shock decomposition

In this section we report the historical contribution of all shocks in our model to the variability of the banking variables. This is important because we have seen in the previous section that the effects of the oil supply and of the oil consumption demand shocks are much more modest compared to those of the economic activity shock for a given change in the real price of oil. That does not necessarily mean, though, that the two former shocks cannot be important drivers of financial variables. We shed light on that here.

Table 1 summarizes the contribution of the several shocks in our model during some historical episodes of interest, namely: the First Persian Gulf War, the Great Recession, the oil price collapse in 2014-2015 and the oil price rebound in 2016. Since we are not interested in each financial shock per se, we group them into one and we label them "US shocks."

The first reflection is that, in all episodes, each financial variable is, on average, mainly explained by US shocks. However, we observe that other shocks in our model also exert a notable influence on financial variables. Let's focus on each historical episode one by one.

Starting with the First Persian Gulf War, we note that the economic activity shock plays an important role in explaining the three financial variables (especially the credit spread and the amount of credit). We also observe that oil supply and oil consumption demand shocks contribute almost equally to changes in the credit spread and net worth. Accordingly, our results are in line with those of Kilian and Murphy (2014) and Baumeister and Hamilton (2018), who found that supply and demand shocks are equally important in explaining oil price fluctuations in this episode.

The Great Recession period is generally associated with worsening financial conditions, i.e., widening credit spreads, falling net worth, and a slump in aggregate credit. This is why US shocks play a very important role for all three financial variables. However, we note that the economic activity shock explains a large part of the variation in the credit spread and the amount of credit during this episode. Similarly, the oil consumption demand shock contributes substantially to the changes in these two variables. On the other hand, we find that oil supply shocks play a trivial role in explaining the movements in all three financial variables.

Moving on to the 2014-16 oil price plunge (a period over which the nominal price per barrel of crude oil dropped by 65 percent), we note that the economic activity shock plays a large role in influencing changes in the amount of credit. Moreover, we note that the oil consumption demand shock has an important role in explaining movements in the credit spread and net worth. On the contrary, we find that the oil supply shock has negligible effects on the three financial variables during this episode.

Finally, we focus on the oil price rebound in 2016. Our results indicate that the economic activity shock contributes substantially to changes in the amount of credit. Moreover, we observe that the oil consumption demand shock has an important role in explaining the movements in the credit spread and net worth. Compared with the previous episodes, we note that the oil supply shock has a larger importance for all three financial variables.

5 Banks' Heterogeneity

In this section we investigate whether or not the effects of oil market shocks differ for different groups of banks. Within the banks in the KBW Nasdaq bank index, comprising basically the largest banks in the US, we separate them into smaller and larger banks and into highly leveraged and low leveraged banks.[9]

We then compute sub-stock market indexes for the different groups. For instance, to create the index for small and large banks, we proceed as follows. First, for each bank we compute the average asset size over the sample we have at our disposal for each bank. There are 26 banks in the KBW index. So, we have 26 average asset values. We compute the sum of all them. To obtain the weights to be used to aggregate the single banks stock price into an index, we divide the single banks average by the sum of the averages. More formally, the asset size value for the single banks $AvAss_j$ is computed as:

$$AvAss_j = \frac{1}{T}\sum_{s=t_0}^{t_f} AvAss_{j,s}$$

where T is the sample size, t_0 is the first observation in the sample and t_f the last one, and j=BAC, BK, C,CFG, CMA, COF, EWBC, FHN, FITB, FRBC, GS, HBAN, JPM, KEY,

[9]In this section we use the KBW Nasdaq bank index because the list of its 26 constituents is publicly available, so we can collect data for each of them. On the contrary, for the Dow Jones US bank stock market index only the top 10 constituents are available. In aggregate they are virtually identical, but the Dow Jones index is available for a slightly longer period, so we prefer the latter for the aggregate analysis.

MS, MTB, NTRS, PNC, RF, SIVBQ, STT, TFC, USB, WAL, WFC, ZION.[10]

Then, we compute the average asset value $AvAss$ as follows:

$$AvAss = \frac{1}{N}\sum_{q=1}^{N} AvAss_q$$

where $N = 26$. In turn, the 26 weights W_j are:

$$W_j = AvAss_j / AvAss$$

As a result, the stock market index for large banks St_L is:

$$St_L = \sum_i W_i St_i$$

where St_i is the price of the stocks of the banks included in this group. Banks in this group are those whose asset value is above the average asset value across all banks in the index, namely, i: BAC, C, GS, JPM, MS, WFC. Similarly, the stock market index for small banks St_S is:

$$St_S = \sum_z W_z St_z$$

where St_z are the price of the stocks of the banks included in this group. Banks in this group are those whose assets value is below the average assets value across all banks in the index, namely those not listed among the large ones.

[10]BAC: Bank of America, BK: Bank of New York Mellon Corp., C: Citygroup Inc., CFG: Citizens Financial Group Inc., CMA: Comerica Inc., COF: Capital One Financial Corp., EWBC: East West Bancorp Inc., FHN: First Horizon Corp., FITB: Fifth Third Bancorp., FRBC: First Republic Bank, GS: Goldman Sachs Group Inc., HBAN: Huntington Bancshares Inc., JPM: JPMorgan Chase & Co., KEY: KeyCorp, MS: Morgan Stanley, MTB: M&T Bank Corp., NTRS: Northern Trust Corp., PNC: PNC Financial Services Group Inc., RF: Regions Financial Corp., SIVBQ: SVB Financial Group, STT: State Street Corp., TFC: Truist Financial Corp., USB: US Bancorp, WAL: Western Alliance Bancorp, WFC: Wells Fargo & Co., ZION: Zions Bancorp.

As for the estimation, we replace the aggregate stock market index with the four sub-indexes and we leave all the other variables in the SVAR unchanged. Results for large versus small banks are reported in Figure 2. All responses are normalized to generate a 10 percent change in the price of oil.[11]

Our results indicate that the stock market index for small banks reacts more than the one for large banks to all shocks. A priori, it was not straightforward to know what to expect. The literature has emphasized both views, according to which large banks can be more or less impacted by shocks in general (but not for oil market shocks).

On the one hand, Diamond (1984), Marcus (1984), Besanko and Thakor (1993), Demsetz et al. (1996), Allen and Gale (2000), Hughes et al. (2001), Marquez (2002), Morgan et al. (2004), Stern and Feldman (2004), Stiroh (2006), Feng and Serletis (2010), Martínez-Miera and Rapullo (2010), and Jiménez et al. (2013) suggest that large banks can be less impacted because they take fewer risks to protect their franchise value, they have lower service costs, they enjoy higher informational rents and prevent informational dispersion, and they can more efficiently diversify risk. Therefore, large banks are better able to maintain the credit they provide to firms in the event of a downturn.

On the other hand, Stiglitz and Weiss (1981), Boyd and De Nicoló (2005), and Wheelock (2012) argue that the level of moral hazard, risk-taking, and operational inefficiencies is higher for large banks. Also, large banks are less disciplined by competition than smaller banks, make poorer lending choices, and lose more in downturns. In this regard, Aysun (2016) finds that the transmission of macroeconomic shocks operates mainly through large banks.

Given the above arguments, our findings lend support to the former view for oil market shocks. Accordingly, the net worth of large banks shows a smoother change than that of small banks in response to the different sources of oil price fluctuations.

As mentioned above, we perform a further analysis on the heterogeneity of banks. Namely,

[11] We assume that the real oil price increases in response to all shocks except for the economic activity shock.

we assess the effects of oil price fluctuations according to the degree of leverage of different banks. The two subgroups of banks are constructed in a way similar to the one described above for small and large banks. In this case, we obtain that the highly leveraged banks are: BAC, BK, CMA, FHN, FRBC, GS, HBAN, JPM, KEY, MS, MTB, NTRS, STT, WFC. All the other banks are classified as low leveraged banks.

Figure 3 shows the IRFs for the different shocks. Again, all responses are normalized to generate a 10 percent change in the price of oil.[12] Our results show that low leveraged banks are more affected than highly leveraged banks. This is consistent with the results that we presented above for small and large banks. In fact, among the 12 banks in the low leverage group, only one also belongs to the large banks group (C). The remaining 11 are in the small banks group. As a result, since smaller banks are more affected by oil price shocks and since low leveraged banks are mostly small banks, they are also those mostly affected. This is also why the IRFs are remarkably similar in Figures 2 and 3.

6 Robustness

This section summarizes the robustness checks we have undertaken. For space reasons, we report results in the appendix.

a. Mixture prior. Following Baumeister and Hamilton, 2020b and Aastveit et al., 2023, we restimate our SVAR model, but this time using a mixture distribution prior on the parameter governing the supply elasticity. Specifically, the mixture distribution places a weight of 99 percent on a Uniform distribution over (0, 0.0258) and 1 percent on a truncated Student's t distribution with parameters location=0.1, scale=0.2, and degrees of freedom=3. The results shown in Appendix E are very similar to the main results, and also, if instead, the weights on the Uniform distribution and Student t are 80 and 20 percent, respectively.

b. Estimation with post-1984 data. Given the well-documented structural break in

[12]As before, all shocks imply an increase in the real price of oil except the economic activity shock.

a range of US macroeconomic and financial variables in the mid-1980s (e.g., see, Aastveit et al., 2017), we repeat our analysis by estimating our SVAR model with a sample starting in January 1985 through December 2019. The results, shown in Appendix F, are qualitatively in line with the main results.

7 Conclusions

What is the effect of oil price fluctuations on US banks' net worth? How do US banks react in terms of the amount of credit they provide to the US economy? Do those effects differ according to the source of the oil market shocks? Is there any difference between small and large US banks or between highly and low leveraged US banks? These are the questions we address in this paper.

We extend BH's oil market SVAR model to incorporate a measure of the US credit spread, a measure of US banks' net worth, and a measure of banks credit to the US economy. We estimate the model with Bayesian techniques using data from January 1974 to December 2019.

We find three main results. First, contractionary oil market shocks unambiguously reduce the amount of credit given to the economy. The effects of such shocks also tend to be negative for net worth and the credit spread, but only if the contraction in economic activity is sufficiently long-lasting. Shocks to world economic activity have stronger and more persistent effects than the oil supply and the oil consumption demand shocks. Second, the historical decomposition highlights that oil market shocks contributed between 40 and 60 percent of the variability in banking variables, with oil demand shocks playing, on average, a bigger role than supply shocks. Third, we find a substantial degree of heterogeneity across banks, with relatively smaller and lower leveraged banks responding more to oil market shocks.

Finally, in terms of the policy implications of our analysis, most central banks care about oil price fluctuations because of their potential impact on price stability. By the same token, authorities with the objective of preserving financial stability should look at oil market shocks because, as we document, they have a significant impact on the banking sector and on the measures of credit to the US economy, the latter typically being target variables for such authorities.

Figures and Tables

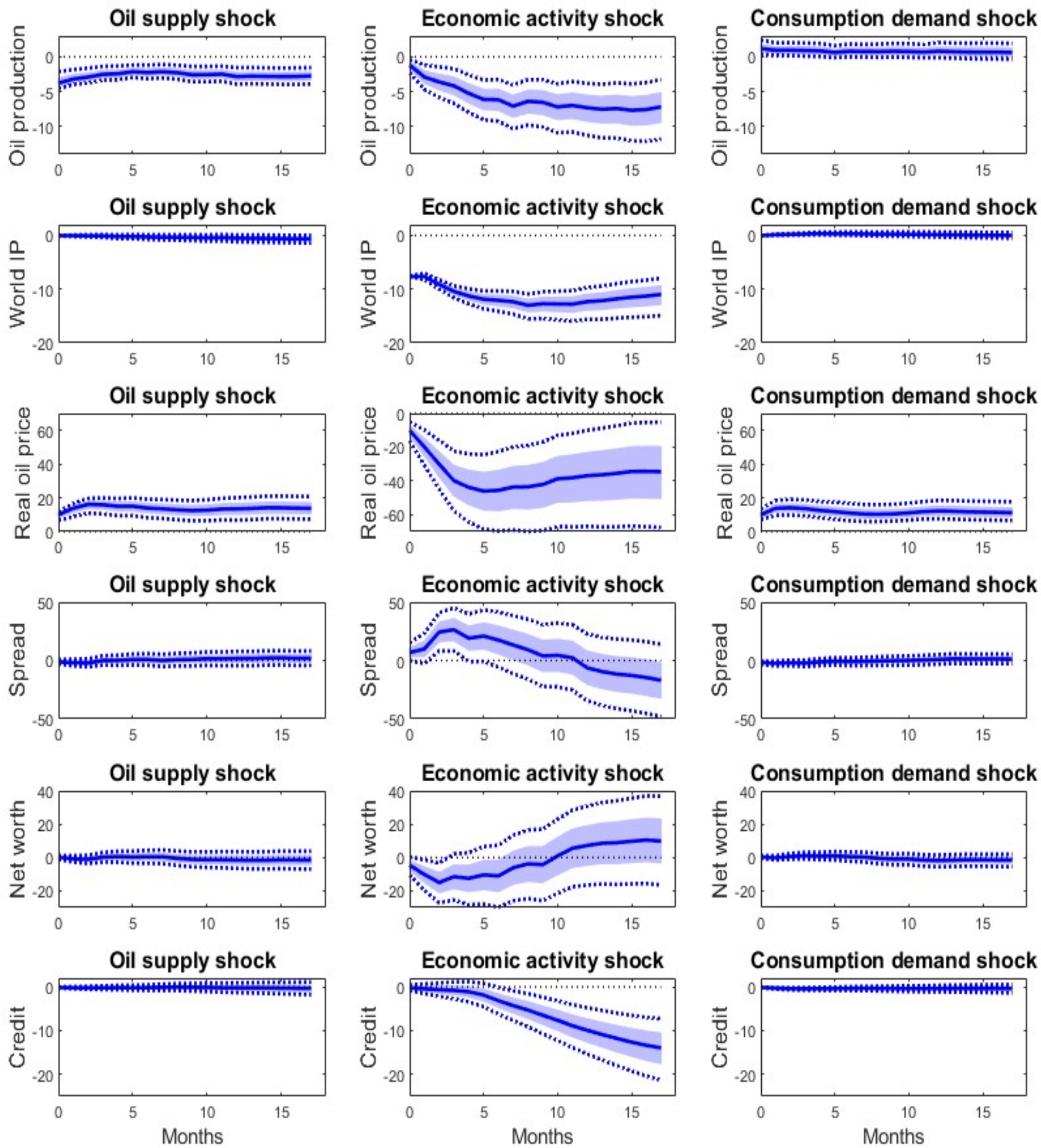

Figure 1: Cumulative response of selected variables to an oil supply, an economic activity, and an oil consumption demand shock. Dashed lines are the 95% posterior credible sets. Shaded areas are the 68% posterior credible sets. Estimation is based on a sample from January 1974 through December 2019. All responses are normalized to generate a 10% change in the real price of oil.

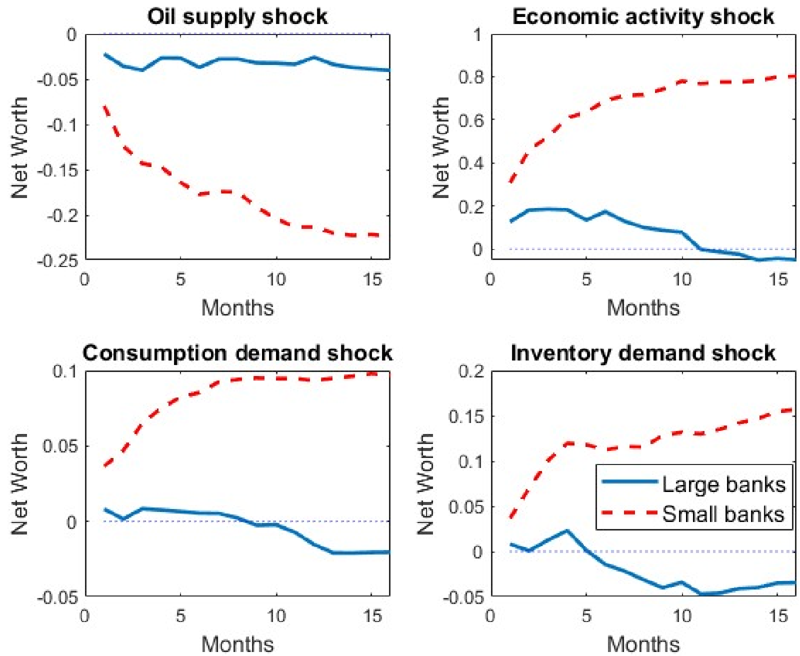

Figure 2: Response of net worth to the four oil market shocks for large and small banks. Shown are the pointwise median estimates. Estimation is based on a sample from June 1974 through December 2019.

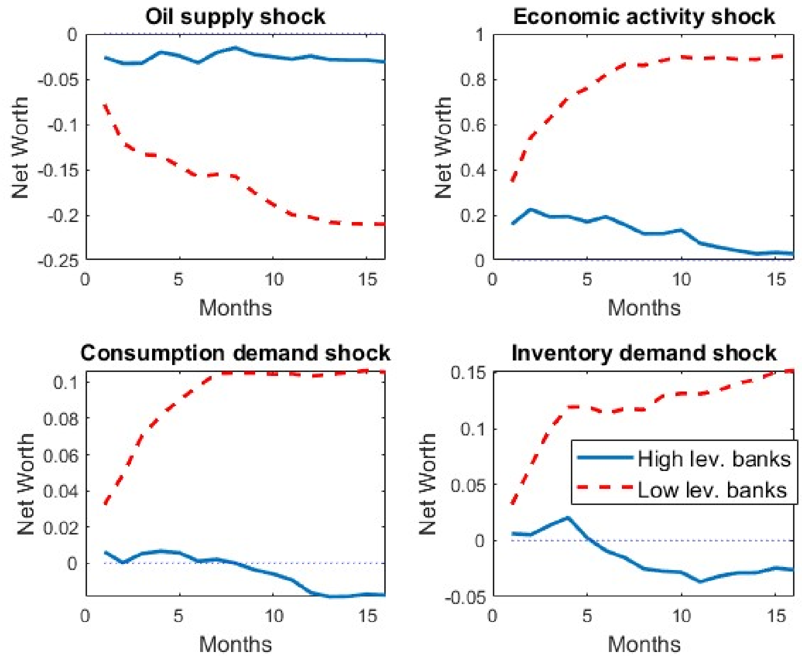

Figure 3: Response of net worth to the four oil market shocks for banks with high and low leverage. Shown are the pointwise median estimates. Estimation is based on a sample from June 1974 through December 2019.

Historical episode	Shock	Spread	Net worth	Credit
June - Oct 90	Oil supply	10.42	9.13	9.41
	Economic activity	14.67	9.32	19.07
	Oil consumption demand	9.42	10.57	18.58
	Inventory demand	0.51	0.78	0.52
	Measurement error	9.95	9.02	10.84
	US shocks	55.01	61.17	41.59
Jul 2008 - June 2009	Oil supply	4.53	1.75	4.82
	Economic activity	23.47	12.54	21.64
	Oil consumption demand	12.03	8.77	14.16
	Inventory demand	0.77	0.60	0.38
	Measurement error	4.82	1.62	2.39
	US shocks	54.38	74.69	59.61
July 2014 - Jan 2016	Oil supply	9.85	5.91	3.62
	Economic activity	15.47	8.81	20.93
	Oil consumption demand	18.36	13.56	11.37
	Inventory demand	1.45	0.96	0.48
	Measurement error	10.89	8.71	4.54
	US shocks	43.98	62.04	59.06
March 2016 - Dec 2016	Oil supply	10.29	6.24	9.32
	Economic activity	15.68	8.50	18.01
	Oil consumption demand	17.70	13.60	8.90
	Inventory demand	0.34	0.72	0.39
	Measurement error	7.09	5.53	3.16
	US shocks	48.90	65.41	60.21

Table 1: Effects on financial variables attributed to several shocks in our model. The above table reports the percentage contribution accounted for by shocks to oil supply, economic activity, oil consumption demand, inventory demand, and measurement error as well as all three financial shocks grouped into one (US shocks). Each entry is computed as the average of the contribution (in absolute value) of each shock in each month of each specified period divided by the sum of the mean of all shocks in the specified period.

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SUPPLEMENTARY APPENDIX
Oil price fluctuations and US banks*

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Contents

A Priors

Table 1: Student's t prior distributions for structural parameters in the financial block

Parameter	Description	Location	Scale	Degrees of freedom	Sign restriction
δ_1	Effect of oil production on credit spread	0	0.5	3	none
δ_2	Effect of economic activity on credit spread	0	0.5	3	none
δ_3	Effect of real oil price on credit spread	0	0.5	3	none
δ_4	Effect of net worth on credit spread	0	0.5	3	none
δ_5	Effect of credit on credit spread	0	0.5	3	none
ω_1	Effect of oil production on net worth	0	0.5	3	none
ω_2	Effect of economic activity on net worth	0	0.5	3	none
ω_3	Effect of real oil price on net worth	0	0.5	3	none
ω_4	Effect of credit spread on net worth	0	0.5	3	none
ω_5	Effect of credit on net worth	0	0.5	3	none
γ_1	Effect of oil production on credit	0	0.5	3	none
γ_2	Effect of economic activity on credit	0	0.5	3	none
γ_3	Effect of real oil price on credit	0	0.5	3	none
γ_4	Effect of credit spread on credit	0	0.5	3	none
γ_5	Effect of net worth on credit	0	0.5	3	none

Note: For Student t distribution, the location parameter refers to the mode.

Table 2: Prior settings for structural parameters in the oil block: Same as BH

Parameter	Description	Location	Scale	Degrees of freedom	Sign restriction
Student t distribution					
α_{qp}	Oil supply elasticity	0.1	0.2	3	Positive
α_{yp}	Effect of oil price on real economic activity	-0.05	0.1	3	Negative
β_{qy}	Income elasticity of oil demand	0.7	0.2	3	Positive
β_{qp}	Oil demand elasticity	-0.1	0.2	3	Negative
ψ_1	Effect of oil production on oil inventories	0	0.5	3	none
ψ_3	Effect of oil price on oil inventories	0	0.5	3	none
h_2	Effect of economic activity shock on output	0.8	0.2	3	none
Beta distribution					
χ	Fraction of inventories observed	0.6	0.1	–	$0 \leq \chi \leq 1$
ρ	Importance of inventory measurement error	0.25χ	0.12χ	–	$0 \leq \rho \leq \chi$
Asymmetric t distribution					
h_1	Determinant of $\tilde{A}$	0.6	1.6	3	skew=2
Gamma distribution					
d_{ii}^{-1}	Reciprocal of variance	$\frac{1}{(a_i' S a_i})$	$\frac{1}{(\sqrt{2} a_i' S a_i})$	–	$d_{ii} > 0$

Note: For Student t distribution, the location parameter refers to the mode. For Beta and Gamma distributions the location parameter refers to the mean and the scale parameter refers to the standard deviation.

B Data

As explained in the main text, our data are at a monthly frequency and the sample period of our analysis is 1958:M1-2019:M12. We perform our main analysis using data for the sample 1974:M1-2019:M12. We use data from 1958:M1 to 1973:M12 to inform prior setting.

B.1 Oil-market block

The data sources for this block are in line with Baumeister and Hamilton (2019). We updated these data series ourselves as part of the process of assembling extended time series as described below.

Monthly world oil production data are measured in thousands of barrels of oil per day and they are obtained from the US Energy Information Administration's (EIA) Monthly Energy Review for the period January 1973:M1 to 2019:M12. Monthly data for global production of crude oil for the period 1958:M1 to 1972:M12 are collected from the weekly Oil and Gas Journal (issue of the first week of each month) as in Baumeister and Hamilton (2019).

The measure for global economic activity is the industrial production index for OECD countries and six major non-member economies (Brazil, China, India, Indonesia, the Russian Federation and South Africa). This series has been used in Baumeister and Hamilton (2019). These data are obtained from Christiane Baumeister's website (https://sites.google.com/site/cjsbaumeister/datasets).

As in Baumeister and Hamilton (2019), the series for the nominal spot oil price is a combination of the West Texas Intermediate (WTI), taken from the St. Louis FRED database (https://fred.stlouisfed.org/series/WTISPLC), and the Refiner Acquisition Cost (RAC) of imported crude oil, taken from the US EIA website (https://www.eia.gov/totalenergy/data/monthly/). To deflate the nominal spot oil price, we use the US consumer price index (CPIAUCSL: consumer price index for all urban consumers: all items, index 1982-1984 = 100), which was taken from the FRED database (https://fred.stlouisfed.org/series/CPIAU

CSL).

Monthly US crude oil stocks in millions of barrels are available from the EIA for the entire period 1958:M1-2019:M12. We obtain an estimate for global stocks as in Baumeister and Hamilton (2019).

B.2 Block for the US financial variables

The credit spread is the annualized Moody's Seasoned Baa Corporate Bond Yield spread over the 10-Year Treasury Note Yield at Constant Maturity, taken from the Federal Reserve Bank of St. Louis (Moody's Seasoned Baa Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity [BAA10Y], https://fred.stlouisfed.org/series/BAA10Y). In FRED this series is only available from 1986. Therefore, we rely on Haver Analytics for data prior to that date.

The DJGL US banks' stock market index is taken from https://markets.businessinsider.com/index/historical-prices/dow-jones-us-banks. This series is only available from 1992. Therefore, to get data prior to that date, we exploit the S&P500 index. The latter has a correlation of 0.75 with the DJ in the period 1992-2019. That makes it a very good proxy for the period 1958-1991. However, it has a lower variance by a factor of 1.65. So, to make the S&P500 a better proxy for the DJ in the period prior to 1992, we multiply it by 1.65.

The series for the Commercial and Industrial Loans, All Commercial Banks is taken from the Federal Reserve Bank of St. Louis ([BUSLOANS], https://fred.stlouisfed.org/series/BUSLOANS).

As for the banks' heterogeneity section, the data for the single constituents of the KBW index are retrieved from the following sources. The total assets figure and total liabilities figure are retrieved from Compustat – S&P Global's Fundamental Quarterly database database on the WRDS platform using the mnemonics ATQ and LTQ. The database uses the total value of assets and the total value of liabilities as reported on the firms' balance sheets in their 10-K and 10-Q filings. The total value of assets is defined as the sum of current assets; net property, plant, and equipment; intangible assets; investments and advances; and other non-current assets. The total value of liabilities is defined as the sum of current liabilities, long-term debt, deferred taxes and investment tax credit, and other non-current liabilities. The total stockholders' equity figure is calculated as the difference between total assets and total liabilities. The leverage figure is calculated as the ratio of total assets to total stockholders' equity. The stock price figure represents the unadjusted close price for the fiscal month end date. It is retrieved from Compustat – S&P Global's Fundamental Quarterly database database on the WRDS platform using the mnemonic PRCCQ. The adjusted stock price figure represents the close price for the fiscal month end date adjusted for stock splits and stock dividends. It is calculated as the unadjusted stock price divided by the cumulative adjustment factor (AJEXQ). The real adjusted stock market index is calculated as the adjusted stock price divided by PCE, taken from the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/series/PCE).

C Prior and Posterior Distributions

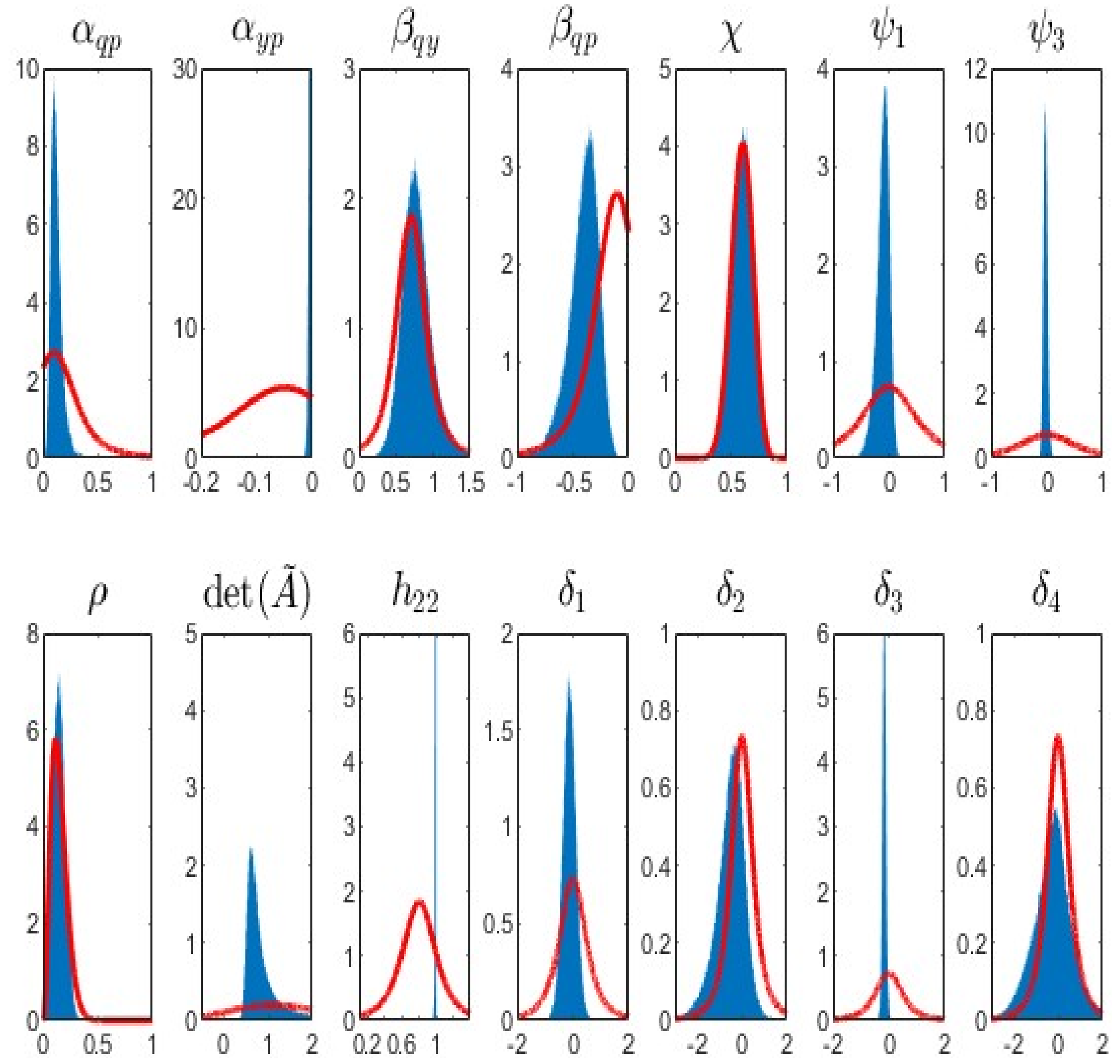

Figure 1: Baseline prior (solid red curves) and posterior (blue histograms) distributions concerning the contemporaneous coefficients in A in baseline 7-variable model.

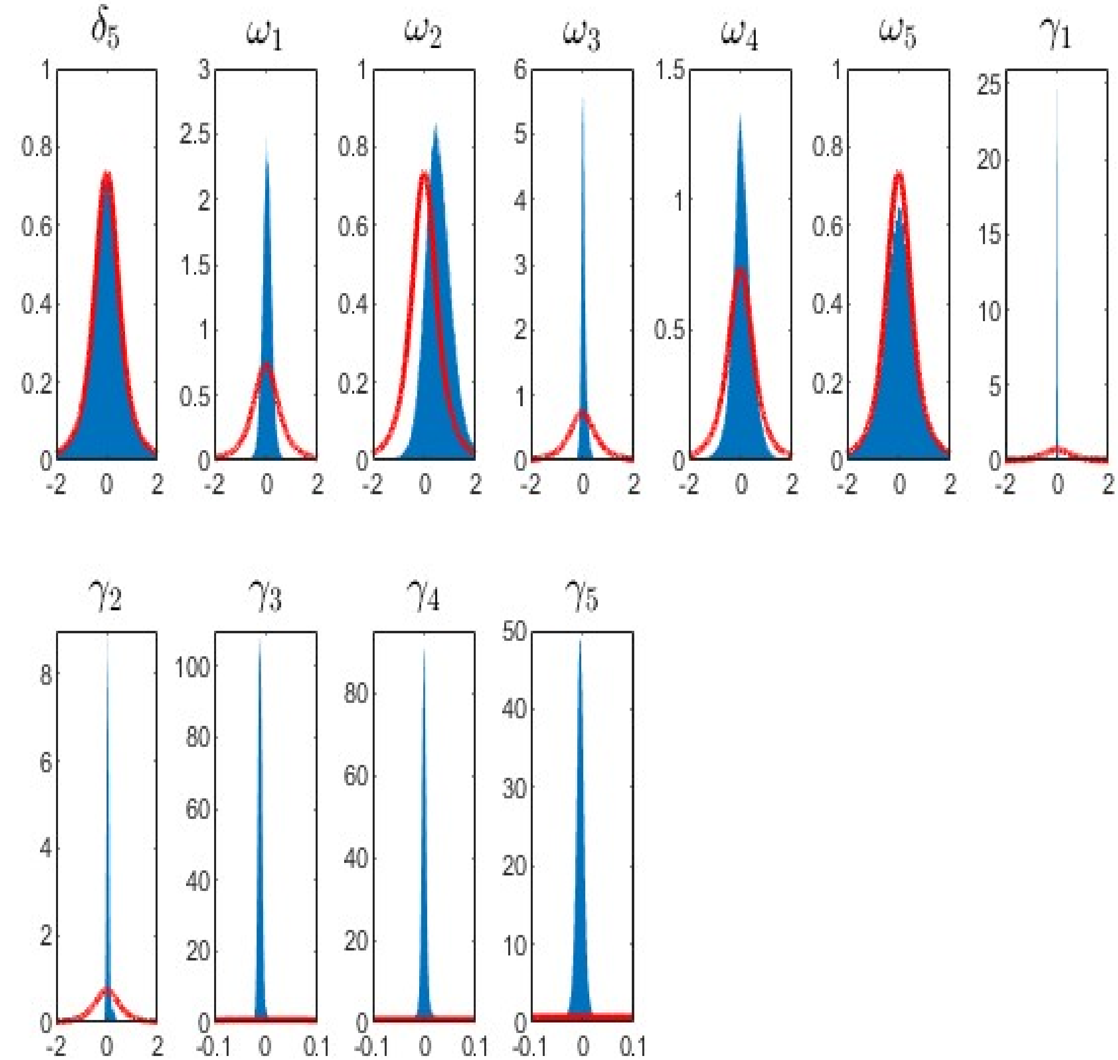

Figure 2: Baseline prior (solid red curves) and posterior (blue histograms) distributions concerning the contemporaneous coefficients in A in baseline 7-variable model.

D Convergence Diagnostics

To assess convergence of our MCMC sampler, we perform formal convergence testing of the MCMC chain using Geweke's convergence diagnostic for equality of the means across the first 10 percent and the last 50 percent of the retained draws. Table 3 reports the Chi-squared probabilities of the null hypothesis of equal means for each parameter chain. As can be seen the results indicate failure to reject the null hypothesis of equal means at the 5 percent significance level, which suggests convergence of the MCMC sampler.

Table 3: Chi-squared probabilities for equality of means using Geweke's Chi-squared test for each parameter chain

Aurocorrelation Taper	α_{qp}	αyp	β_{qy}	β_{qp}	χ	ψ_1	ψ_3
4 percent	0.18	0.62	0.67	0.34	0.21	0.18	0.59
8 percent	0.17	0.58	0.65	0.34	0.20	0.18	0.61
15 percent	0.16	0.60	0.59	0.32	0.17	0.20	0.60
Aurocorrelation Taper	ρ	$\det(\tilde{A})$	h_{22}	δ_1	δ_2	δ_3	δ_4
4 percent	0.76	0.26	0.57	0.14	0.21	0.57	0.84
8 percent	0.76	0.20	0.59	0.13	0.26	0.56	0.85
15 percent	0.71	0.19	0.57	0.08	0.23	0.48	0.85
Aurocorrelation Taper	$\delta 5$	ω_1	ω_2	ω_3	ω_4	ω_5	γ_1
4 percent	0.23	0.91	0.20	0.77	0.93	0.57	0.98
8 percent	0.34	0.93	0.25	0.82	0.94	0.66	0.98
15 percent	0.41	0.94	0.23	0.84	0.94	0.71	0.98
Aurocorrelation Taper	γ_2	γ_3	γ_4	γ_5			
4 percent	0.65	0.75	0.63	0.64			
8 percent	0.68	0.80	0.70	0.60			
15 percent	0.63	0.83	0.73	0.61			

E Results: Mixed Prior Distribution for Oil Supply Elasticity

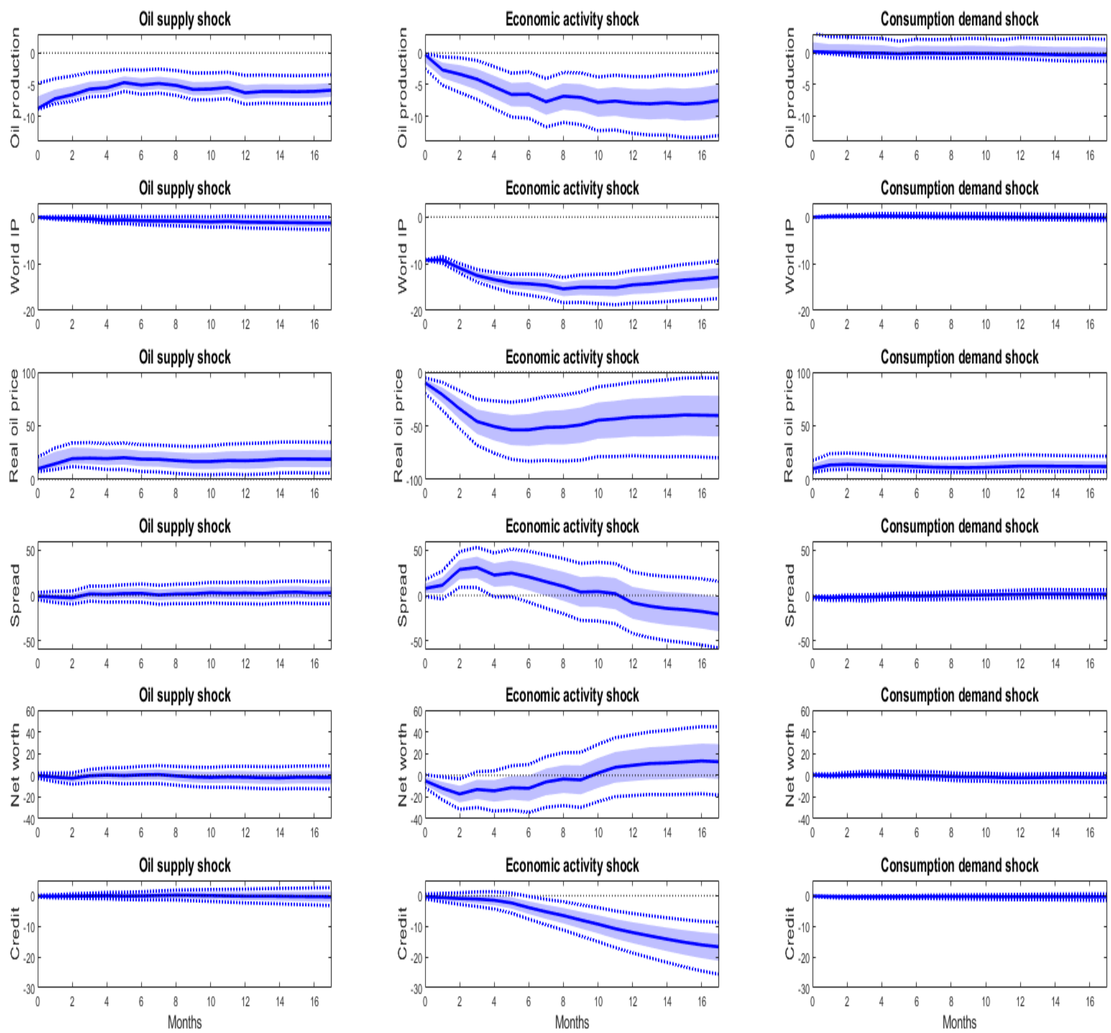

Figure 3: Cumulative response of selected variables to an oil supply, an economic activity, and an oil consumption demand shock. Dashed lines are the 95% posterior credible sets. Shaded areas are the 68% posterior credible sets. Estimation is based on a sample from January 1974 through December 2019. All responses are normalized to generate a 10% change in the real price of oil. The mixture distribution places a weight of 99 percent on a Uniform distribution over (0, 0.0258) and 1 percent on a truncated Student's t distribution with parameters location=0.1, scale=0.2, and degrees of freedom=3.

F Results: 1985+ Sample

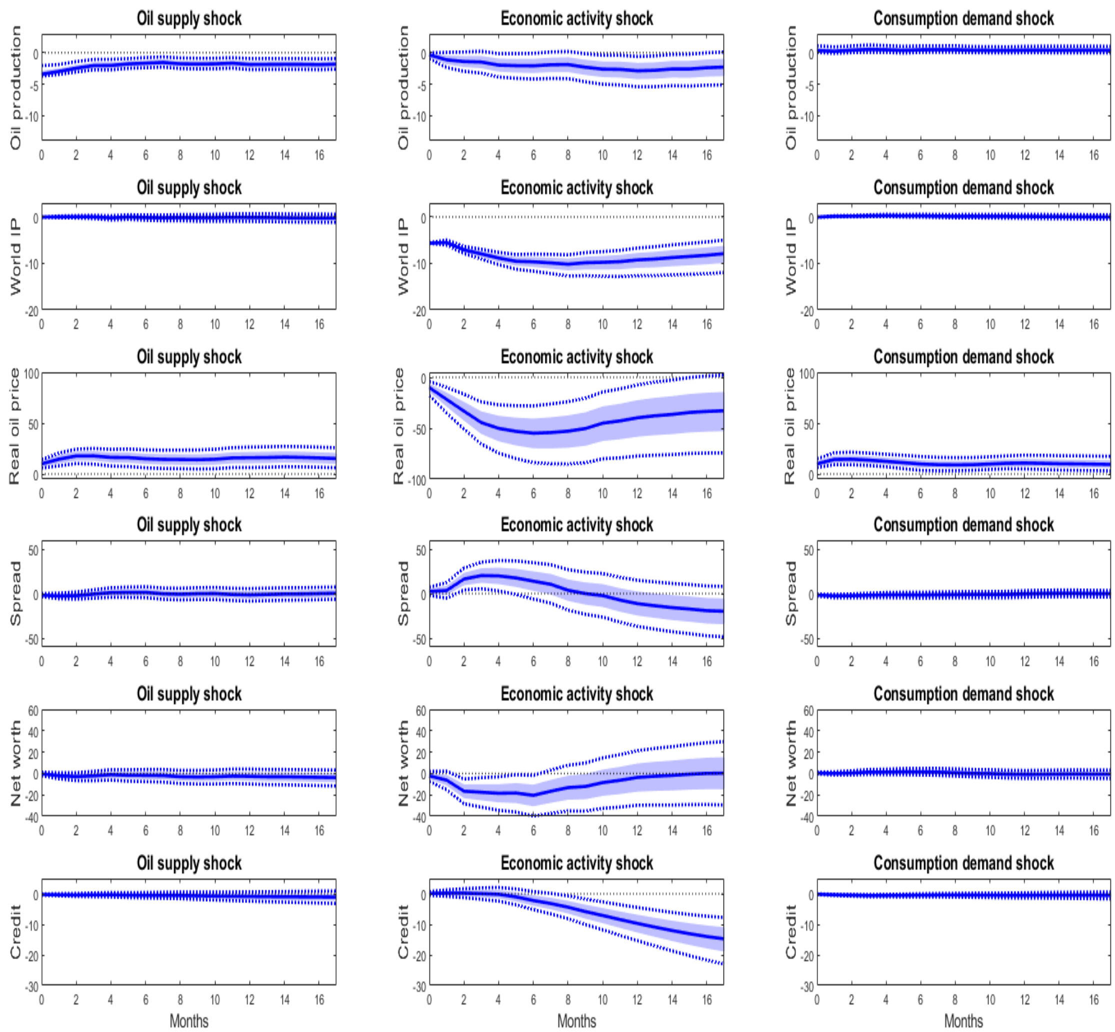

Figure 4: Cumulative response of selected variables to an oil supply, an economic activity, and an oil consumption demand shock. Dashed lines are the 95% posterior credible sets. Shaded areas are the 68% posterior credible sets. Estimation is based on a sample from January 1985 through December 2019. All responses are normalized to generate a 10% change in the real price of oil.

References

Baumeister, Christiane and James D. Hamilton (2019). "Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks." *American Economic Review*, 109(5), pp. 1873–1910. doi:10.1257/aer.20151569.